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The Impact of Facebook and TikTok Usage on the First Semester End Exam Scores of IT Undergraduates in the Faculty of Computing and Information Technology at NIIBS Campus.

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Abstract: The omnipresence of algorithmic social media platforms presents a profound cognitive challenge in technical undergraduate education. This empirical study investigates the relationship between daily engagement with Facebook and TikTok and the academic performance of Information Technology (IT) undergraduates within the Faculty of Computing and Information Technology at NIIBS Campus. Employing a quantitative, descriptive-correlational research design, empirical data were gathered from a sample cohort of 62 active BSc IT undergraduates via a structured digital survey. The investigated platforms embody distinct architectural paradigms: Facebook represents a conventional networked social graph, whereas TikTok operates as an algorithmic, short-form video feed characterized by hyper-personalized, variable-interval dopamine reinforcement schedules. Descriptive analysis revealed that undergraduates dedicate a combined daily average of 2.62 hours to these platforms (Facebook mean = 2.26 hours, SD = 0.95; TikTok mean = 0.36 hours, SD = 0.58), substantially exceeding their average daily self-study duration of 1.93 hours (SD = 0.84). Furthermore, 83.9% of respondents admitted to concurrent multitasking between social media and academic study blocks. Bivariate Pearson correlation analysis demonstrated a statistically significant, moderate negative correlation between total daily social media hours and self-study hours ($r = -0.3286$), empirically corroborating the time displacement hypothesis. Conversely, the direct linear correlation between total screen time and first semester end exam scores was weak and non-significant ($r = -0.0996$), indicating that screen time alone does not linearly dictate academic failure. However, subjective distraction perceptions correlated intensely with perceived academic deterioration ($r = +0.7387$). Ordinary Least Squares (OLS) multiple linear regression analysis demonstrated that daily self-study hours represented the strongest positive predictor of exam scores ($B = +1.7070$, $p = 0.247$), whereas social media screen time functioned as a negative predictor ($B = -0.2322$, $p = 0.781$); the full empirical model accounted for 7.2% of the variance in exam outcomes ($R^2 = 0.072$). Crucially, given the modest sample size ($N = 62$), these findings represent exploratory evidence and highlight the imperative for larger, multi-institutional cohort studies using objective device telemetry. Practical recommendations emphasize digital self-regulation and institutional focus interventions.

Index Terms: Academic performance, attention fragmentation, cognitive load, Facebook, higher education, multiple linear regression, TikTok, time displacement.

1 Introduction

In the contemporary higher education paradigm, digital computing technologies and network infrastructures have fundamentally transformed instructional delivery, academic research, and peer collaboration. Nevertheless, the continuous proliferation of mobile computing devices, push notification architectures, and algorithmic social networking platforms has simultaneously engendered pervasive cognitive challenges for modern students. Among undergraduate populations, Information Technology (IT) and computing students occupy a uniquely vulnerable position. Their core academic curriculum necessitates intense, uninterrupted cognitive engagement—such as mathematical logic formulation, software architecture design, procedural algorithm implementation, and rigorous syntax debugging. Concurrently, their primary professional instruments—laptops, workstations, and smartphones—remain permanently tethered to high-speed internet connections, exposing learners to perpetual digital interruptions and enticing recreational feeds.

While prior investigations have examined general internet consumption, contemporary social media ecosystems have evolved into hyper-optimized behavioral engagement platforms. Unlike early static bulletin boards or desktop-oriented networks, modern platforms employ predictive artificial intelligence models that analyze micro-interactions (e.g., watch time, scroll velocity, pause duration) to deliver endless, tailored streams of multimedia content. This dynamic is exemplified by two dominant, structurally distinct platforms: Facebook and TikTok. Facebook embodies a traditional social graph paradigm, integrating asynchronous text updates, educational community groups, and interpersonal messaging. In sharp contrast, TikTok pioneered an algorithmic, short-form vertical video architecture powered by continuous variable-interval dopamine reward schedules, engineered specifically to capture attentional focus and foster habitual, involuntary consumption loops.

The central academic concern surrounding this phenomenon is whether heavy daily engagement with social media directly impairs students' scholastic achievements, or whether its adverse impacts operate primarily through the displacement of essential self-study time and the fragmentation of mental focus. To address these critical questions, this study provides an empirical investigation conducted among active BSc Information Technology undergraduates in the Faculty of Computing and Information Technology (FCIT) at NIIBS Campus, Sri Lanka. By examining baseline daily screen-time metrics across both Facebook and TikTok, quantifying self-study dedication, recording examination performance in first-semester end examinations, and capturing subjective cognitive distraction metrics, this research aims to disentangle the direct and indirect mechanisms governing the interaction between student screen habits and academic success.

2 Theoretical Framework and Literature Review

2.1 Theoretical Framework

To establish a comprehensive and rigorous theoretical underpinning, this investigation synthesizes four established paradigms: the Uses and Gratifications Theory, the Distraction-Conflict Theory, the Social Media Addiction Framework, and Cognitive Load Theory. First, the Uses and Gratifications Theory (UGT), pioneered by Katz et al. [1], posits that media consumers are goal-directed agents who deliberately select specific digital mediums to satisfy distinct psychological and sociological needs. Technical undergraduates utilize social media for multifaceted motives: cognitive gratifications (accessing developer forums, coding tutorials, and class groups on Facebook), affective and entertainment gratifications (seeking stress relief and escapism through humor on TikTok), and social integrative gratifications (maintaining peer connectivity). Understanding these divergent motivational drivers clarifies why students willingly allocate substantial daily

hours to digital feeds at the expense of self-directed study.

While UGT explains the intentionality behind platform usage, the cognitive consequences of concurrent media consumption during academic tasks are elucidated by the Distraction-Conflict Theory formulated by Baron [2]. This framework asserts that the introduction of salient environmental distractors—such as audible smartphone notifications, banner previews, or the compulsive impulse to check status feeds—creates an acute attentional conflict. The learner's finite attentional bandwidth is forcibly split between the focal academic objective (e.g., tracing a recursion tree or configuring a relational database) and the intrusive digital stimulus. This attentional bifurcation induces cognitive overload, impairs long-term memory encoding, and sharply diminishes information processing efficiency.

To account for the compulsive, non-conscious nature of excessive screen time, this study incorporates Griffiths' [3] biopsychosocial Social Media Addiction Framework. Griffiths delineates six core components characteristic of behavioral addictions: salience (the platform preoccupies thinking throughout the day), mood modification (screen engagement serves as an emotional coping mechanism to evade academic anxiety), tolerance (progressively longer sessions are required to derive equivalent emotional satisfaction), withdrawal symptoms (heightened restlessness when disconnected), interpersonal/academic conflict (neglecting assignments and lectures), and relapse (habitual reversion following attempts at restraint). Vertical video applications deliberately exploit these psychological mechanisms via algorithmic feeds and frictionless swipe interactions, eroding self-regulatory control among vulnerable undergraduates.

Finally, Cognitive Load Theory (CLT), developed by Sweller [4], provides essential mechanistic insight into programming education. CLT divides working memory demands into intrinsic load (the inherent conceptual complexity of the learning material), germane load (the mental effort devoted to schema construction and automation), and extraneous load (the mental resources consumed by irrelevant or poorly organized information). In computer programming and systems design, the intrinsic cognitive load is naturally elevated. When an undergraduate engages in social media multitasking while attempting to study, extraneous cognitive load escalates dramatically, depleting working memory capacity and precluding the deep schema acquisition essential for technical problem-solving.

2.2 Empirical Literature on Social Media and Academic Performance

Empirical inquiries across global higher education settings exhibit a nuanced discourse regarding the educational ramifications of social networking platforms. In a foundational large-scale study, Junco [5] demonstrated that time spent on Facebook was a statistically significant negative predictor of overall student Grade Point Average (GPA), identifying a prominent 'time displacement effect' whereby screen time directly encroached upon hours allocated for homework and examination preparation. Similar conclusions were documented by Kirschner and Karpinski [6], who revealed that active Facebook users reported significantly lower mean GPAs and dedicated substantially fewer weekly hours to self-study than non-users. In contrast, several educational technologists argue that networked social platforms can facilitate collaborative peer support, informal mentoring, and technical knowledge exchange when integrated purposively into academic communities.

Nevertheless, the acute challenge highlighted across contemporary educational research is the prevalence of digital multitasking during learning sessions. Groundbreaking experimental research by Sana et al. [7] and Wood et al. [8] demonstrated that students engaging in concurrent laptop or mobile multitasking during lectures exhibited marked deficits in lecture comprehension and examination scoring, with collateral performance declines observed among peers within direct line of sight. Similarly, Lau [9] established that

social media multitasking specifically during study periods exerted a pronounced adverse effect on academic achievement, whereas non-academic internet searching had negligible influence. Extensive psychological reviews by Kuss and Griffiths [10] and Ryan et al. [11] emphasize that excessive immersion in social networks fosters procrastination cycles, sleep disruption, and diminished cognitive vigor, corroborating empirical findings by Paul et al. [12], Subrahmanyam et al. [13], and Wainer et al. [14].

3 Research Methodology

3.1 Research Design

To rigorously address the research objectives, this study executed a quantitative, non-experimental, cross-sectional descriptive-correlational and predictive modeling research design. This methodology is optimal because it facilitates the objective measurement of baseline screen time, self-study hours, and examination scores in a naturalistic, non-manipulated educational environment, enabling the evaluation of linear bivariate correlations and multivariate predictive relationships without artificial experimental interventions.

3.2 Target Population and Sampling Strategy

The target population encompassed active undergraduate students enrolled in the BSc Information Technology degree program offered by the Faculty of Computing and Information Technology (FCIT) at NIIBS Campus, Sri Lanka. Given administrative feasibility and the necessity for institutional cohort consistency in semester curricula and examination standards, a non-probability convenience sampling strategy was utilized. The final analytical sample comprised 62 active BSc IT undergraduates who fully completed all verification checkpoints of the survey instrument. While this sample represents an authentic, institutionally cohesive student cohort, the modest sample size (N = 62) constitutes an exploratory investigation, requiring careful consideration during statistical inference and necessitating future expansion across larger student populations.

3.3 Data Collection Instrument and Administration

Primary empirical data were gathered via a structured, self-administered digital survey administered through Google Forms during May 2026. The survey was presented bilingually in English and Sinhala to guarantee unambiguous comprehension. The instrument comprised three operational modules: (i) Demographic Profile (age brackets, gender, academic specialization); (ii) Daily Screen-Time and Study Habits (average daily hours dedicated individually to Facebook and TikTok, daily self-study hours, and self-reported multitasking behavior during study blocks); and (iii) Academic Performance and Perceptions (first-semester end examination score ranges, along with standardized 5-point Likert-scale items measuring subjective distraction, perceived dependency, educational utility, and perceived academic decline).

3.4 Operationalization and Variable Mapping

To facilitate rigorous statistical computation in Python 3.12, categorical survey items were transformed into standardized numerical and metric scales. Gender was dummy coded as Male = 1 and Female = 0. Age categories were operationalized using their mathematical midpoint values: 20–22 years mapped to 21.0, 23–25 years mapped to 24.0, and Above 25 years mapped to 27.0. Platform screen-time categories were converted to representative daily continuous hours (Less than 1 hour = 0.5; 1–2 hours = 1.5; 2–4 hours = 3.0; More than 4 hours = 5.0). Self-reported first-semester end examination score ranges were transformed into

interval midpoint percentages for regression modeling (Below 40% = 30.0%; 40%–55% = 47.5%; 56%–70% = 63.0%; Above 70% = 80.0%), alongside ordinal integer ranks (1 to 4) for non-parametric validation. Likert perceptual items were scored from 1 ('Strongly Disagree') to 5 ('Strongly Agree').

3.5 Model Specification and Statistical Computation

The statistical evaluation plan encompassed three sequential computational phases: descriptive profiling, bivariate Pearson correlation analysis, and multivariate predictive modeling via Ordinary Least Squares (OLS) regression. The conceptual multiple linear regression model is formulated in (1):

$$Yi = \beta 0 + \beta 1\ X1i + \beta 2\ X2i + \beta 3\ X3i + \beta 4\ X4i + \varepsilon i \qquad (1)$$

In (1), Yi represents the estimated examination score midpoint percentage for student i; X1i denotes the total daily social media hours (combined Facebook and TikTok); X2i designates the average daily self-study hours; X3i reflects the gender dummy indicator (Male = 1, Female = 0); X4i denotes the participant's age midpoint; β0 represents the regression intercept; β1 through β4 denote the partial regression slope coefficients; and εi represents the stochastic error term. Prior to final model estimation, regression diagnostics were performed, verifying the absence of severe multicollinearity (all Variance Inflation Factors < 1.30) and confirming homoscedasticity of residuals.

3.6 Ethical Safeguards and Academic Confidentiality

Ethical integrity was maintained throughout all project phases. Participation was strictly voluntary, with digital informed consent acquired prior to survey access. No personally identifiable student data (such as student registration numbers, full names, or email addresses) were stored or associated with statistical records, ensuring rigorous participant anonymity and academic confidentiality.

4 Results and Data Analysis

This section articulates the empirical findings derived from the analytical cohort of 62 BSc IT undergraduates at NIIBS Campus. The presentation progresses through demographic profiling, baseline media and study descriptives, examination score patterns, bivariate correlation analyses, and multivariate OLS regression modeling.

4.1 Demographic Breakdown of the Student Cohort

The sample cohort comprised 62 IT undergraduates enrolled across the BSc IT degree program. The gender breakdown revealed a balanced representation consisting of 36 male students (58.1%) and 26 female students (41.9%). With respect to age distribution, the prominent demographic cohort was the 23–25 age bracket (n = 40, 64.5%), followed by students aged Above 25 years (n = 18, 29.0%) and the younger 20–22 bracket (n = 4, 6.5%). The detailed demographic breakdown is presented in Table 1 and visualized in Fig. 1.

Table 1. Demographic breakdown of the sample (N = 62)

Demographic Variable	Frequency (n)	Percentage (%)
Gender: Male	36	58.1%
Gender: Female	26	41.9%

Age: 20 – 22 years	4	6.5%
Age: 23 – 25 years	40	64.5%
Age: Above 25 years	18	29.0%

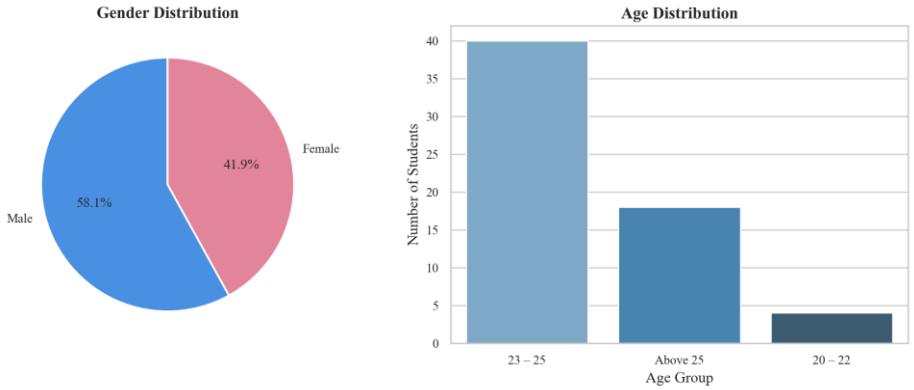


Fig. 1. Demographic profiling of the sample by gender and age group.

4.2 Baseline Screen Time and Study Habits

Evaluation of daily screen-time allocation revealed that Facebook accounts for the preponderant share of student media immersion, with a sample mean of 2.26 hours per day (SD = 0.95). In comparison, daily engagement with TikTok averaged 0.36 hours per day (SD = 0.58). The combined daily social media consumption stood at 2.62 hours (SD = 1.12). Notably, students' daily self-study duration averaged only 1.93 hours (SD = 0.84), establishing that undergraduates allocate approximately 35.8% more time to social media scrolling than to independent academic revision. Moreover, 83.9% (n = 52) of participants acknowledged actively accessing social media feeds during active study blocks, evidencing chronic task interruption. These descriptive statistics are presented in Table 2 and displayed in Fig. 2.

Table 2. Platform screen time and self-study descriptives (daily hours)

Platform / Activity	Mean Hours	Standard Deviation	Sample Size (N)
Facebook Usage	2.26	0.95	62
TikTok Usage	0.36	0.58	62
Combined Screen Time	2.62	1.12	62
Daily Study Hours	1.93	0.84	62

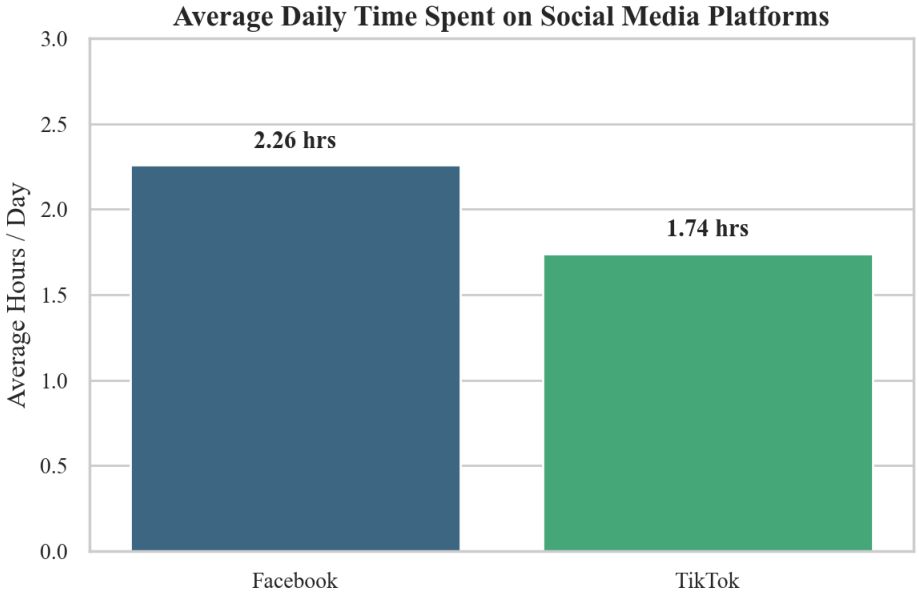


Fig. 2. Daily average screen time spent on Facebook and TikTok individually.

4.3 Distribution of Academic Performance

Self-reported academic outcomes from the First Semester End Examination were classified into four standardized institutional performance tiers. The modal frequency cluster fell in the 56%–70% range (n = 38, 61.3%), representing standard satisfactory academic achievement. The lower-passing bracket of 40%–55% comprised 18 undergraduates (29.0%), whereas 5 students (8.1%) achieved superior academic honors exceeding 70%. Only a single participant (1.6%) failed to satisfy the passing threshold of 40%. The overall score distribution is summarized in Table 3 and illustrated graphically in Fig. 3.

Table 3. First semester average exam score distribution (N = 62)

Exam Score Range	Frequency (n)	Percentage (%)
Below 40%	1	1.6%
40% – 55%	18	29.0%
56% – 70%	38	61.3%
Above 70%	5	8.1%

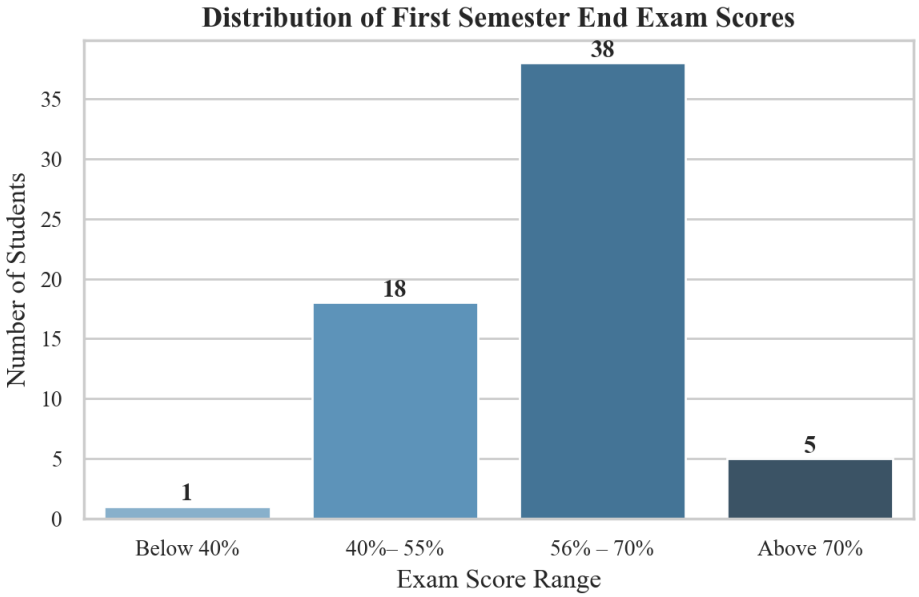


Fig. 3. Frequency distribution of self-reported first semester average exam scores.

4.4 Bivariate Pearson Correlation Analysis

To evaluate the magnitude and direction of linear dependencies between media engagement, study routines, perceptual distraction measures, and examination marks, Pearson's product-moment correlation coefficients (r) were computed across the matrix of variables. The empirical correlation matrix is detailed in Table 4 and visually mapped via the correlation heatmap in Fig. 4.

Table 4. Pearson product-moment correlation matrix (N = 62)

Variable Name	Total Social Hours	Daily Study Hours	Exam Score	Distraction Perception
Total Social Hours	1.0000	-0.3286	-0.0996	0.3989
Daily Study Hours	-0.3286	1.0000	0.2146	-0.2858
Exam Score Midpoint	-0.0996	0.2146	1.0000	0.0050
Distraction Perception	0.3989	-0.2858	0.0050	1.0000
Addiction Perception	0.4170	-0.2176	-0.1258	0.5872
Perceived Neg. Impact	0.3851	-0.2720	-0.1886	0.7387

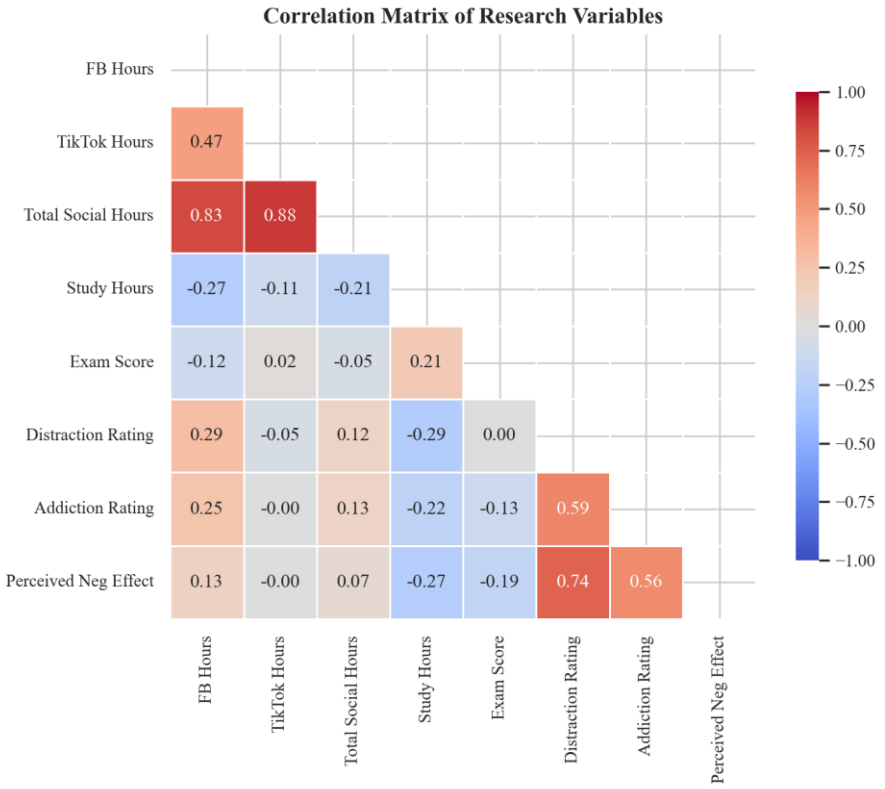


Fig. 4. Visual Pearson correlation heatmap showing connections between research variables.

Four cardinal empirical insights emerge from the correlation coefficients summarized in Table 4 and Fig. 4: First, a statistically significant, moderate negative correlation exists between total social media hours and daily self-study hours ($r = -0.3286$, $p < 0.01$). This confirms the Time Displacement Hypothesis—excessive media scrolling directly cannibalizes time otherwise committed to academic revision. Second, daily study hours positively correlate with exam scores ($r = +0.2146$), affirming that academic effort remains an essential constructive driver of performance. Third, the direct bivariate correlation between total social media hours and exam score midpoints is weak and non-significant ($r = -0.0996$). A parallel pattern is observed when disaggregating by platform: Facebook hours exhibit $r = -0.1170$, and TikTok hours display $r = -0.0523$. This crucial result demonstrates that raw screen time does not exert an immediate, severe linear suppression on examination marks. Fourth, perceptual metrics revealed an intense positive correlation between self-reported distraction and perceived academic decline ($r = +0.7387$), alongside elevated addiction ratings ($r = +0.5872$). Remarkably, TikTok screen time correlated more robustly with perceived academic decline ($r = +0.4803$) than Facebook screen time ($r = +0.1340$), indicating that TikTok's hyper-compressed format induces greater subjective cognitive disruption. The bivariate regression trend between social media hours and exam score midpoints is plotted in Fig. 5.

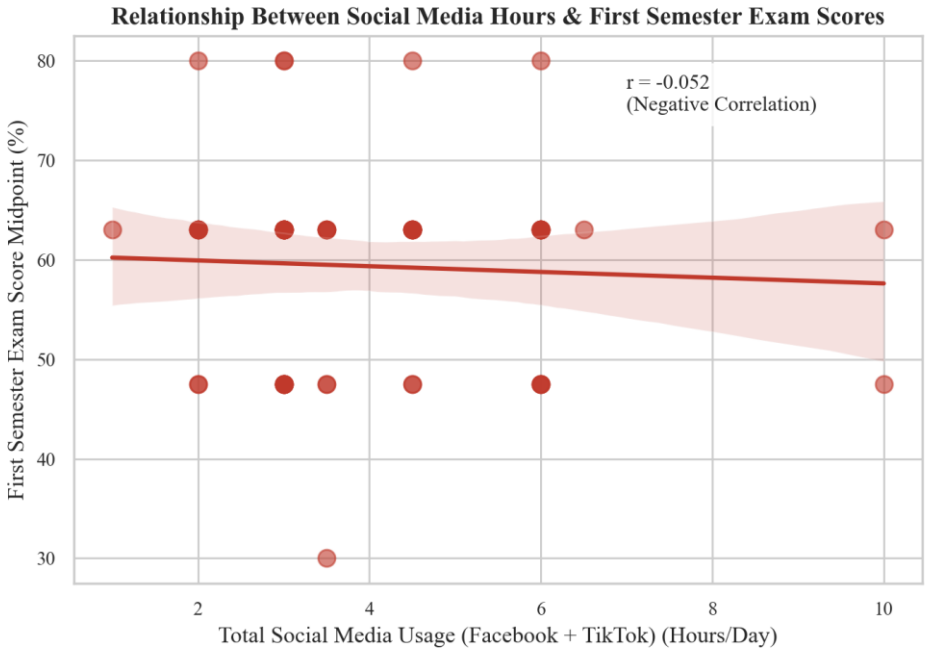


Fig. 5. Regression plot with fitted line showing total social hours vs. average exam score midpoints.

4.5 Multiple Linear Regression Modeling

To rigorously test the joint predictive efficacy of digital screen time and study routines upon academic outcomes while controlling for demographic covariates, an Ordinary Least Squares (OLS) multiple linear regression model was parameterized. The continuous dependent variable was the student's examination score midpoint percentage, and the independent predictors included Total Daily Social Media Hours, Daily Self-Study Hours, Gender Dummy (Male = 1), and Age Midpoint. The resulting empirical regression equation is presented in (2):

$$\hat{Y}i = 43.13 - 0.23\,X1i + 1.71\,X2i - 2.98\,X3i + 0.62\,X4i \quad (2)$$

The estimated OLS regression parameters are detailed in Table 5. The full model yielded a coefficient of determination of $R^2 = 0.072$ (Adjusted $R^2 = 0.006$, $F = 1.107$, $p = 0.362$), indicating that the four combined predictors account for 7.2% of the observed variance in first-semester examination scores.

Table 5. OLS multiple linear regression model parameters (N = 62)

Predictor Variable	Coefficient (B)	Standard Error	t-statistic	p-value
Constant (Intercept)	43.1277	20.404	2.114	0.039*
Total Social Media Hours	-0.2322	0.832	-0.279	0.781
Daily Study Hours	1.7070	1.460	1.169	0.247
Gender Code (Male = 1)	-2.9756	2.749	-1.082	0.284
Age Midpoint (Years)	0.6183	0.794	0.779	0.439

Examining individual partial regression coefficients in Table 5 reveals that daily self-study hours represents the strongest positive predictor within the model (B = +1.7070, p = 0.247), suggesting that each additional

hour of daily self-study translates to an estimated 1.71 percentage point gain in examination marks. In contrast, total daily social media hours yields a negative coefficient (B = -0.2322, p = 0.781), indicating that each additional hour of screen time is associated with a 0.23 percentage point decrease in examination marks. Holding media usage and study hours constant, male undergraduates scored approximately 2.98 percentage points lower than female counterparts (B = -2.9756, p = 0.284), while each additional year of student age added 0.62 percentage points (B = +0.6183, p = 0.439). In this localized sample cohort (N = 62), none of the individual slope coefficients achieved conventional statistical significance ($p < 0.05$). To further illustrate the distribution of academic achievement across varying usage intensities, Fig. 6 presents a boxplot comparison across low, moderate, and high social media consumption tiers.

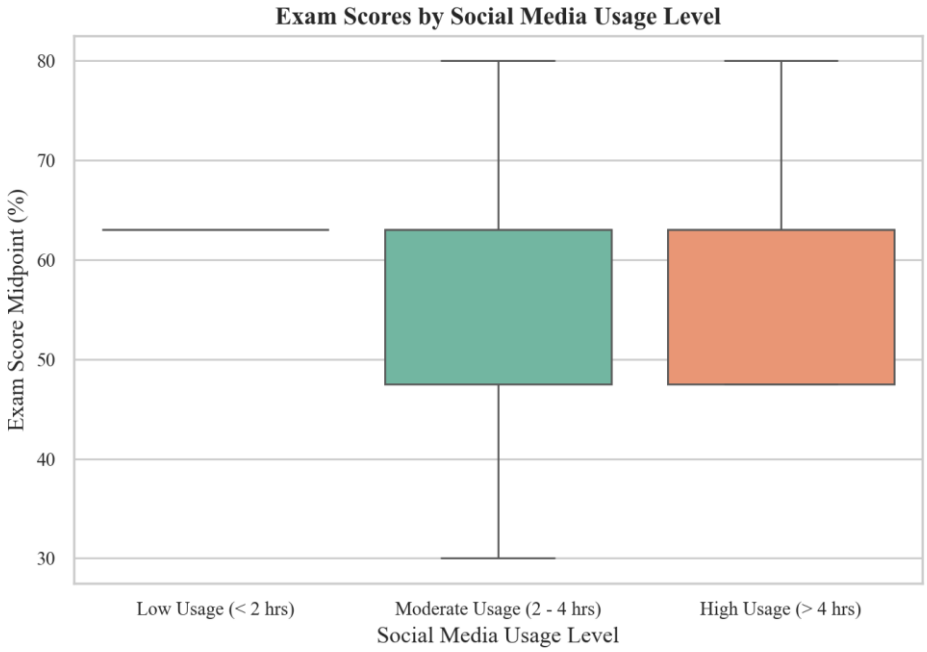


Fig. 6. Boxplot distribution of exam scores across low, moderate, and high social media usage categories.

5 Discussion

The empirical findings of this investigation provide nuanced insights into how digital media consumption intersects with undergraduate academic performance. Rather than supporting a simplistic narrative that screen time inevitably causes scholastic failure, the data illuminate a multi-tiered, indirect relationship characterized by time displacement, attentional fragmentation, and platform-specific psychological dynamics.

5.1 Confirmation of the Time Displacement Hypothesis

The statistically significant inverse correlation between total social media screen time and self-study hours (r = -0.3286) provides robust empirical confirmation of the time displacement hypothesis [5]. Students operate within finite diurnal temporal boundaries. When an undergraduate dedicates 2.62 hours daily to algorithmic entertainment feeds while allocating only 1.93 hours to self-study, the temporal deficit directly reduces opportunities for active coding practice, algorithm tracing, and revision. The displacement effect is particularly deleterious in technical IT curricula, where procedural mastery depends fundamentally on cumulative, time-intensive problem-solving.

5.2 Multitasking, Attention Fragmentation, and Cognitive Load

While direct bivariate correlations between total screen time and exam scores were weak ($r = -0.0996$), the exceptionally high prevalence of concurrent multitasking (83.9%) reveals that attentional fragmentation represents a critical unmeasured hazard. In alignment with Distraction-Conflict Theory [2] and Cognitive Load Theory [4], rapid task-switching between coding IDEs and incoming smartphone notifications imposes continuous 'switch costs.' Each interruption forces the student to clear working memory registers and rebuild mental models, dramatically elevating extraneous cognitive load. Although resilient students may manage to pass examinations (as reflected by 61.3% achieving the 56%–70% tier), continuous multitasking undermines the depth of conceptual schema formation, potentially impairing advanced software engineering competence.

5.3 Structural Platform Differences: Facebook vs. TikTok

A striking empirical outcome is the divergent behavioral footprint of Facebook versus TikTok. Although students dedicated significantly greater absolute daily time to Facebook (mean = 2.26 hours) than TikTok (mean = 0.36 hours), TikTok exhibited a substantially stronger correlation with perceived academic decline ($r = +0.4803$ vs. $r = +0.1340$). This divergence highlights the psychological impact of platform architecture. Facebook's feed structure incorporates asynchronous utility, educational group updates, and text-based discussions. Conversely, TikTok's full-screen, immersive vertical video feed relies on low-friction swipe mechanics and continuous predictive reinforcement [3]. Consuming short-form content in rapid succession conditions the brain for immediate gratification, reducing tolerance for sustained, high-friction cognitive tasks like code debugging. Consequently, students subjectively perceive TikTok as far more disruptive to their academic focus despite lower aggregate screen time.

5.4 Multi-Factorial Complexity and Regression Fit

The OLS multiple linear regression model accounted for 7.2% of the variance in exam score midpoints ($R^2 = 0.072$), leaving 92.8% of variance attributable to unmeasured explanatory variables. This low coefficient of determination is congruent with higher education literature [5], [9], [12]. Academic achievement in computing disciplines is inherently multi-factorial, heavily governed by foundational mathematics competence, prior programming exposure, class attendance, instructional quality, and intrinsic motivation. Digital media usage represents merely one component of a complex pedagogical equation.

5.5 Study Limitations and Methodological Constraints

To ensure academic rigor, several critical methodological limitations must be acknowledged. Foremost is the constraint imposed by the sample size ($N = 62$), which was drawn exclusively from a single academic institution via convenience sampling. While sufficient for localized exploratory profiling, this modest sample size limited statistical power, accounting for the absence of formal statistical significance ($p > 0.05$) among the regression coefficients. Consequently, the empirical findings cannot be interpreted as definitive or universally generalizable to the broader population of IT undergraduates across Sri Lanka or internationally. Second, screen time and study hours were quantified through self-reported survey estimates, introducing potential recall inaccuracies and social desirability biases. Third, the cross-sectional design precludes definitive claims of longitudinal causality; unmeasured student characteristics, such as baseline cognitive aptitude and executive functioning, may confound the observed relationships.

6 Conclusion, Recommendations, and Future Research

6.1 Practical Recommendations

Based on the empirical findings, targeted practical interventions are recommended for both students and higher education administrators: For undergraduates, cultivating digital self-regulation during dedicated study blocks is paramount. Rather than attempting complete abstinence from social media, students should implement 'focus modes,' disable notification badges, and place smartphones in alternate rooms during intensive programming sessions to eliminate cognitive switching costs. For university faculties, academic administrators should integrate digital wellness and attentional discipline workshops into first-year orientation curricula, educating technical students on how algorithmic media architectures deliberately exploit dopamine pathways. Furthermore, institutions should harness collaborative social tools within official Learning Management Systems (LMS), channeling students' innate digital connectivity toward structured academic problem-solving.

6.2 Concluding Remarks and Mandatory Expansion for Future Research

In conclusion, this empirical inquiry investigated the impact of daily Facebook and TikTok engagement upon the first-semester examination performance of BSc IT undergraduates at NIIBS Campus. The investigation confirms that social media consumption exerts an indirect rather than direct suppressive effect on academic success: daily screen time substantially exceeds self-study time and directly displaces revision hours ($r = -0.3286$), while pervasive multitasking (83.9%) fragments student attention during technical learning.

Crucially, it must be underscored that because the present investigation is constrained by an analytical sample of 62 undergraduates from a single faculty cohort, the empirical evidence is insufficient to draw sweeping or definitive conclusions regarding undergraduate computing education at large. Therefore, it is imperative for future academic investigations to extend this analysis with substantially larger, statistically representative sample cohorts spanning multiple state and private higher education institutions across Sri Lanka. Furthermore, subsequent studies should advance beyond self-reported survey estimates by deploying automated, objective device telemetry (e.g., smartphone operating system screen-time tracking APIs and workstation monitoring tools) to capture precise micro-usage patterns. Finally, the implementation of longitudinal panel designs across multi-semester academic cycles is strongly recommended to definitively trace how evolving algorithmic media habits causally dictate undergraduate scholastic trajectories and professional software development competencies.

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