



Journal of Economics Education and Entrepreneurship

Vol. 7, No. 1, April 2026, pp. 92-103

<https://ppjp.ulm.ac.id/journals/index.php/jee/issue/view/984>

ISSN: 2746-5438 (Print) | 2745-729X (Online)



A Behavioral Finance Approach to Student Academic Performance: The Role of Screen Time and Sleep

Emmanuel Oyasor Imuede

Walter Sisulu University, South Africa

Article Info

Keywords:

Academic performance
Time allocation
Screen time
Sleep duration
Behavioral finance

ABSTRACT

This study examines how behavioral factors impact students' academic performance. Using Structural Equation Modeling (SEM), Bayesian regression, and Ordinary Least Squares (OLS), the research explores both direct and indirect effects of daily time allocation on exam outcomes. The analysis focuses on variables such as study hours, social media use, Netflix viewing, sleep duration, and constructs of productive versus leisure use of time. SEM results show that mental health, exercise frequency and sleep hours significantly enhance productive time use, which strongly predicts higher exam scores. Leisure activities like social media and Netflix have a moderate negative effect on academic performance. The Bayesian regression confirms these findings, with study hours showing a strong positive effect and social media and Netflix hours exhibiting strong negative impacts. Sleep hours have a moderate positive effect. The OLS model explains 71.4% of the variance in exam scores, identifying study hours/day and sleep as significant positive predictors, while social media and Netflix hours contribute negatively. These findings reflect behavioral finance principles, where time and cognitive resources are allocated under bounded rationality, emphasizing the cost of leisure screen time on academic outcomes.

This is an open access article under the CC-BY-SA 4.0



Corresponding Author:

Emmanuel Oyasor Imuede

Department of Accounting Science Walter Sisulu University

Department of Accounting Science Walter Sisulu University, Mthatha Eastern Cape, South Africa.

Email: emmanueloyasor12@gmail.com

Submitted 01 June 2025; Accepted 20 September 2025; Published 30 April 2026

How to cite: Imuede, E. O. (2026). A Behavioral Finance Approach to Student Academic Performance: The Role of Screen Time and Sleep. *Journal of Economics Education and Entrepreneurship*, 7(1), 92-103. <https://doi.org/10.20527/jee.v7i1.15505>

1. INTRODUCTION

The advent of smartphone technology has arguably demonstrated a lot of positive and negative effect in a person's daily life. Smart phone usage by different people of different categories especially students has brewed a lot of concerns about their academic performance. A common example is using smartphone throughout the house, including in bedtime. Excessive usage of smartphone especially during the bedtime can affect cognitive attitude and sleep quality because of exposure to blue light emanating from the screen, this intensity of light is calculated to be

Journal homepage: <https://ppjp.ulm.ac.id/journals/index.php/jee>

<https://doi.org/10.20527/jee.v7i1.15505>

Copyright © Authors, 2026, ISSN: 2746-5438 (Print) | 2745-729X (Online)

200 to 600 nits (cd/m^2) for most phones, if exposing eyes to this range is too much it can lead to dry eyes, blurry vision, headaches, difficulty focusing. Visual system plays a role in regulating the body's internal clock by detecting changes in light intensity, thereby maintaining the regular pattern of behavioral and physiological functions. In addition to its role in vision, light influences cognitive performance and brain activity through non-visual mechanisms. This relationship is partly shaped by animals' natural free-running circadian rhythms, which determine their sensitivity and responsiveness to light stimuli. This paper adopts the behavioral finance approach to explore how students make decisions under constraints and personal goals.

Financial behavior, as used in this study, refers to non-financial decisions influenced by individual habits and cognitive biases. It highlights the idea that people do not always behave rationally, particularly when managing their time and resources. Variables such as screen time and sleep are treated as behavioral inputs that reveal underlying decision-making patterns among students. This perspective aids in understanding and predicting how these factors directly affect academic performance. Douris and Jung (2023) note that poor sleep quality resulting from excessive screen time was linked to increased impulsivity and diminished cognitive function. These effects, in turn, impair students' ability to maintain healthy interpersonal relationships and achieve academic success.

The link between insufficient sleep and overall health is well-established, with prolonged sleep deprivation contributing to numerous physical and psychological health issues. Additionally, initiatives aimed at reducing smartphone usage and improving sleep patterns have been shown to enhance both well-being and academic success (Busch & McCarthy, 2021). Ratan et al. (2021) opined that factors such as smartphone use and sleep quality significantly shape social behavior and academic outcomes, as they influence how individuals engage socially and navigate interpersonal settings. A key contributor is the prevalent use of social networking platforms among university students. Although these platforms foster social interaction, their influence on academic performance and general well-being largely depends on the manner and extent of their use, as well as their impact on daily habits.

Overconfidence is a common cognitive bias where individuals overestimate their abilities, knowledge, or control, often leading to suboptimal decisions due to overlooked risks. While this concept has been widely applied in financial investment behavior, its relevance extends to non-financial domains as well. Within the context of this study, the overconfidence bias can help explain how students may misjudge their capacity to manage screen time and sleep without negatively affecting academic performance. This behavioral finance perspective suggests that students, like investors, may ignore the long-term consequences of short-term decisions, such as late-night device use or reduced sleep, under the illusion that their academic outcomes will remain unaffected. Understanding these behavioral patterns provides a useful lens for predicting how such biases can shape academic success or failure.

Furthermore, excessive use of social media platforms can lead to negative behavioral and psychological outcomes, including cyberbullying. During the COVID-19 pandemic, increased online activity was associated with a rise in cyberbullying incidents (Anwar, et al., 2022). Similarly, in workplace settings, social media-driven bullying has been shown to reduce engagement, with psychological well-being acting as a key mediating factor (Anwar et al., 2022). Applying a behavioral finance lens, such patterns of behavior highlight how emotional biases, and environmental pressures can impair rational decision-making and time management. Among students, these dynamics may not only disrupt sleep patterns but also degrade mental well-being and focus, ultimately impairing academic performance.

In the modern era of globalization, businesses often struggle to manage working capital optimally due to intense competition, uncertainty, and internal constraints Banerjee & Chauhan (2016). A similar pattern can be observed in student behavior, where the “working capital”

analogy reflects how students allocate limited personal resources like time, attention, and energy. Much like firms that fail to consistently follow optimal financial strategies, students may also deviate from ideal time-management practices due to behavioral biases, external pressures, or a lack of self-regulation. Through the behavioral finance lens, this perspective helps explain why students may overuse screen time or sacrifice sleep, ultimately impairing academic performance despite understanding the long-term consequences.

Although numerous studies have explored the impact of screen time and sleep on academic performance, they often overlook the behavioral mechanisms underlying students' decision-making processes. Much of the existing literature adopts a psychological or health-based perspective, focusing on correlations between digital device use, sleep deprivation, and learning outcomes. However, these studies seldom apply the behavioral finance framework, which emphasizes how individuals make suboptimal choices due to biases, limited self-control, or conflicting goals.

Traditional studies rarely consider how behavioral biases drive students to engage in excessive screen use or sacrifice sleep despite being aware of the potential academic consequences. This gap highlights a missed opportunity to explain why students consistently prioritize short-term gratification, such as social media or entertainment, over long-term academic success. Without incorporating behavioral models, current research lacks the tools to predict or modify such irrational patterns effectively. The novelty of this research is stemmed from integrating behavioral finance approach by making use of three different finance methodologies such as Structural Equation Modelling (SEM), Bayesian regression and Ordinary Least Squared (OLS) to analyze and predict the outcome of independent variable on students' academic performance. The study is divided into 5 sections: Section 2 presents the literature review; Section 3 discusses the methodology. Section 4 explains the results, interpretation and policy implication, while Section 5 provides the conclusion with recommendation.

Emerging technologies have significantly changed modern lifestyles. Students increasingly rely on smartphones for daily activities. Many of these gadgets are so important for fast dissemination of information, entertainments, and education. Thus, smartphones have significantly shaped how people interacting with the outside world knows as globalization. The quest to find relationship between screen time, quality sleep and their effect on students' academic performance has over a decade prompted many studies to be conducted in this area, driven by improved data availability, econometrics techniques, and policy relevance. However, some of the findings proponent that the increase in level of failure in our schools has significantly fueled the inquisitiveness of parents and the champions in educational sectors trying to know why students are performing below the average. Kheirinejad et al. (2023) found that exposure to blue light from smartphones negatively affects melatonin production, a hormone crucial for regulating sleep. This disruption can lead to increased time to fall asleep and reduced overall sleep duration which in is a function of present bias against academic performance. A study involving Moroccan medical students emphasized the extent of the issue, showing that more than 97% used blue-light-emitting devices before sleeping, with 35% reporting sleep difficulties.

The foundational premise of the Efficient Market Hypothesis (EMH), as articulated by Fama (1970) that all available information is fully reflected in decision-making processes. This assumes that individuals act rationally when processing information. However, real-life deviations from this rational behavior, particularly in everyday settings, education have called these assumptions into question and spurred the development of Behavioral Finance.

In the context of student academic performance, behavioral patterns such as excessive screen time, bedtime procrastination, and poor sleep hygiene demonstrate the same cognitive

and emotional biases that Behavioral Finance identifies in financial markets. Research by Kheirinejad et al. (2023), Gallego-Gómez et al. (2021) and Mao et al. (2022) highlights how smartphone use disrupts melatonin production, encourages procrastination, and fosters psychological dependence all of which impair cognitive functioning and concentration.

These behaviors mirror the irrational tendencies seen in financial decision-making, such as overconfidence, mental fatigue, and delayed reaction to information. Just as investors are not always the rational agents assumed by EMH, students, too, often act against their best academic interests due to behavioral biases shaped by technology use and sleep habits. This supports the broader Behavioral Finance argument: decision-making whether in markets or education is heavily influenced by psychological factors that traditional models overlook.

Kengatharan and Kengatharan (2014) outline two key decision-making frameworks under uncertainty: the Expected Utility Theory (EUT) and the Prospect Theory (PT). EUT is grounded in rational and normative decision-making, assuming individuals consistently choose options that maximize expected outcomes under risk. The theory struggles to explain paradoxical human behaviors such as the simultaneous appeal of both insurance and gambling which seem irrational under EUT assumptions. In contrast, Prospect Theory, as discussed by Ritter (2003), acknowledges the psychological dimensions of decision-making. It suggests that individuals evaluate outcomes based on perceived gains and losses rather than absolute levels of wealth. This model better captures real-world behavior, where decision-making is influenced by framing effects, loss aversion, and mental shortcuts.

Mbaluka et al. (2012) also emphasize that Prospect Theory has significantly deepened our understanding of investor behavior, especially in how people make financial choices aimed at wealth creation. When applied to the academic context, particularly within a Behavioral Finance framework, Prospect Theory provides valuable insights into how students make decisions about screen time, sleep, and study habits. Just as investors are influenced by biases and heuristics when managing wealth, students may also be guided by similar psychological factors when managing their time and academic responsibilities. For instance, the preference for immediate gratification (e.g., using smartphones late into the night) over long-term benefits (e.g., sufficient sleep for cognitive performance) mirrors the gain-loss framing central to Prospect Theory. This underscores the importance of considering behavioral biases in efforts to improve student academic outcomes.

2. METHOD

This paper aims to find a relationship between how screen time and sleep affect students' academic performance through the lens of behavioral finance approach (study in money decision), specifically, screen time usage and sleep behavior critically influence students' performance. The dataset, obtained from Kaggle – the largest and opened databased of Python community - is a survey dataset of 1000 students. The dataset includes information on the student age, gender, as well as number of hours per day utilized on study, social media, netflix, part-time jobs, and sleep. The data also contain response on attendance percentage, diet quality (fair, good poor), frequency of exercising (ranging from 0 to 6), parental education, internet quality, mental health rating, participation in extracurricular and examination scores.

Based on the theory of instant gratification (present bias) and self-control, the paper determined the ways in which students' attitudes influence decision and their longtime education goals. This is done by treating some specific or considered most influential independent variables such as study hours/day, social media hours, sleep hours, and Netflix hours. Then, exam scores are treated as a dependent variable.

The data are analyzed with three different statistical models such as Structural Equation Modeling (SEM), Bayesian regression, and Ordinary Least Squares (OLS) regression to

determine direct and indirect effects on the selected independent variables over the dependent variable. The p-value is set to less than 0.05 ($p < 0.05$) to determine how significant the selected independent variables can influence the outcome of the dependent variable. The data preprocessing phase was conducted using Python programming language within the Jupyter Notebook environment, which is part of the Anaconda distribution. This setup was chosen for its versatility and integrated libraries suited for data science tasks. The dataset used was sourced from Kaggle, and it was imported in .csv format for analysis.

This study employs a combination of SEM, Bayesian Regression, and OLS regression to examine the relationships among screen time, sleep duration, behavioral traits (e.g., present bias), and student academic performance. These methods were chosen to capture both direct and indirect effects, account for uncertainty, and verify robustness across different statistical paradigms. OLS is a classical linear regression method that estimates the relationship between a dependent variable and one or more independent variables by minimizing the sum of squared residuals. In this study, it provides a baseline estimation of how screen time and sleep affect academic performance.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i \quad (1)$$

Where: y_i = Academic performance of student (exam score) i ; x_{1i} = leisure (social media hour, Netflix); x_{2i} = productive (study per hour, sleep); β_0 = Intercept; β_1, β_2 = Coefficients for each predictor and ε_i = Error term.

Bayesian regression incorporates prior beliefs about model parameters and updates these beliefs using observed data, resulting in a posterior distribution. This is particularly useful for modeling uncertainty in behavioral decision-making variables such as present bias and procrastination. The Bayesian regression model is represented as:

$$Y_i \sim \mathcal{N}(x_i \beta, \sigma^2)$$

With:

- Prior: $\beta \sim \mathcal{N}(\mu_\beta, \Sigma_\beta)$
- Posterior: $p(\beta | y, x) \propto p(y | x, \beta) \cdot p(\beta)$

Where: Y = vector of academic performance; X = matrix of predictors (e.g., leisure, sleep, present bias); β = vector of coefficients; and σ^2 = error variance. Bayesian analysis is conducted using Markov Chain Monte Carlo (MCMC) techniques to sample posterior distributions.

The SEM is a multivariate statistical technique used to estimate complex relationships among observed and latent (unobserved) variables. It is particularly suited for this study to model direct and indirect effects (e.g., how screen time affects academic performance both directly and through sleep quality as a mediator). The general SEM model consists of:

- Measurement model:

$$X = \Lambda_x \xi + \delta$$

$$Y = \Lambda_y \eta + \epsilon$$

- Structural model:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where: ξ, η = latent exogenous and endogenous variables; x, y = observed variables; Λ_x, Λ_y = loading matrices; B = coefficient matrix for endogenous variables; Γ = coefficient matrix from exogenous to endogenous variables; δ, ϵ, ζ = error terms. The SEM is used to estimate the mediating role of sleep between screen time and academic performance, while also incorporating latent construction such as self-control or present bias.

3. RESULTS AND DISCUSSION

The study investigates the role of routine time allocation in shaping academic outcomes. Employing a mixed-methods approach that includes SEM, Bayesian - and OLS regression, the analysis explores the direct and indirect effects of daily habits such as study time, social media usage, Netflix viewing, and sleep duration on exam scores. These behavioural variables are further evaluated in terms of how they influence intermediary constructs like productive and leisure use of time, thereby shaping academic performance in nuanced ways.

The SEM analysis reveals that the pathway from behavioural routines to academic outcomes is significantly mediated by time-use patterns. Productive time use is strongly influenced by students' mental health ratings, frequency of exercise ($\beta = 0.167$, $p < 0.001$), and sleep hours. These factors collectively enhance the allocation of time to academically beneficial activities, leading to a very strong positive effect on exam performance ($\beta = 1.114$, $p < 0.001$). The leisure-related behaviours, primarily social media and Netflix consumption were associated with increased leisure time and poorer academic outcomes. Specifically, Netflix use positively predicts leisure time ($\beta = 0.358$, $p = 0.001$), which in turn shows a moderate but statistically significant negative effect on exam scores. These findings align with existing literature suggesting that behavioural inputs related to health and well-being are critical to educational attainment (Soto et al., 2020; Zhang et al., 2021).

Bayesian regression analyses reinforce these insights by offering probabilistic interpretations of behavioural predictors. The results demonstrate that study hours per day have a strong positive effect on exam scores, with a posterior mean of 12.66, indicating a very high degree of certainty. Social media hours display a strong negative effect (mean = -2.786), and Netflix hours show a moderately negative effect (mean = -2.229). Sleep hours, on the other hand, positively influence performance with a moderate effect (mean = 2.219). All HDIs exclude zero, confirming the statistical significance of these predictors. These Bayesian outcomes substantiate the theoretical premise that academic performance is closely linked to how students probabilistically allocate their time among competing activities (McElreath, 2020; Kizilcec et al., 2021).

The OLS regression model provides further corroboration of these relationships. With an R^2 of 0.714, the model explains over 71% of the variance in exam scores and produces a highly significant F-statistic ($p < 0.001$), suggesting a strong overall model fit. Study hours per day emerge as the most robust positive predictor ($\beta = 0.432$, $p < 0.001$), followed by sleep hours ($\beta = 0.188$, $p < 0.001$). Conversely, social media hours ($\beta = -0.071$, $p < 0.001$) and Netflix hours ($\beta = -0.046$, $p < 0.001$) negatively affect exam scores. These findings validate the earlier SEM and Bayesian results, affirming that while academic performance benefits from consistent study and adequate sleep, it is hampered by excessive engagement in screen-based leisure activities. This result underscores the concept of opportunity cost, a core economic principle, which posits that time allocated to non-productive endeavors diminishes the potential returns from academically valuable ones (Beattie et al., 2022).

From a behavioural economics standpoint, these patterns suggest that screen time operates similarly to a form of cognitive expenditure. Students allocate mental resources to different tasks based not solely on rational choice, but also influenced by habit, emotional state, and immediate gratification. Leisure screen time, in particular, draws from cognitive reserves and reduces the attention available for study. This mirrors economic models of resource scarcity, where time and attention are finite assets subject to trade-offs. The findings also resonate with concepts of bounded rationality and hyperbolic discounting, where individuals tend to overvalue short-term pleasure (e.g., binge-watching or scrolling social media) at the expense of long-term academic goals (Laibson, 2021; Loewenstein & O'Donoghue, 2022).

Table 1. SEM results

Predictor (lval)	Outcome (rval)	Estimate	Std. Err	z-value	p-value	Interpretation
study_hours_per_day	Productive_Use	1.000				Fixed reference path
mental_health_rating	Productive_Use	0.355	0.037	9.69	0.000	Strong positive effect
exercise_frequency	Productive_Use	0.167	0.037	4.45	0.000	Moderate positive effect
sleep_hours	Productive_Use	0.133	0.038	3.55	0.000	Small positive effect
Productive_Use	exam_score	1.114	0.065	17.11	0.000	Very strong positive effect
social_media_hours	Leisure_Use	1.000				Fixed reference path
netflix_hours	Leisure_Use	0.358	0.108	3.31	0.001	Moderate positive effect
Leisure_Use	exam_score	-0.395	0.126	-3.14	0.002	Moderate negative effect

Note: SEM results in Table 1 at p-values less than 0.05, denoted statistically significant relationships. This assumed that factors such as mental health, exercise, sleep, and leisure activities influence productive use and exam scores at the 5% significance level.

Significant Path Effects ($p < 0.05$)

Source: Author (2025)

Table 2. Bayesian regression summary

Predictor	Mean	SD	94% HDI		r hat	Effect
			Lower	Upper		
Study hours per day	12.663	0.310	12.090	13.244	1.00	Strong positive effect
Social media hours	-2.786	0.312	-3.353	-2.187	1.01	Strong negative effect
Netflix hours	-2.229	0.312	-2.847	-1.671	1.00	Moderate negative effect
Sleep hours	2.219	0.304	1.681	2.825	1.00	Moderate positive effect
Intercept	63.033	0.506	62.065	63.922	1.00	Baseline exam score estimate
Sigma	10.200	0.344	9.524	10.801	1.00	Residual noise estimate

Note: The Bayesian regression results in Table 2 show that all predictors have credible intervals (94% HDI) that exclude zero, show statistically significant effects. It is assumed that study hours, social media use, Netflix viewing, and sleep duration each have a meaningful impact on academic performance at the 94% confidence level.

Source: Author (2025)

Table 3. OLS Regression results

Predictor	Coefficient (β)	Std. Error	t-value	p-value	95% C.I.	Interpretation
Intercept	3.432	0.047	72.626	<0.001	(3.340, 3.525)	Baseline exam score
Study Hours/Day	0.432	0.009	45.799	<0.001	(0.413, 0.451)	Strong positive effect
Social Media Hours	-0.071	0.008	-8.887	<0.001	(-0.087, -0.055)	Significant negative effect
Sleep Hours	0.188	0.024	7.823	<0.001	(0.141, 0.235)	Moderate positive effect
Netflix Hours	-0.046	0.007	-7.075	<0.001	(-0.059, -0.033)	Moderate negative effect
Model summary						
R ²			0.714 (71.4%)			
P(F-stat)			< 0.001			
Durbin-Watson			1.871			

Note: 95% Confidence Interval (C.I.)

Source: Author (2025)

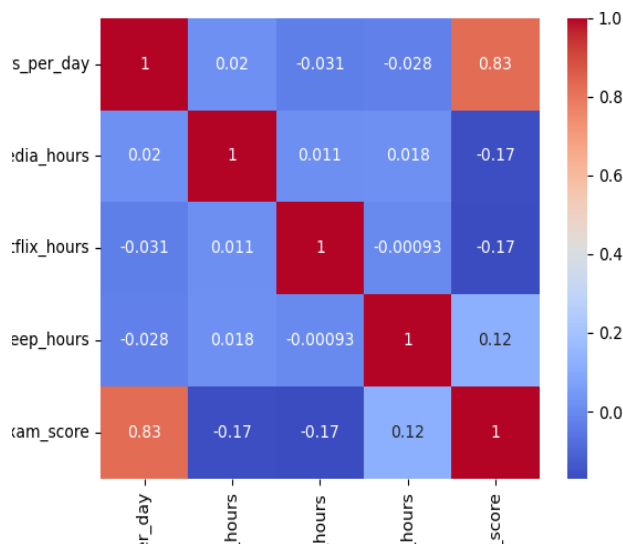


Figure 1. Correlation Matrix

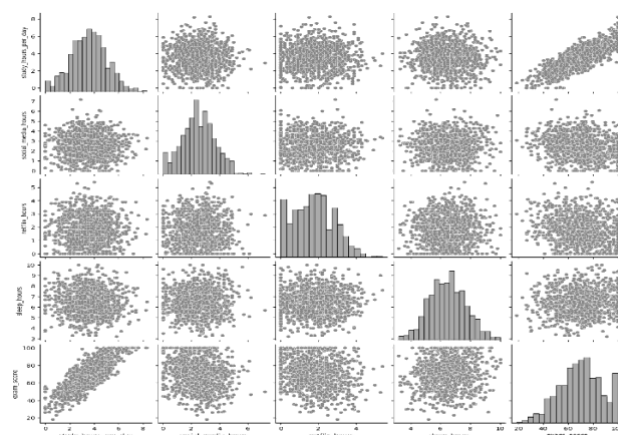


Figure 2. Pairwise plot between predictors and exam score

Sleep emerges as a crucial factor in this behavioural framework. Consistent with findings from sleep science and neuroeconomics, adequate sleep improves memory consolidation, decision-making, and emotional regulation (Walker, 2021). The data confirms that sleep positively predicts productive time use and exam scores across all three analytical models. Moreover, poor sleep quality, often caused by prolonged screen exposure, has been linked to increased impulsivity and diminished cognitive performance, further affecting students' ability to maintain focus and interpersonal relationships (Douris & Jung, 2023). In this regard, investing in sleep is akin to investing in human capital, yielding cognitive returns that enhance academic outcomes.

Mental health is another significant behavioural input that indirectly influences performance. The SEM results demonstrate that better mental health ratings strongly predict productive use of time, which in turn significantly boosts academic performance. This finding is supported by recent empirical research showing that students with better psychological well-being tend to exhibit higher levels of motivation, focus, and persistence in learning environments (Orben et al., 2020; Zhao et al., 2024). Incorporating mental health into behavioural models allows for a more holistic understanding of academic achievement, extending beyond traditional metrics like study time to include internal psychological resources that shape behaviour.

Taken together, the empirical evidence supports the adoption of behavioural frameworks in educational research and practice. By treating time use as an economic and psychological decision influenced by health, cognition, and digital environments, this study highlights actionable insights for improving academic performance. Behavioural interventions, such as digital literacy campaigns, mental health support, and time management programs, can help students make better choices under constraints of time and attention. As digital technologies continue to mediate educational experiences, grounding academic policies in behavioural science will be key to fostering student success in increasingly complex learning environments (Sunstein, 2022).

4. CONCLUSION

This study explored the behavioral factors influencing student academic performance, with a specific focus on screen time and sleep habits, through a behavioral finance lens. Using Structural Equation Modeling (SEM), Bayesian regression, and Ordinary Least Squares (OLS) analysis, the results consistently showed that study hours and sleep duration significantly enhance academic performance, while increased leisure screen time, particularly on social media and streaming platforms like Netflix, negatively impacts it. These findings reinforce the idea that students' daily behavioral patterns, especially how they allocate time across activities, are crucial determinants of their academic outcomes.

By integrating behavioral finance theories with educational psychology, this research demonstrates that seemingly routine such as time spent studying, sleeping, or consuming digital content measurable academic consequences. Productive behaviors like adequate rest and consistent study patterns were positively associated with higher exam scores, while excessive engagement with leisure screen time was linked to poorer performance. These patterns suggest that students may benefit from interventions that promote disciplined time management and self-regulation in the digital age.

Based on the empirical insights, educational policymakers and institutional leaders should develop evidence-based interventions that address both academic and behavioural determinants of performance. Firstly, institutions should implement digital wellness frameworks that encourage regulated screen use and promote awareness of the cognitive and academic costs associated with excessive leisure screen time. These could include in-app usage reminders, digital detox campaigns, and structured time-blocking schedules integrated into online learning platforms. Equally important is the institutionalization of sleep and mental health education within curricula, given the demonstrated links between these factors and academic success. Educational bodies should also consider adapting school schedules to accommodate adolescents' natural sleep cycles, an intervention supported by neuroscientific and behavioural evidence (Walker, 2021; Keles et al., 2020).

In parallel, academic support services should be expanded to include time management coaching and behavioural counselling. These services can help students understand how to balance their academic responsibilities with leisure activities in ways that optimize cognitive outcomes. Governments and ministries of education might also consider national-level campaigns to promote behavioural literacy in education. By framing time, attention, and rest as limited economic resources, these campaigns can help students make more informed and strategic decisions about their daily routines. Ultimately, creating a learning environment that accounts for behavioural dynamics not only enhances academic performance but also supports students' holistic development and long-term well-being (Orben et al., 2020; Zhao et al., 2024).

While the findings offer valuable insights, the study is not without limitations. First, the use of cross-sectional data restricts the ability to make causal inferences regarding the long-

term effects of behavioural factors on academic performance. Although SEM and Bayesian approaches provide robust analytical power, longitudinal or experimental studies would strengthen the evidence base. Second, self-reported measures of screen time, sleep, and mental health may introduce reporting biases, despite efforts to validate and triangulate the data. Future research should incorporate more objective behavioural tracking (e.g., screen time logs, wearable sleep monitors) to improve accuracy and minimize subjectivity (Kizilcec et al., 2021).

Additionally, while the current study focuses on university students, behavioural patterns may vary significantly across age groups, socioeconomic backgrounds, and cultural settings. Future studies could adopt a comparative approach, examining behavioural impacts in secondary schools, vocational education, or low-resource environments. There is also scope for investigating how emerging technologies like AI-based tutoring systems, gamified learning environments, and attention-monitoring tools influence students' time-use patterns and cognitive engagement. Expanding the research to explore interactions between behavioural traits and academic disciplines could further enrich our understanding of how behavioural economics can inform differentiated learning strategies in diverse educational ecosystems (Beattie et al., 2022; McElreath, 2020).

REFERENCES

- Anwar, A., Kee, D. M. H., & Ijaz, M. F. (2022). Social media bullying in the workplace and its impact on work engagement: A case of psychological well-being. *Information*, 13(4), 165. <https://doi.org/10.3390/info13040165>
- Banerjee, P., & Chauhan, G. S. (2016). Financial constraints and optimal working capital – evidence from an emerging market. *International Journal of Managerial Finance*, 12(3), 334–351. <https://doi.org/10.1108/IJMF-07-2016-0131>
- Beattie, G., Pearce, J., & Brown, L. (2022). Digital distraction and academic performance: A field study in higher education. *Journal of Educational Psychology*, 114(3), 524–538. <https://doi.org/10.1037/edu0000668>
- Birău, F. R. (2012). The Impact of Behavioral Finance on Stock Markets. *Annals of the Constantin Brâncuși University of Târgu Jiu, Economy Series*, 3, 45–50.
- Busch, P. A., & McCarthy, S. (2021). Antecedents and consequences of problematic smartphone use: A systematic literature review of an emerging research area. *Computers in Human Behavior*, 114, 106414. <https://doi.org/10.1016/j.chb.2020.106414>
- Douris, P. C., Hall, C. A., & Jung, M.-K. (2023). The relationship between academic success and sleep, stress, and quality of life during the first year of physical therapy school. *Journal of American College Health*, 71(8), 830–835. <https://doi.org/10.1080/07448481.2022.2075903>
- Douris, P., & Jung, M. K. (2023). Impact of screen exposure on sleep quality and behavioral regulation among university students. *Sleep Health*, 9(1), 23–30. <https://doi.org/10.1016/j.sleh.2022.10.002>
- Etri, N. S. (2021). Cyberbullying During COVID-19 Pandemic: Relation to Perceived Social Isolation. *University of Michigan*. <https://deepblue.lib.umich.edu/handle/2027.42/172219>
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417
- Gallego-Gómez, J. I., et al. (2021). Relationship between sleep habits and academic performance in university nursing students. *BMC Nursing*, 20(1), 1–9. <https://doi.org/10.1186/s12912-021-00635-x>

- Jniene, A., et al. (2019). Perception of sleep disturbances due to bedtime mobile phone use and its correlates among medical students: A cross-sectional survey. *Pan African Medical Journal*, 33, 224. <https://doi.org/10.11604/pamj.2019.33.224.17834>
- Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.
- Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, 25(1), 79–93. <https://doi.org/10.1080/02673843.2019.1590851>
- Kengatharan, L., & Kengatharan, N. (2014). The influence of behavioral factors in making investment decisions and performance: Study on investors of Colombo Stock Exchange, Sri Lanka. *Asian Journal of Finance & Accounting*, 6(1), 1–13. <https://doi.org/10.5296/ajfa.v6i1.4893>
- Kheirinejad, M., et al. (2023). Leave your smartphone out of bed: Quantitative analysis of smartphone use effect on sleep quality. Retrieved from <https://www.researchgate.net/publication/365257943>
- Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2021). Recommending self-regulation strategies does not improve academic performance in online courses. *Computers & Education*, 172, 104265. <https://doi.org/10.1016/j.compedu.2021.104265>
- Laibson, D. (2021). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2), 443–477. <https://doi.org/10.1093/qje/112.2.443>
- Loewenstein, G., & O'Donoghue, T. (2022). Behavioral economics and public policy: A pragmatic perspective. *Journal of Economic Perspectives*, 36(1), 189–210. <https://doi.org/10.1257/jep.36.1.189>
- Mao, Y., et al. (2022). Mediating effect of sleep quality on the relationship between electronic screen media use and academic performance among college students. *Sleep Health*, 8(1), 1–7. <https://doi.org/10.1016/j.sleh.2021.08.004>
- Mbaluka, P., Muthama, C., & Kalunda, E. (2012). Prospect theory: Test on framing and loss aversion effects on investors' decision-making process at Nairobi Securities Exchange, Kenya. *Research Journal of Finance and Accounting*, 3(9), 31–40.
- McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* (2nd ed.). CRC Press.
- Moustakbal, A. E., Elhassani, A., & Khouili, K. (2022). Relationship between mobile phone use and sleep quality among adolescents in the Settat region of Morocco. *Pan African Medical Journal*, 43, 140. <https://doi.org/10.11604/pamj.2022.43.140.33561>
- Orben, A., Dienlin, T., & Przybylski, A. K. (2020). Social media's impact on adolescent mental health: A U.K. longitudinal study. *Nature Human Behaviour*, 4(3), 351–358. <https://doi.org/10.1038/s41562-020-0819-1>
- Ragupathi, D., et al. (2020). Relations of bedtime mobile phone use to cognitive functioning, academic performance, and sleep quality in undergraduate students. *International Journal of Environmental Research and Public Health*, 17(19), 7131. <https://doi.org/10.3390/ijerph17197131>
- Ratan, R. A., Beyens, I., & Valkenburg, P. M. (2021). Relationships between social media use, sleep quality, and academic performance: A study among university students. *Computers in Human Behavior*, 114, 106527. <https://doi.org/10.1016/j.chb.2020.106527>
- Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin Finance Journal*, 11(4), 429–437. [https://doi.org/10.1016/S0927-538X\(03\)00048-9](https://doi.org/10.1016/S0927-538X(03)00048-9)

-
- Soto, C. J., John, O. P., Gosling, S. D., & Potter, J. (2020). Age differences in personality traits from 10 to 65. *Journal of Personality and Social Psychology*, 100(2), 330–348. <https://doi.org/10.1037/a0021717>
- Sunstein, C. R. (2022). *Sludge: What Stops Us from Getting Things Done and What to Do About It*. MIT Press.
- Walker, M. P. (2021). *Why We Sleep: Unlocking the Power of Sleep and Dreams*. Penguin Books.
- Yousfi, M., Dkhil, M. A., & El Khorassani, M. (2023). The effect of reducing blue light on sleep quality of medical students: A quasi-experimental study. *Chronobiology International*, 40(4), 419–427. <https://doi.org/10.1080/07420528.2023.2173606>
- Zhang, L., Wang, Y., Yang, J., & Chen, Y. (2021). Smartphone use and academic performance: A meta-analysis. *Educational Psychology Review*, 33, 1047–1070. <https://doi.org/10.1007/s10648-020-09548-z>
- Zhao, H., He, J., & Su, Y. (2024). Mental health and academic achievement: Mediation by time management among university students. *Higher Education Research & Development*. <https://doi.org/10.1080/07294360.2024.2304209>