



# When Achievement Becomes Overload: A Quantitative Study of Academic Pressure, Emotional Strain, and Equity in School-Based Predictive Systems

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## KEYWORDS

academic pressure, emotional strain, Strain Index Model, predictive systems, student well-being, equity, sleep deprivation, parental pressure

## ABSTRACT

Academic performance optimization has increasingly become a central priority in contemporary educational systems; however, the psychological costs of this optimization drive remain underexplored in the context of data-driven, school-based predictive frameworks. This study investigates the quantitative relationships between five independent stressor variables — daily study hours, sleep duration, recreational screen time, perceived parental pressure, and exam frequency — and a composite measure of emotional strain among secondary school students (N = 412, aged 14–18). A structured survey instrument was administered across four urban and peri-urban school districts, yielding data subsequently analyzed through multiple linear regression, Pearson correlation analysis, and a purpose-formulated Strain Index Model (SIM). Findings indicate that parental pressure ( $\beta = 0.47, p < .001$ ) and inadequate sleep duration ( $\beta = -0.38, p < .001$ ) are the strongest predictors of elevated emotional strain, while high screen time moderates stress responses in a non-linear fashion. Students in lower-income cohorts demonstrated disproportionately higher composite strain scores, raising equity concerns regarding the use of performance-based predictive algorithms in school settings. The study argues for the integration of socio-emotional equity metrics into predictive systems and recommends targeted interventions targeting parental expectation management and sleep hygiene. The implications extend to educational policymakers, school counselors, and EdTech developers designing next-generation student support platforms.

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## 1. INTRODUCTION

The pursuit of academic excellence in modern educational systems has generated an environment in which students are simultaneously expected to perform at high levels, manage a growing volume of curricular content, and navigate increasingly digitized and competitive learning landscapes. The tension between institutional demands for performance and individual student capacity to manage those demands has given rise to an expansive body of literature on academic stress, burnout, and mental health deterioration among school-going populations (Lazarus & Folkman, 1984; Suldo et al., 2009). Yet despite this scholarly momentum, the structural integration of emotional well-being metrics into school-based predictive and decision-support systems remains notably absent — a gap this study directly addresses.

Academic pressure, broadly defined as the subjective experience of demand exceeding perceived capacity within an educational context (Misra & McKean, 2000), manifests through multiple proximate causes. These include excessive study loads, competitive examination cycles, parental expectations tied to career aspirations, digital distractions from pervasive screen-based technologies, and chronic sleep deficits driven by early school start times and late-night study habits. Individually, each of these factors has been associated with elevated cortisol levels, attentional dysregulation, and depressive symptomatology in adolescent populations (Pascoe et al., 2020; Lund et al., 2010). Collectively, their compounding effects create what Selye (1956) termed *allostatic overload* — a systemic breakdown of adaptive stress management.

The emergence of predictive analytics in educational settings has opened promising avenues for early identification of at-risk students and personalized instructional planning (Baker & Inventado, 2014). Learning Management Systems (LMS) and school-based dashboards now routinely aggregate student performance data to flag declining trajectories before they manifest as visible academic failure. However, the dominant paradigm in these systems is performance-centric: metrics such as test scores, submission timeliness, and attendance rates serve as primary input variables, systematically excluding emotional and physiological strain indicators (Cope & Kalantzis, 2016; Williamson, 2017). This absence is

particularly consequential in equity terms — students from socioeconomically disadvantaged backgrounds, who carry compounding burdens of resource scarcity and high parental expectation simultaneously, are rendered invisible to systems calibrated for surface-level performance data (Selwyn, 2019).

Several research gaps motivate this study. First, most academic stress research relies on qualitative or mixed-method approaches that provide valuable context but offer limited statistical support for building predictive models (Ang & Huan, 2006). Second, many quantitative studies focus on one or two stressors at a time, overlooking the multivariate interactions that shape students' lived experience (Reddy et al., 2018). Third, equity considerations—how strain varies by socioeconomic status and school type—are rarely incorporated into predictive model design (Perrotta & Williamson, 2018). To address these gaps, this study uses a quantitative, multivariable design that produces inferential results and a composite Strain Index Model (SIM) for integration into school-level predictive systems. The remainder of this paper is structured as follows: Section 2 reviews relevant literature across the key stressor domains; Section 3 details the research design and SIM formulation; Section 4 presents findings with graphical analysis; Section 5 concludes with implications and future research directions.

## 2. LITERATURE REVIEW

### 2.1 Academic Stress in Secondary Education

The conceptual scaffolding for academic stress research rests predominantly on two theoretical frameworks: the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984) and the Demand-Control Model (Karasek, 1979). Lazarus and Folkman's model emphasizes the cognitive appraisal processes through which individuals evaluate the significance of stressors and their available coping resources, providing a mechanism for understanding why identical academic demands produce differential stress responses across students. Karasek's model, originally developed for occupational contexts, has been adapted to school environments to explain how high academic demand paired with low student agency produces chronic strain (Salmela-Aro et al., 2009).

Empirical studies have consistently demonstrated that academic pressure is among the most frequently

reported stressors in secondary school populations globally. Reddy et al. (2018) conducted a survey of 1,500 Indian secondary students and reported that 72% identified academic competition as a primary stressor, with significant correlations between perceived pressure and anxiety scores on the Beck Anxiety Inventory. In South Korean contexts, Lee and Larson (2000) found that Korean adolescents reported significantly higher academic stress compared to American peers, attributing the difference to the high-stakes examination culture prevalent in East Asian educational systems. Suldo et al. (2009), examining U.S. middle schoolers, found that academic stressors accounted for 41% of the variance in life satisfaction measures — a finding with direct implications for the present study's operationalization of emotional strain.

Importantly, academic stress does not operate as a unidimensional construct. Misra and McKean (2000) distinguished between academic stressors (sources of stress) and stress reactions (responses), establishing that time management efficacy significantly moderates the stressor-to-strain pathway. Students who perceived themselves as having low temporal control — a characteristic associated with heavy examination schedules — reported substantially higher strain scores. This aligns with the present study's inclusion of exam frequency as an independent variable.

## 2.2 Sleep Duration and Student Performance

Sleep science has produced a compelling evidence base linking sleep deprivation to cognitive impairment, emotional dysregulation, and academic underperformance in adolescent populations. The American Academy of Sleep Medicine (Paruthi et al., 2016) recommends 8–10 hours of sleep per night for teenagers aged 13–18, yet studies consistently find that secondary students average well below this threshold. Lund et al. (2010) surveyed 1,125 U.S. high school students and reported a mean weeknight sleep duration of 6.9 hours, with 68% reporting daytime sleepiness that interfered with classroom engagement.

The mechanistic pathways connecting sleep insufficiency to emotional strain are well-established. Reduced REM sleep impairs amygdala regulation, increasing emotional reactivity and reducing the prefrontal cortex's capacity to contextualize threat — a process directly relevant to the experience of

exam-related anxiety (Walker, 2017). Carskadon et al. (1998) demonstrated that circadian rhythm misalignment in adolescents — driven in part by early school start times — compounds sleep debt and produces measurable increases in depressive affect. More recently, Cheng et al. (2020) conducted a longitudinal study of 2,042 Chinese secondary students and found that each additional hour of sleep deficit per night was associated with a 1.3-point increase on the General Health Questionnaire-12 (GHQ-12), a standardized measure of psychological distress.

The relationship between sleep duration and academic outcomes further complicates the picture. Wolfson and Carskadon (1998) found that students with shorter sleep durations earned lower grade point averages and reported poorer school performance even after controlling for study time — suggesting that sleep quality mediates the effectiveness of study hours, a relationship the present study captures through its multivariate regression approach.

## 2.3 Parental Pressure and Its Psychological Consequences

Parental involvement in academic achievement spans a broad spectrum from supportive engagement to performance-oriented pressure, with meaningfully different outcomes at each end. Pomerantz et al. (2007) distinguish between autonomy-supportive parenting, which fosters intrinsic motivation and academic resilience, and controlling involvement, which correlates with performance anxiety, fear of failure, and reduced academic self-efficacy. The latter mode is particularly prevalent in cultural contexts where educational attainment is strongly linked to family honour and upward social mobility (Phillipson, 2010).

Ang and Huan (2006) conducted a structural equation modeling study of 2,680 Singaporean adolescents and found that parental academic support had a direct negative relationship with suicidal ideation, while parental academic pressure was a positive predictor. Critically, the distinction between support and pressure was mediated by adolescent self-efficacy — students with lower academic confidence were most vulnerable to the harmful effects of pressure. Similar findings emerged from Yamamoto and Holloway's (2010) cross-cultural review, which synthesized studies from the U.S., Japan, China, and South Korea, concluding that the correlation

between parental academic pressure and adolescent anxiety was robust across cultural contexts, though modulated by parenting style and academic culture.

More recent work by Hu et al. (2021) further established that perceived parental expectations – rather than objective academic demands per se – were the more potent predictor of students' academic anxiety. This finding supports the present study's survey-based measure of perceived parental pressure as a psychologically meaningful variable, rather than relying solely on institutional metrics such as parental education level.

#### 2.4 Screen Time and Its Impact on Academic and Emotional Outcomes

The rapid growth of smartphones, tablets, and streaming services has made screen time an important behavioral factor in research on adolescent well-being. Using data from more than 500,000 U.S. adolescents, Twenge and Campbell (2018) reported a non-linear association between recreational screen use and emotional well-being: moderate use (1–2 hours per day) was not linked to adverse outcomes, whereas heavy use (>5 hours per day) was strongly associated with higher depressive symptoms, greater loneliness, and sleep disruption. Adelantado-Renau et al. (2019) examined 272 Spanish adolescents and found that recreational screen time was inversely associated with academic performance and cognitive function, independently of physical activity levels. Crucially, they found that students who used screens extensively in the hours before sleep exhibited the most severe impacts on attention and memory consolidation, linking the screen time and sleep duration variables in a compounding pathway. This inter-variable relationship is directly relevant to the correlation analysis presented in Section 4 of the present study.

It is important to note, however, that not all screen time is created equal. Wood et al. (2012) distinguished between passive screen consumption and active, socially engaged digital interaction, finding differential outcomes for each. This nuance is partially addressed in the present study's survey instrument, which distinguishes between recreational passive screen use and educationally oriented digital engagement.

### 3. METHODOLOGY

#### 3.1 Research Design

This study adopts a quantitative, cross-sectional survey research design. Quantitative methodology was selected for its capacity to yield statistically generalizable findings, to support multivariate analysis across a large sample, and to produce a mathematical model suitable for integration into predictive system architectures. The cross-sectional design allows for simultaneous examination of all independent and dependent variables at a single time point, offering a representative snapshot of academic stressor conditions during a standardized examination period.

#### 3.2 Participants and Sampling

A total of 412 secondary school students (grades 9–12; ages 14–18;  $M = 15.9$ ,  $SD = 1.2$ ) were recruited from eight secondary schools across Chennai, Nellore, Hyderabad, Vizag, Warangal. Stratified random sampling was employed to ensure representation across school type (government-aided:  $n = 186$ ; private unaided:  $n = 226$ ), gender (female: 52.4%; male: 47.6%), and socioeconomic status (SES) quartiles. Institutional ethics review board approval was obtained from Ithaka international school, Ravindra bharathi global schools and written informed assent was collected from all student participants along with parental consent for those under 16 years of age.

#### 3.3 Variables

**Independent Variables (IVs):** Five independent variables were operationalized as continuous or ordinal measures: (1) Daily Study Hours – self-reported average hours per day devoted to academic study, excluding school attendance (range: 1–12 hours); (2) Sleep Duration – average nightly sleep in hours (range: 4–10 hours); (3) Recreational Screen Time – hours per day on non-academic digital media (range: 0–8 hours); (4) Perceived Parental Pressure – a 7-point Likert scale composite score derived from six items adapted from the Perceived Parental Pressure Scale (Ang & Huan, 2006); (5) Exam Frequency – number of formal assessments per month as reported by students.

**Dependent Variable (DV):** Emotional Strain was operationalized as a composite score derived from three validated sub-scales: (i) the PSS-10 (Perceived Stress Scale; Cohen et al., 1983), (ii) the GAD-7 (Generalized Anxiety Disorder scale; Spitzer et al., 2006), and (iii) a

four-item emotional exhaustion subscale adapted from the Maslach Burnout Inventory–Student Survey (MBI-SS; Schaufeli et al., 2002). All three scales were normalized to a 0–100 range before aggregation into a composite Emotional Strain Score (ESS). Higher scores indicate greater strain.

### 3.4 Data Collection and Instrumentation

A structured paper-and-pen survey was administered during a single 45-minute session per class group, scheduled during non-examination periods. The complete instrument comprised 62 items across all scales, with an additional 12 items collecting demographic and contextual data. Pilot testing on a sample of 35 students not included in the main study yielded Cronbach's  $\alpha$  coefficients of .82, .86, and .79 for the PSS-10, GAD-7, and MBI-SS subscales respectively, confirming adequate internal reliability. Items were reviewed by two educational psychologists for content validity and translated into two regional languages to mitigate comprehension barriers.

### 3.5 Strain Index Model (SIM)

To produce a unified, interpretable strain score suitable for integration into school-based predictive systems, this study formulates the Strain Index Model (SIM) – a weighted composite function that aggregates the five independent variables into a single normalized index reflecting total predicted emotional strain. The model was derived through iterative multiple linear regression, with standardized beta coefficients from the regression analysis serving as empirically-determined weights.

$$SIM = w_1 \cdot H_s + w_2 \cdot (1 - S_d/10) + w_3 \cdot T_{sc} + w_4 \cdot P_{par} + w_5 \cdot F_{ex} - C$$

Where:  $H_s$  = normalized daily study hours (0–1 scale);  $S_d$  = sleep duration in hours (0–10);  $T_{sc}$  = normalized screen time (0–1);  $P_{par}$  = normalized parental pressure index (0–1);  $F_{ex}$  = normalized exam frequency (0–1);  $C$  = baseline calibration constant (derived from sample mean ESS). The empirically derived weights from the regression analysis are:  $w_1 = 0.29$  (study hours),  $w_2 = 0.38$  (sleep deficit),  $w_3 = 0.19$  (screen time),  $w_4 = 0.47$  (parental pressure),  $w_5 = 0.23$  (exam frequency). The term  $(1 - S_d/10)$  inverts the sleep

variable so that shorter sleep duration produces higher strain scores, consistent with the negative relationship between sleep and well-being. The SIM output ranges from 0 to 1, where scores above 0.65 are flagged as high-strain and warranting targeted intervention. Multicollinearity diagnostics yielded VIF values below 3.2 for all predictors, confirming model stability.

## 4. RESULTS AND ANALYSIS

Data analysis was conducted using SPSS v.28 and Python (pandas, scipy, matplotlib). Descriptive statistics, Pearson correlations, multiple linear regression, and Strain Index Model computations were performed across the full sample (N = 412). The following subsections present the key findings sequentially, organized by variable domain. All p-values are reported at  $\alpha = .05$  significance threshold unless otherwise stated.

### 4.1 Descriptive Statistics

Table 1. Descriptive statistics for all study variables (N = 412).

Variable	Mean	Std. Dev.	Min	Max	Skewness
Daily Study Hours	6.2	1.84	1.0	12.0	0.43
Sleep Duration (hrs)	6.1	1.12	4.0	9.5	-0.31
Screen Time (hrs/day)	3.7	1.53	0.0	8.0	0.62
Parental Pressure (0–7)	4.8	1.39	1.0	7.0	-0.18
Exam Frequency (per mo.)	5.4	2.11	1.0	12.0	0.77
Emotional Strain Score	61.3	14.20	18.0	97.0	0.09

Table 1 reveals that the sample exhibited high mean emotional strain (M = 61.3 out of 100), substantially above the clinical threshold of 50 commonly used in PSS-based research (Cohen et al., 1983). Mean sleep duration (M = 6.1 hours) falls considerably below the recommended 8–10 hours for adolescents (Paruthi et al., 2016), confirming the pervasiveness of sleep deficits in this population. Mean parental pressure scores (M = 4.8 on a 7-point scale) indicate moderate-to-high levels of perceived academic expectation pressure.

### 4.2 Emotional Strain by Study Hours Category

← Emotional Strain Score (Mean) →

Study Category	Hours	Mean ESS	n	Std. Dev.	High-S train %
Low (1-3 hrs/day)		44.2	68	11.3	18%
Moderate (4-6 hrs/day)		57.8	142	13.1	39%
High (7-9 hrs/day)		68.4	134	14.7	61%
Very High (10-12 hrs/day)		78.6	68	12.9	74%

Fig. 1. Mean Emotional Strain Score by daily study hours category. Scores escalate monotonically across study load bands, with students in the Very High category averaging an ESS of 78.6 – 77% above the sample low. High-strain prevalence (ESS ≥ 70) rises from 18% to 74% across the four categories, indicating a dose-response relationship between study load and emotional strain.

Figure 1 reveals a clear monotonic increase in mean ESS across study hours categories, supporting the hypothesis that academic time investment, beyond a threshold of approximately 6 hours/day, is associated with rapidly escalating emotional strain. This finding aligns with the diminishing returns principle in educational psychology (Pascoe et al., 2020), suggesting that raw study time is an inefficient predictor of performance once strain effects are accounted for. The proportion of high-strain students (ESS ≥ 70) in the Very High category (74%) substantially exceeds the WHO threshold for distress intervention, warranting systemic policy attention.

#### 4.3 Emotional Strain vs. Sleep Duration

Sleep Duration (hrs)	Mean ESS	n	95% Lower CI	95% Upper CI
≤ 5 hours	76.8	62	73.4	80.2
5-6 hours	68.3	98	65.7	70.9
6-7 hours	61.1	112	58.9	63.3
7-8 hours	51.4	94	48.8	54.0
> 8 hours	42.7	46	38.9	46.5

Fig. 2. Mean Emotional Strain Score plotted against sleep duration bands (N = 412). A pronounced inverse relationship is observed: students sleeping ≤5 hours report an average ESS 79.6% higher than those sleeping

>8 hours. Confidence intervals narrow at intermediate sleep durations, reflecting the concentration of the sample in the 5–8 hour range.

Figure 2 demonstrates a strong inverse, approximately linear relationship between sleep duration and emotional strain (Pearson  $r = -0.61$ ,  $p < .001$ ), consistent with Walker's (2017) neurobiological framework linking REM sleep deprivation to amygdala hyperactivation. The steepest decline in mean ESS occurs between the ≤5 hour and 5–6 hour bands ( $\Delta = 8.5$  points), suggesting that even marginal improvements in sleep adequacy among chronically sleep-deprived students could yield meaningful reductions in emotional strain. This observation carries direct implications for school scheduling policy, particularly regarding early start times and examination-period study norms.

#### 4.4 Screen Time and Emotional Strain: A Non-Linear Relationship

Screen Time (hrs/day)	Mean ESS	$\Delta$ from Previous Band	Anxiety Subscore	Exhaustion Subscore
0-1 hour	55.2	—	52.1	51.4
1-2 hours	56.8	+1.6	53.7	52.3
2-3 hours	59.4	+2.6	56.2	54.8
3-4 hours	62.1	+2.7	60.4	57.9
4-5 hours	66.7	+4.6	65.8	63.3
> 5 hours	74.3	+7.6	73.1	71.8

Fig. 3. Mean ESS, anxiety subscore, and exhaustion subscore across recreational screen time bands. The relationship is non-linear, with incremental strain increases accelerating markedly beyond 4 hours/day. Both anxiety and exhaustion subscores track the overall ESS trend, with anxiety scores consistently exceeding exhaustion in high-use bands.

Figure 3 reveals a non-linear, progressively steepening relationship between recreational screen time and emotional strain, consistent with the threshold effects described by Twenge and Campbell (2018). Moderate screen use (1–3 hours/day) is associated with only modest ESS increases (+4.2 points), possibly reflecting the stress-buffering role of social digital interaction for some students. However, beyond the 4-hour threshold, the per-band increment in mean ESS accelerates sharply

(+7.6 for >5 hours), consistent with the compounding effects of screen-induced sleep disruption identified by Adelantado-Renau et al. (2019). The steeper trajectory for anxiety scores relative to exhaustion in high-use bands suggests that high screen time may specifically amplify anxious reactivity, potentially through social comparison mechanisms on social media platforms.

#### 4.5 Parental Pressure as the Dominant Predictor

Parental Pressure Level	Mean ESS	Fear-of-Failure Subscore	Self-Efficacy (Inverse)	n
Very Low (1-2)	41.3	38.2	71.4	48
Low (2-3)	51.6	48.7	64.8	74
Moderate (3-4)	60.4	57.9	58.2	89
High (4-5)	69.2	67.4	49.6	97
Very High (5-6)	76.8	75.1	41.3	71
Extreme (6-7)	84.1	82.6	33.7	33

Fig. 4. Mean Emotional Strain Score and sub-domain scores across perceived parental pressure levels. A dose-response pattern is clearly evident: ESS increases by an average of 8.6 points per pressure level. The inverse self-efficacy column (adapted Bandura scale, higher = lower self-efficacy) confirms that high parental pressure erodes academic self-belief, amplifying the emotional strain response.

Figure 4 provides perhaps the most striking finding of the study: parental pressure exhibits the strongest and most consistent association with emotional strain across all measured dimensions. The regression coefficient ( $\beta = 0.47$ ,  $p < .001$ ) confirms parental pressure as the dominant predictor in the multivariate model, echoing Ang and Huan's (2006) structural equation modeling results. Critically, Figure 4 also illustrates the inverse relationship between parental pressure and student self-efficacy — as pressure increases from Very Low to Extreme, self-efficacy drops from 71.4 to 33.7, a decline of 52.8%. This aligns with Hu et al.'s (2021) finding that perceived parental expectations, rather than objective demands, are the primary emotional burden on students.

#### 4.6 Strain Index Model (SIM) Output and Equity Analysis

Student Group	Mean SIM Score	High-Strain % (SIM $\geq 0.65$ )	Pearson r (SIM, ESS)	n
Private school, High SES	0.51	28%	0.91	118
Private school, Low SES	0.63	49%	0.89	108
Government school, High SES	0.58	41%	0.90	82
Government school, Low SES	0.72	67%	0.93	104
Full Sample	0.61	46%	0.92	412

Fig. 5. Strain Index Model (SIM) scores disaggregated by school type and socioeconomic status (SES). Government school students from low-SES backgrounds exhibit the highest mean SIM score (0.72) and the highest prevalence of high-strain status (67%), underscoring systemic equity concerns. The SIM demonstrates strong convergent validity ( $r = 0.92$  with observed ESS across full sample).

Figure 5 illustrates the most consequential equity finding of the study: the compounding disadvantage experienced by students in government schools from low socioeconomic backgrounds. This group's mean SIM score of 0.72 exceeds the high-strain intervention threshold (0.65) and is 41.2% higher than that of private school students from high-SES backgrounds. This disparity cannot be explained by study hours alone — government low-SES students actually reported fewer mean daily study hours (5.4) than private high-SES students (7.1). Rather, the elevated SIM scores in this group are driven by the compounding effects of higher parental pressure, shorter sleep duration (mean: 5.7 hours vs. 6.5 hours for private high-SES), and greater financial stress acting as an unmeasured latent stressor (Selwyn, 2019). The SIM's strong convergent validity ( $r = 0.92$  with observed ESS) confirms its suitability as a proxy indicator in data-limited settings where full psychometric battery administration is impractical.

#### 4.7 Correlation Matrix Summary

Variable	Study Hrs	Sleep Dur.	Screen Time	Par. Pressure	Exam Freq.	ESS
Study Hours	1.00	-0.34**	0.18**	0.29**	0.41**	0.53*
Sleep Duration		1.00	-0.42**	-0.27**	-0.31**	-0.61**
Screen Time			1.00	0.14*	0.08	0.44*
Parental Pressure				1.00	0.22**	0.67*
Exam Frequency					1.00	0.48*
ESS						1.00

Table 2. Pearson correlation matrix for all study variables. \*\*  $p < .001$ ; \*  $p < .05$ .

Table 2 confirms the theoretically anticipated directional relationships across all variable pairs. The strongest correlation with ESS is observed for parental pressure ( $r = 0.67$ ), followed by sleep duration ( $r = -0.61$ ), exam frequency ( $r = 0.48$ ), study hours ( $r = 0.53$ ), and screen time ( $r = 0.44$ ). The significant negative correlation between sleep duration and screen time ( $r = -0.42$ ,  $p < .001$ ) quantitatively confirms the screen-sleep interference pathway identified by Adelantado-Renau et al. (2019), supporting the view that high screen time exerts its emotional strain effects partly through sleep disruption. The study hours–exam frequency correlation ( $r = 0.41$ ) suggests that examination cycles directly drive study hour increases, creating a self-reinforcing pressure loop.

#### 5. DISCUSSION:

The present study sets out to quantitatively examine how multiple academic and psychosocial stressors interact to produce emotional strain among secondary school students, while explicitly foregrounding equity implications for school-based predictive systems. The findings empirically confirm that emotional strain is not merely an individual psychological outcome, but a structurally patterned phenomenon produced by interacting institutional, familial, and behavioral pressures. Second, they demonstrate that models relying exclusively on performance indicators risk

systematically disadvantaging already vulnerable student populations. Third, they provide evidence that a composite, multivariable metric such as the Strain Index Model (SIM) can function as a pragmatic bridge between emotional well-being research and data-driven educational decision-making.

Among the five stressors examined, perceived parental pressure emerged as the most powerful predictor of emotional strain, exceeding the effects of study hours, exam frequency, screen time, and even sleep deprivation. This finding substantially extends prior research by showing that parental pressure retains its dominant influence even when competing stressors are simultaneously modeled. Importantly, the results reinforce theoretical distinctions between parental involvement and parental pressure: while the former may foster motivation and resilience, the latter appears to erode self-efficacy, amplify fear-of-failure, and accelerate emotional exhaustion. The observed decline in self-efficacy across parental pressure levels suggests a mechanistic pathway through which pressure transforms effort into strain—students invest more time and emotional capital but experience diminishing psychological returns. This dynamic helps explain why high-achieving students are not immune to distress and why performance-only metrics can obscure latent risk.

Sleep duration emerged as the second strongest predictor, with a notably steep inverse relationship to emotional strain. The sharp ESS differences observed between the lowest sleep bands indicate that chronic sleep deprivation functions as a strain multiplier rather than a simple background condition. Even relatively small improvements in sleep duration among severely sleep-deprived students were associated with meaningful reductions in stress, highlighting sleep as a high-impact intervention lever. These findings underscore the structural nature of sleep deprivation, driven by examination schedules, early school start times, and digitally mediated study habits, rather than by individual choice alone. In this context, student well-being cannot be adequately addressed without institutional attention to time structures within schooling.

The non-linear relationship between recreational screen time and emotional strain adds nuance to polarized debates around adolescent technology use. Moderate screen engagement did not correspond to

dramatic increases in strain, suggesting that digital interaction may serve compensatory or socially regulating functions for some students. However, beyond a clear threshold—approximately four hours per day—emotional strain increased rapidly, particularly in anxiety-related dimensions. This pattern supports the interpretation that screen time acts less as an independent stressor and more as a secondary amplifier through sleep disruption, attentional fragmentation, and social comparison processes. The differentiated escalation of anxiety relative to exhaustion further implies that digital environments may disproportionately heighten anticipatory stress and self-evaluative concerns.

One of the most consequential contributions of this study lies in its equity analysis. Students from low-SES backgrounds in government schools consistently exhibited the highest SIM scores and the greatest prevalence of high-strain status, despite not reporting the highest study hours. This finding decisively challenges meritocratic assumptions embedded in many predictive analytics systems. Emotional strain in these contexts appears to be driven by compounded disadvantage—higher parental expectations tied to mobility aspirations, greater exposure to resource scarcity, and more severe sleep deficits—rather than by academic workload alone. Predictive systems calibrated exclusively on grades, attendance, or task completion thus risk misclassifying high-strain students as “low risk,” reinforcing institutional blind spots rather than mitigating them.

The Strain Index Model (SIM) addresses this gap by translating complex psychosocial dynamics into a parsimonious, interpretable metric that demonstrates strong convergent validity with observed emotional strain. Importantly, the SIM is not proposed as a replacement for clinical assessment, but as an early-warning heuristic suited to data-constrained educational settings. Its strength lies in capturing interaction effects across stressor domains, enabling schools to identify risk clusters before emotional strain manifests as burnout, disengagement, or crisis. From a systems perspective, the SIM reframes student success as a balance between demand and human capacity, rather than as a unidirectional output.

Nonetheless, several limitations warrant careful consideration. The cross-sectional design precludes

definitive causal inference, particularly in relationships where bidirectionality is plausible (e.g., screen time and anxiety). Self-reported measures introduce potential response biases, especially for socially sensitive constructs such as parental pressure. Additionally, cultural norms surrounding achievement and family expectations may influence perceived pressure, limiting direct generalizability across contexts without recalibration. Future research should prioritize longitudinal designs, objective sleep measurement, and cross-cultural validation of SIM weights to strengthen both causal interpretation and portability.

## 6. CONCLUSION

This study set out to quantify the multivariate relationships between academic stressors and emotional strain in secondary school students, and to assess the equity implications of integrating such a model into school-based predictive systems. Across five independent stressor variables measured in a sample of 412 students, parental pressure emerged as the dominant predictor of emotional strain ( $\beta = 0.47$ ), followed by sleep deprivation ( $\beta = -0.38$ ), exam frequency, study hours, and screen time. The composite Strain Index Model achieved strong convergent validity ( $r = 0.92$  with observed ESS), confirming its potential as a scalable, data-efficient tool for identifying high-risk students in real time.

The study's equity analysis reveals a deeply concerning socioeconomic gradient: students from low-SES backgrounds in government schools exhibit mean SIM scores 41% above those of high-SES students in private institutions, driven not primarily by study load differentials but by compounding psychosocial disadvantages including elevated parental pressure, more severe sleep deficits, and resource scarcity. This finding challenges the adequacy of performance-only predictive models (Williamson, 2017), which, by failing to capture strain dynamics, risk perpetuating rather than addressing systemic educational inequity (Selwyn, 2019).

The implications for educational systems are substantial. First, school counseling frameworks should prioritize parental expectation management workshops, particularly targeting families in competitive academic cultures where achievement pressure is most intense (Yamamoto & Holloway, 2010). Second, examination

schedules should be critically reviewed to reduce frequency-driven strain accumulation, and school start times should be adjusted to accommodate adolescent circadian biology (Carskadon et al., 1998; Wolfson & Carskadon, 1998). Third, EdTech developers and institutional data officers should incorporate the SIM or analogous composite wellness indices into student dashboards, enabling early, preventive intervention rather than reactive crisis management (Baker & Inventado, 2014). Fourth, equity-disaggregated reporting should be embedded as a mandatory component of school data governance frameworks.

Several limitations must be acknowledged. The cross-sectional design precludes causal inference; the directionality of several relationships — particularly the screen time–strain nexus — cannot be definitively established from survey data alone. The reliance on self-report measures introduces social desirability bias, particularly for parental pressure items. Future research should employ longitudinal designs to track strain trajectories across academic years, incorporate objective sleep metrics via actigraphy, and test the SIM's predictive validity against later academic outcomes and mental health diagnoses. Cross-national replication studies are also warranted to assess the cultural portability of the model's empirical weights, given the significant cultural variation in academic pressure norms documented by Phillipson (2010) and Yamamoto and Holloway (2010).

In sum, this study contributes a validated quantitative framework for understanding academic emotional strain that moves beyond descriptive characterization toward predictive utility. The finding that achievement orientation, while institutionally celebrated, produces measurable and inequitably distributed emotional costs, should serve as a call to action for educational policymakers, technologists, and welfare practitioners to re-centre student well-being — not merely student performance — in the design of school-based data systems.

#### Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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