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Short-Video Addiction, Academic Burnout, and Sleep Quality: Testing a Serial Mediation Model with Emotion Regulation as a Protective Factor

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ABSTRACT: *Short-video platforms now occupy a large share of student leisure time, yet the psychological route linking compulsive viewing to impaired sleep remains poorly specified. This study tested a serial mediation model in which short-video addiction predicts sleep quality through emotion regulation and then academic burnout, treating emotion regulation as a protective resource. A cross-sectional survey collected complete responses from 375 undergraduate students aged seventeen to twenty-five, who reported on twenty-eight Likert items alongside behavioural sleep indicators. Confirmatory factor analysis established the four-factor measurement structure, and the serial mediation model was estimated with 10,000 bootstrap resamples. Short-video addiction predicted poorer sleep quality directly (β = −0.228) and through three indirect routes that were all significant. Academic burnout carried the largest specific indirect effect (β = −0.132), the emotion regulation route carried β = −0.053, and the serial route running through regulation and then burnout carried β = −0.045. Indirect transmission accounted for 50.3 per cent of the total effect of −0.458, and the model explained 39.6 per cent of the variance in sleep quality. Emotion regulation operated as a mediator rather than as a buffer, since its interaction with short-video addiction was not significant. Interventions should therefore target regulatory capacity and academic workload rather than screen time alone.*

Keywords: short-video addiction; academic burnout; sleep quality; emotion regulation; serial mediation

I. INTRODUCTION

Short-video platforms have reorganised how young adults spend the hours between classes and sleep. Content arrives in clips of seconds, autoplay removes any natural stopping point, and recommendation systems learn quickly enough to hold attention beyond what the viewer intended. The design produces a pattern of use that researchers now describe as short-video addiction, characterised by loss of control over viewing, preoccupation between sessions, and continued use despite recognised costs (*Ye et al., 2025; Yang et al., 2023*). Undergraduates are among the heaviest users, and the behaviour concentrates in the late evening when competing

demands are lowest. That timing places short-video viewing in direct competition with sleep. Students in developing education systems meet that competition on the same screens that carry their coursework, since digital classroom media and learning management platforms have spread quickly through schools, madrasahs, and universities in those settings (*Zh et al., 2026*). The mechanics that sustain attention are engineered into instructional applications as well, where randomised evidence from Indonesian primary classrooms reports gains in reading proficiency (*Ardiansyah et al., 2026*), so sustained absorption is not by itself the feature that distinguishes the behaviour examined here. Surveys of Generation Z students in Indonesia describe the same platforms serving study and leisure at once, with no boundary that the student can easily locate (*Muttaqin et al., 2026*).

Evidence linking this behaviour to impaired sleep is accumulating but remains mechanistically thin. Studies of the wider family of problematic technology use consistently report associations with shorter sleep, longer time to fall asleep, and poorer subjective sleep quality (*Demirci et al., 2015; Leow et al., 2023; Chen & Wu, 2021*). Work focused specifically on short-video platforms has found similar associations and has begun to identify intervening variables, including physical activity and procrastination (*Zhao & Kou, 2024*). What most of this literature explains is that the association exists rather than how it is produced. Displacement of sleep time is the obvious candidate, yet displacement alone cannot explain why viewing predicts subjective sleep quality even after viewing hours are controlled (*Tandon et al., 2020; Exelmans & Van den Bulck, 2016*).

Emotion regulation offers one route that the displacement account overlooks. Regulation refers to the processes through which people influence which emotions they have, when they have them, and how they experience and express them (*Gross, 2015; McRae & Gross, 2020*). Compensatory accounts of problematic internet use argue that people turn to absorbing digital content precisely because it relieves negative affect quickly, and that repeated reliance on this shortcut weakens the more effortful regulatory strategies that would otherwise develop (*Kardefelt-Winther, 2014; Brand et al., 2019*). Meta-analytic evidence links deficits in regulation to a broad range of psychopathology, and reviews of expressive suppression and cognitive reappraisal show that the strategies people habitually use predict emotional outcomes reliably (*Aldao et al., 2010; Dryman & Heimberg, 2018*). Regulation is therefore both a plausible casualty of compulsive viewing and a plausible protective resource.

Academic burnout supplies a second route that operates through the student role rather than through affect alone. Burnout among students is understood as exhaustion, cynicism toward study, and a reduced sense of academic efficacy, and it arises when demands persistently exceed the resources available to meet them (*Schaufeli et al., 2002; Maslach et al., 2001*). Conservation of resources theory frames the process as a spiral in which resource loss accelerates further loss, which fits a student who sacrifices study time to viewing, falls behind, and then faces heavier demands with less energy (*Hobfoll, 1989*). Reviews of burnout theory and measurement confirm that the construct behaves as an outcome of chronic resource depletion rather than as a transient mood state (*Edú-Valsania et al., 2022*). Baseline demand varies across systems, and Indonesian students following integrated general and religious curricula carry a scheduled load heavier than

a single-track programme imposes (*Manaf et al., 2025*). Empirical work has already connected problematic internet use to burnout across many samples (*Mao et al., 2024*).

Burnout in turn has a well-documented relationship with sleep. Exhausted and cynical students report more rumination at bedtime, and experimental reviews confirm that emotional states affect sleep onset and continuity rather than merely accompanying them (*Krizan et al., 2024; Armstead et al., 2019*). Bedtime procrastination provides a behavioural expression of the same process, since students who feel depleted delay sleep in order to reclaim discretionary time (*Kroese et al., 2014*). Placing burnout downstream of emotion regulation and upstream of sleep therefore produces a testable chain, in which compulsive viewing erodes regulatory capacity, weakened regulation raises burnout, and burnout degrades sleep.

Three gaps in the literature motivate the present study. The first concerns model specification, because most published work tests single mediators and cannot establish whether affective and academic pathways operate in sequence or in parallel (*Zhao & Kou, 2024; Li et al., 2024*). The second concerns the role assigned to emotion regulation, which is usually described as a protective factor without any test of whether it protects by mediating the effect or by buffering it. The two possibilities carry different intervention implications and are rarely distinguished. The third concerns outcome validity, since subjective sleep scales are seldom examined alongside behavioural indicators such as sleep duration, sleep latency, and late bedtime frequency (*Buysse et al., 1989*).

This study addresses those gaps by estimating a serial mediation model among undergraduate students. Nine hypotheses guide the analysis and are displayed in Figure 1. The first six concern direct paths, namely that short-video addiction predicts poorer sleep quality, weaker emotion regulation, and higher academic burnout, that emotion regulation predicts lower burnout and better sleep, and that burnout predicts poorer sleep. The remaining three concern indirect transmission through emotion regulation alone, through academic burnout alone, and through the serial chain running from regulation to burnout. The unit of analysis is the individual student, and all constructs are measured through self-report instruments supplemented by behavioural sleep indicators.

The article proceeds through four further sections after this introduction. The method section describes the design, participants, sampling, instruments, ethical procedures, and the analytical sequence covering measurement validation, common method variance, and bootstrap estimation of indirect effects. The results section reports respondent characteristics, measurement quality, descriptive relationships, the structural estimates with their decomposition, and a set of robustness checks including a test of emotion regulation as a moderator. The discussion interprets each finding against the compensatory use and resource depletion literatures and gives particular attention to the distinction between mediation and buffering. The conclusion states the answers, the limitations of a cross-sectional design, and the research that should follow.

II. METHOD

This study used a quantitative approach with a cross-sectional explanatory survey design. The design suits the research question because the hypotheses concern the strength and sequence of associations among latent constructs rather than the meaning students attach to their viewing. Serial mediation requires that the two intervening variables be ordered on theoretical grounds before estimation, and that ordering was fixed in advance from the compensatory use and resource depletion accounts described in the introduction (*Hayes, 2022*). The design cannot establish temporal precedence, and the indirect effects reported below should therefore be read as statistical mediation rather than as demonstrated causation (*Zhao et al., 2010*).

Participants were 375 undergraduate students aged between seventeen and twenty-five years, with a mean age of 20.58 years and a standard deviation of 1.52. The sample contained 239 women and 136 men distributed across all four years of study, and respondents reported three living arrangements covering residence with family, dormitory or boarding accommodation, and shared rental housing. Sampling followed a purposive procedure targeting students who reported regular use of at least one short-video platform, since the construct under study has no meaning for non-users. The achieved sample exceeds the minimum required for a model with three predictors of the most complex endogenous variable and provides ample power for the bootstrap tests reported below.

Four latent constructs were measured with twenty-eight items scored on a five-point Likert scale. Short-video addiction was measured with eight items covering difficulty stopping, exceeding intended viewing time, urge to check content repeatedly, continued viewing despite interference with study, loss of time awareness, restlessness when access is unavailable, postponement of important activities, and unsuccessful attempts to cut down. This item structure follows the symptom domains used in contemporary measures of problematic short-video use (*Ye et al., 2025; Kuss & Griffiths, 2017*). Emotion regulation was measured with six items covering the capacity to calm oneself, to identify feelings before reacting, to reappraise a situation, to remain goal-focused when upset, to choose constructive responses to stress, and to recover after emotionally difficult experiences, which corresponds to the process model of regulation (*Gross, 2015; Gross & John, 2003*).

Academic burnout was measured with eight items covering emotional exhaustion from workload, feeling drained after tasks, reduced enthusiasm, cynicism toward academic activities, difficulty maintaining motivation, feeling overwhelmed by demands, doubt about the value of one's effort, and mental fatigue when thinking about study. The domain structure follows the exhaustion, cynicism, and efficacy dimensions established for student populations (*Schaufeli et al., 2002*). Sleep quality was measured with six items covering sufficiency of restorative sleep, ease of falling asleep, continuity of sleep, feeling refreshed on waking, regularity of schedule, and freedom from daytime interference. Higher scores denote better sleep, so the construct is scored in the opposite direction to the two risk variables, and no item required reverse coding.

Behavioural and contextual variables were collected alongside the scales. Sleep duration in hours, sleep latency in minutes, and the number of nights per week with a bedtime substantially after midnight provided behavioural indicators that do not share method variance with the sleep quality scale (*Buysse et al., 1989*). Daily device use, daily short-video viewing hours, frequency of short-video use near bedtime, daily caffeinated drink consumption, and weekly study hours outside class were recorded as covariates. Demographic variables covered age, gender, year of study, and living arrangement. These variables allow the structural estimates to be re-examined with plausible confounders held constant.

Data collection followed standard ethical procedures for research with adult volunteers. Institutional ethics approval and permission from the participating faculties were obtained before administration, participants received a written explanation of the purpose and of their right to withdraw at any point, and informed consent was recorded before the questionnaire opened. Responses were anonymous, no identifying information was collected, and data were stored in encrypted form accessible only to the research team. Because the instrument asks about study-related exhaustion and sleep difficulty, the closing page provided contact details for the campus counselling service for any student who wished to seek support.

Analysis proceeded in three stages that follow established reporting practice. Measurement quality was assessed first through confirmatory factor analysis of the four-factor structure, with model fit judged against conventional thresholds for the comparative fit index, the Tucker-Lewis index, the root mean square error of approximation, and the standardised root mean square residual (*Hu & Bentler, 1999; Kline, 2023*). Internal consistency was estimated through Cronbach's alpha and McDonald's omega, since omega does not assume that all items contribute equally to the composite (*Hayes & Coutts, 2020*). Convergent validity was judged from standardised loadings, composite reliability, and average variance extracted, and discriminant validity from the Fornell and Larcker criterion together with the heterotrait-monotrait ratio (*Fornell & Larcker, 1981; Henseler et al., 2015*).

Common method variance was examined in the second stage. Harman's single factor test provided a first indication, and the full collinearity procedure provided a more sensitive check in which variance inflation factors above 3.3 would signal contamination (*Podsakoff et al., 2003; Kock, 2015*). Distributional behaviour of every item was inspected through skewness and kurtosis before estimation, and bivariate relationships among constructs, behavioural sleep indicators, and viewing hours were examined to establish the descriptive pattern that the structural model would need to reproduce.

The third stage estimated the serial mediation model. All variables were standardised so that path coefficients could be compared directly, and three regression equations were fitted following the logic of a two-mediator sequential model (*Hayes, 2022; Preacher & Hayes, 2008*). Specific indirect effects were computed as products of the constituent paths, and inference used percentile confidence intervals from 10,000 bootstrap resamples rather than the normal theory test, because products of coefficients are not normally distributed. Pairwise contrasts between the three specific indirect effects were computed within the same bootstrap distribution so that their relative magnitudes could be compared formally. Explanatory power was judged from the

coefficient of determination and from the effect size statistic, and collinearity was inspected before interpreting any coefficient (*Cohen, 1988*). Four robustness checks completed the analysis, namely re-estimation with the full covariate set, a test of emotion regulation as a moderator rather than a mediator, replication of the outcome with three behavioural sleep indicators, and comparison of construct means across demographic and usage groups.

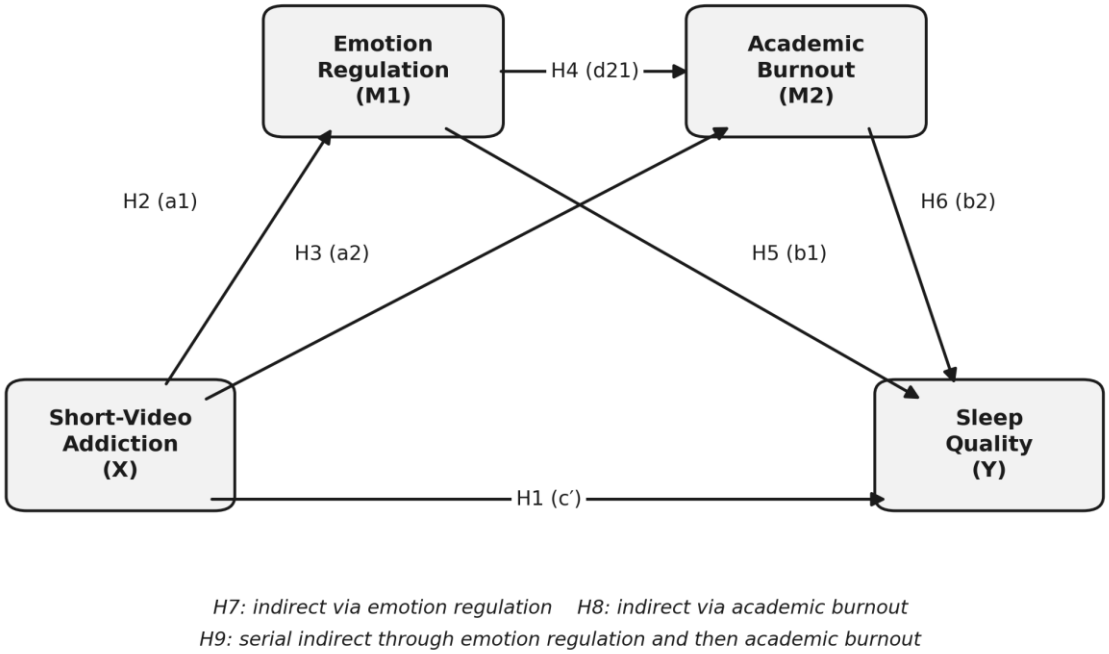

Figure 1. Hypothesised serial mediation model linking short-video addiction to sleep quality through emotion regulation and academic burnout

Source: Authors' analysis of the survey data (2026)

III. RESULT

Results follow the analytical sequence set out in the method section. Respondent characteristics and measurement quality come first, descriptive relationships come second, and the structural estimates with their decomposition and robustness checks close the section. Computational detail is not reproduced, because reporting conventions call for the outcome of each test rather than the arithmetic behind it.

Respondent Characteristics and Usage Behaviour

Table 1 summarises the composition of the sample. Women account for 63.7 per cent of respondents and the four years of study are represented in declining proportions from 30.7 per cent in the first year to 20.0 per cent in the fourth. Almost half the sample lives with family, while roughly a third lives in dormitory or boarding accommodation. Reported short-video use near bedtime is widespread, since only 14.1 per cent report using such platforms rarely at that time while 51.4 per cent report using them often or very often. No case contained missing values on any of the forty-five variables, so all 375 respondents contribute to every analysis reported below.

Table 1. Respondent Characteristics and Usage Behaviour (n = 375)

Characteristic	Category	n	%	M (SD)
Gender	Female	239	63.7	–
	Male	136	36.3	–
Year of study	First year	115	30.7	–
	Second year	101	26.9	–
	Third year	84	22.4	–
	Fourth year	75	20.0	–
Living arrangement	With family	172	45.9	–
	Dormitory or boarding	117	31.2	–
	Shared rental	86	22.9	–
Short-video use near bedtime	Rarely	53	14.1	–
	Sometimes	129	34.4	–
	Often	137	36.5	–
	Very often	56	14.9	–
Daily caffeinated drinks	None	86	22.9	–
	One	182	48.5	–
	Two	80	21.3	–
	Three or more	27	7.2	–
Age in years	–	375	100.0	20.58 (1.52)
Daily device use, hours	–	375	100.0	6.82 (2.06)
Daily short-video viewing, hours	–	375	100.0	2.10 (1.26)
Weekly study hours outside class	–	375	100.0	19.03 (4.87)
Sleep duration, hours per night	–	375	100.0	6.69 (0.83)
Sleep latency, minutes	–	375	100.0	25.16 (10.96)
Late bedtimes, nights per week	–	375	100.0	1.99 (0.92)

Source: Authors' analysis of the survey data (2026)

Usage and sleep behaviour show the pattern that motivated the study. Students report a mean of 6.82 hours of daily device use and 2.10 hours of short-video viewing, and they sleep an average of 6.69 hours per night with a mean sleep latency of 25.16 minutes. Late bedtimes occur on an average of 1.99 nights per week. Mean sleep duration falls below the range usually recommended for young adults, which means the sample as a whole is mildly sleep-restricted rather than merely varying around an adequate level. Item distributions are well behaved throughout, with skewness between minus 0.084 and 0.178 and kurtosis between minus 1.002 and minus 0.702.

Measurement Model and Common Method Variance

Table 2 reports the confirmatory factor analysis and the reliability assessment. The four-factor model fits the data well, with a chi-square of 322.216 on 344 degrees of freedom and an associated probability value of 0.795, which indicates that the model-implied and observed

covariance matrices do not differ significantly. The comparative fit index and the Tucker-Lewis index both reach their upper bound of 1.000, the root mean square error of approximation is 0.000, and the standardised root mean square residual is 0.034. Every standardised loading falls between 0.674 and 0.760 and every loading is significant, so no item was removed.

Table 2. Confirmatory Factor Analysis, Reliability, and Convergent Validity

Construct	Loading range	α	ω	CR	AVE
Short-video addiction (8 items)	0.674–0.758	0.892	0.914	0.892	0.509
Emotion regulation (6 items)	0.677–0.760	0.864	0.898	0.864	0.515
Academic burnout (8 items)	0.689–0.753	0.896	0.917	0.896	0.519
Sleep quality (6 items)	0.681–0.733	0.866	0.900	0.866	0.519

Source: Authors' analysis of the survey data (2026)

Reliability and convergent validity meet conventional standards for all four constructs. Cronbach's alpha ranges from 0.864 to 0.896 and McDonald's omega from 0.898 to 0.917, which places every scale inside the acceptable band and below the ceiling that would indicate redundant items. Composite reliability ranges from 0.864 to 0.896 and average variance extracted from 0.509 to 0.519, so each construct explains slightly more than half the variance in its own indicators. Table 3 reports discriminant validity, where the square root of average variance extracted exceeds every corresponding inter-construct correlation and every heterotrait-monotrait ratio falls below the conservative threshold of 0.85. The highest ratio reaches 0.646 between academic burnout and sleep quality, and the lowest reaches 0.386 between short-video addiction and emotion regulation.

Table 3. Discriminant Validity and Model Fit Indices

Construct	SVA	ER	AB	SQ
Panel A. Fornell and Larcker criterion				
Short-video addiction (SVA)	0.713			
Emotion regulation (ER)	−0.388	0.718		
Academic burnout (AB)	0.491	−0.507	0.720	
Sleep quality (SQ)	−0.526	0.482	−0.647	0.720
Panel B. Heterotrait-monotrait ratio				
Emotion regulation (ER)	0.386			
Academic burnout (AB)	0.495	0.502		
Sleep quality (SQ)	0.522	0.475	0.646	
Panel C. Confirmatory factor analysis fit				
χ^2 = 322.216; df = 344; p = .795	χ^2/df = 0.937	CFI = 1.000	TLI = 1.000	GFI = 0.937
RMSEA = 0.000; SRMR = 0.034	AGFI = 0.931	NFI = 0.937	–	–

Source: Authors' analysis of the survey data (2026)

Common method variance does not appear to threaten the estimates. Harman's single factor test returns a first unrotated factor accounting for 34.48 per cent of total variance, which falls below the customary 50 per cent criterion, and four factors with eigenvalues above unity emerge from the item pool. The more sensitive full collinearity test returns variance inflation factors between 1.326 and 1.678 across the four constructs, well below the 3.3 threshold at which

contamination would be suspected (*Kock, 2015*). Both tests are indirect rather than definitive, but together they reduce the concern that a single response tendency produced the observed pattern.

Descriptive Relationships

Table 4 reports construct descriptives and the bivariate correlation matrix. The four construct means cluster near the scale midpoint, between 2.968 and 2.995, with standard deviations close to 0.9. Every correlation among the four constructs is significant and runs in the hypothesised direction. Short-video addiction correlates negatively with emotion regulation at minus 0.339 and with sleep quality at minus 0.458, and positively with academic burnout at 0.443. Emotion regulation correlates negatively with burnout at minus 0.443 and positively with sleep quality at 0.412, while burnout and sleep quality correlate at minus 0.569, the strongest association in the matrix.

Table 4. Descriptive Statistics and Bivariate Correlations

Variable	M	SD	1	2	3	4	5	6
1. Short-video addiction	2.968	0.882	–					
2. Emotion regulation	2.972	0.913	−.339	–				
3. Academic burnout	2.995	0.888	.443	−.443	–			
4. Sleep quality	2.973	0.905	−.458	.412	−.569	–		
5. Sleep duration, hours	6.692	0.827	−.475	.358	−.477	.736	–	
6. Sleep latency, minutes	25.160	10.957	.549	−.310	.431	−.609	−.545	–
7. Late bedtimes per week	1.990	0.924	.571	−.282	.434	−.472	−.423	.415
8. Short-video hours per day	2.102	1.261	.549	−.177	.238	−.208	−.215	.272

Source: Authors' analysis of the survey data (2026)

The behavioural indicators support the same picture from a different measurement source. Short-video addiction correlates 0.549 with daily viewing hours, minus 0.475 with sleep duration, 0.549 with sleep latency, and 0.571 with the number of late bedtimes each week. Sleep quality correlates 0.736 with sleep duration and minus 0.609 with sleep latency, which supports the criterion relevance of the subjective scale. One comparison is worth noting for the discussion, since short-video addiction correlates far more strongly with sleep quality at minus 0.458 than viewing hours do at minus 0.208. The compulsive quality of the behaviour therefore carries more information about sleep than the amount of time it consumes. Two students who both view for two hours may consequently differ substantially in sleep outcomes depending on whether that viewing was chosen or simply could not be stopped.

Serial Mediation Model and Hypothesis Testing

Table 5 reports the structural estimates and Figure 2 displays the fitted model. All six of the hypothesised direct paths are supported. Short-video addiction predicts weaker emotion

regulation at minus 0.339 and higher academic burnout at 0.331, while emotion regulation predicts lower burnout at minus 0.331 and better sleep quality at 0.158. Academic burnout carries the strongest single coefficient in the model at minus 0.398 on sleep quality. The direct path from short-video addiction to sleep quality remains significant at minus 0.228 once both mediators are included, compared with a total effect of minus 0.458. Collinearity is unproblematic, with inner variance inflation factors between 1.285 and 1.416.

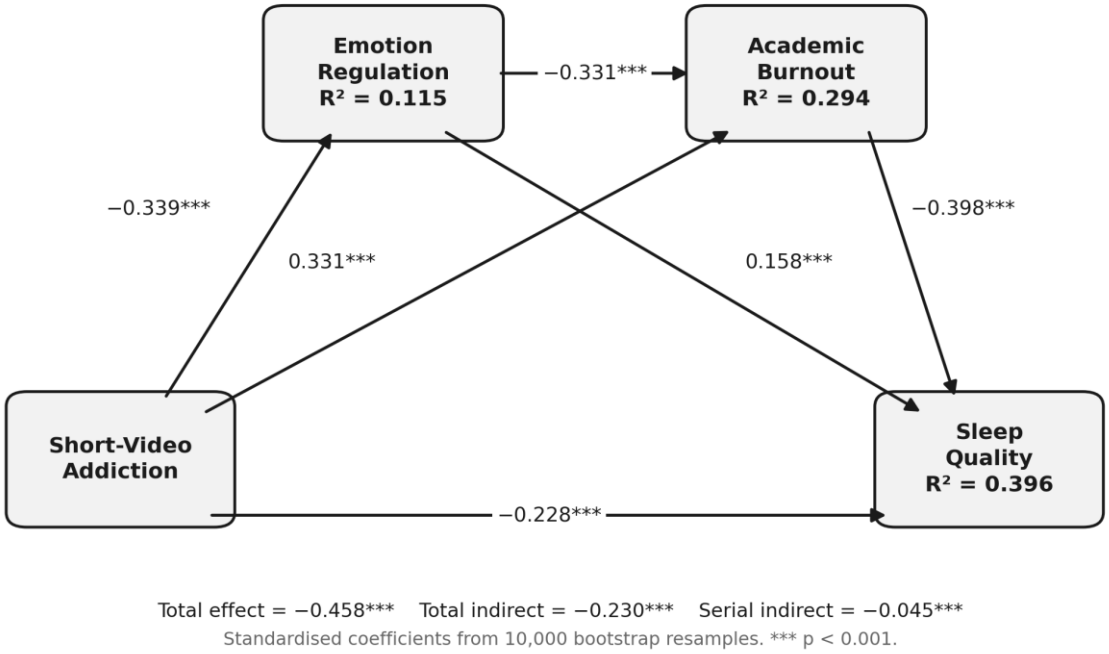

Figure 2. Estimated serial mediation model with standardised path coefficients and coefficients of determination

Source: Authors' analysis of the survey data (2026)

The model accounts for 11.5 per cent of the variance in emotion regulation, 29.4 per cent in academic burnout, and 39.6 per cent in sleep quality, and the adjusted values of 0.112, 0.290, and 0.391 confirm that the fit is not inflated by the number of predictors. Emotion regulation adds 9.7 percentage points of explained variance to the burnout equation beyond short-video addiction alone, which establishes it as a substantive rather than incidental predictor. Effect sizes in the sleep quality equation place burnout well ahead of the other predictors at 0.186, against 0.067 for short-video addiction and 0.032 for emotion regulation.

Table 5. Path Coefficients, Indirect Effects, and Hypothesis Testing

Path or effect	β	SE	t	p	95% bootstrap CI	Decision
Panel A. Direct paths						
H1 SVA → SQ (direct, c′)	−0.228	0.046	−4.982	<.001	[−0.320, −0.136]	Supported
H2 SVA → ER (a1)	−0.339	0.049	−6.952	<.001	[−0.429, −0.247]	Supported
H3 SVA → AB (a2)	0.331	0.046	7.148	<.001	[0.236, 0.422]	Supported
H4 ER → AB (d21)	−0.331	0.046	−7.151	<.001	[−0.418, −0.241]	Supported

H5 ER → SQ (b1)	0.158	0.046	3.454	<.001	[0.075, 0.241]	Supported
H6 AB → SQ (b2)	−0.398	0.048	−8.301	<.001	[−0.496, −0.299]	Supported
Total effect SVA → SQ (c)	−0.458	0.046	−9.947	<.001	[−0.547, −0.368]	Significant
Panel B. Indirect effects						
H7 SVA → ER → SQ	−0.053	0.016	–	–	[−0.088, −0.024]	Supported
H8 SVA → AB → SQ	−0.132	0.025	–	–	[−0.183, −0.085]	Supported
H9 SVA → ER → AB → SQ	−0.045	0.011	–	–	[−0.067, −0.026]	Supported
Total indirect effect	−0.230	0.030	–	–	[−0.291, −0.173]	Significant
Panel C. Contrasts between indirect effects						
H7 minus H8	0.078	0.033	–	–	[0.015, 0.143]	Different
H7 minus H9	−0.009	0.019	–	–	[−0.046, 0.028]	Equivalent
H8 minus H9	−0.087	0.025	–	–	[−0.139, −0.040]	Different

Source: Authors' analysis of the survey data (2026)

All three indirect effects are significant and Figure 3 displays the decomposition. The route through academic burnout carries minus 0.132 with a bootstrap interval from minus 0.183 to minus 0.085, the route through emotion regulation carries minus 0.053 with an interval from minus 0.088 to minus 0.024, and the serial route running from regulation to burnout carries minus 0.045 with an interval from minus 0.067 to minus 0.026. The seventh, eighth, and ninth hypotheses are therefore supported. Total indirect transmission reaches minus 0.230 and accounts for 50.3 per cent of the total effect, so exactly half the association between compulsive viewing and poor sleep passes through the two mediators. Because the direct effect remains significant and carries the same sign, the pattern represents complementary partial mediation (*Zhao et al., 2010*).

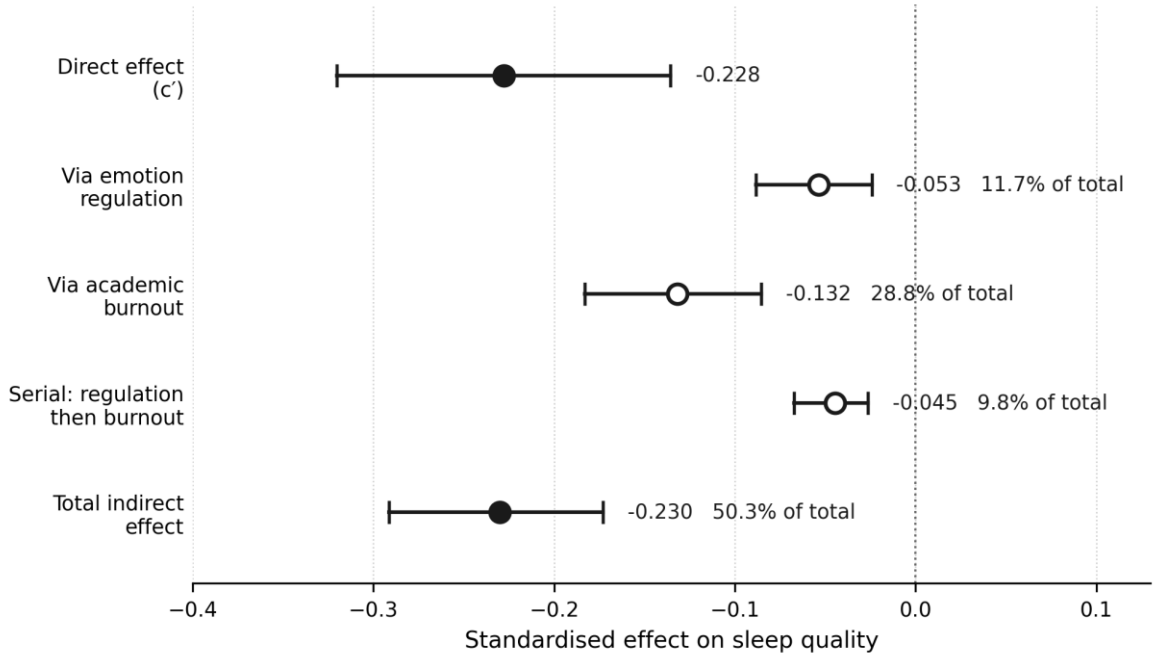

Figure 3. Decomposition of the total effect of short-video addiction on sleep quality with 95 per cent bootstrap confidence intervals

Source: Authors' analysis of the survey data (2026)

Pairwise contrasts computed within the same bootstrap distribution establish that the three routes are not equivalent. The burnout route exceeds the emotion regulation route by 0.078 with an interval from 0.015 to 0.143, and it exceeds the serial route by 0.087 with an interval from 0.040 to 0.139. The contrast between the emotion regulation route and the serial route is not significant, since its interval from minus 0.046 to 0.028 contains zero. Academic burnout is therefore the dominant transmission channel, while the two routes involving emotion regulation are of comparable and smaller magnitude. Formal contrast testing of this kind is rarely reported in mediation studies, yet without it a reader cannot tell whether an apparent difference between routes reflects a real ordering or ordinary sampling variation.

Robustness Checks and Supplementary Analyses

Table 6 reports the checks on the primary estimates. Re-estimating every equation with age, gender, year of study, living arrangement, daily device use, daily viewing hours, nighttime use frequency, caffeine consumption, and weekly study hours held constant leaves the pattern intact. The adjusted path coefficients reach minus 0.349, 0.350, minus 0.335, 0.160, minus 0.399, and minus 0.250, and the adjusted indirect effects reach minus 0.056, minus 0.140, and minus 0.047 for a total of minus 0.242. Explained variance rises modestly to 15.0 per cent for emotion regulation, 33.1 per cent for burnout, and 42.1 per cent for sleep quality. Every conclusion survives the inclusion of viewing hours, which means the model does not merely restate a time displacement effect.

Table 6. Robustness Checks and Supplementary Analyses

Check or analysis	SVA	ER	AB	Model R^2
Panel A. Covariate-adjusted path coefficients				
Emotion regulation equation	−0.349	–	–	0.150
Academic burnout equation	0.350	−0.335	–	0.331
Sleep quality equation	−0.250	0.160	−0.399	0.421
Adjusted indirect effects	−0.056	−0.140	−0.047	−0.242
Panel B. Emotion regulation as moderator				
SVA × ER predicting burnout, b	0.003	p = .941	$\Delta R^2 < .001$	–
SVA × ER predicting sleep quality, b	−0.006	p = .892	$\Delta R^2 < .001$	–
Panel C. Behavioural sleep outcomes, standardised b				
Sleep duration, hours	−0.252	0.107	−0.235	0.327
Sleep latency, minutes	4.737	−0.778 (ns)	2.278	0.349
Late bedtimes per week	0.431	−0.027 (ns)	0.198	0.367
Panel D. Group comparisons				
Gender difference, largest d	0.157 (ns)	–	–	–
Nighttime use categories, means	2.68 to 3.21	–	–	F = 4.448, p = .004
Sleep latency across the same categories	21.13 to 28.12	–	–	F = 4.027, p = .008

Source: Authors' analysis of the survey data (2026)

The second check addresses the role that emotion regulation actually plays. Adding the product of short-video addiction and emotion regulation to the burnout equation produces a coefficient of 0.003 with a probability value of 0.941 and an increment in explained variance of less than one hundredth of a percentage point. The same product added to the sleep quality equation returns minus 0.006 with a probability value of 0.892. Emotion regulation therefore functions as a mediator that transmits part of the effect rather than as a buffer that weakens it, and the discussion returns to the consequences of that distinction.

The third and fourth checks concern outcome validity and group differences. Replacing the subjective sleep scale with behavioural indicators reproduces the substantive conclusions, since short-video addiction and academic burnout both predict shorter sleep duration, longer sleep latency, and more frequent late bedtimes, with explained variance between 32.7 and 36.7 per cent. Emotion regulation predicts sleep duration significantly but does not predict latency or late bedtimes, which suggests that its influence operates on restorative quality rather than on timing. No construct differs significantly between female and male respondents. Short-video addiction rises monotonically across the four categories of nighttime use from 2.68 to 3.21, and sleep latency rises from 21.13 to 28.12 minutes across the same categories.

IV. DISCUSSION

The discussion interprets each result against the compensatory use and resource depletion literatures and gives extended attention to two findings that carry consequences beyond the hypothesis set. Interpretation moves from the magnitude of the total effect, through the relative weight of the three transmission routes, to the distinction between mediation and buffering that the moderation test settles. Practical implications for institutions close the section that follows.

Compulsion Rather Than Duration

The total effect of short-video addiction on sleep quality reaches minus 0.458, which is substantial for a single behavioural predictor of a multiply determined outcome. More informative than its size is a comparison that the correlation matrix makes available. Daily viewing hours correlate with sleep quality at only minus 0.208, while the addiction construct correlates at minus 0.458, and the structural estimates survive the inclusion of viewing hours as a covariate. Time spent viewing is therefore a poor proxy for the harm associated with viewing, and the loss of control that defines the construct carries the information that duration does not.

This result has an immediate consequence for how the problem is measured in practice. Screen-time dashboards, institutional guidelines expressed in hours, and parental or self-imposed limits all operate on duration because duration is easy to record. If duration explains roughly four per cent of the variance in sleep quality while the compulsive pattern explains more than twenty, then monitoring hours will identify the wrong students. Conceptual work on problematic internet use has argued for years that quantity and pathology are distinct, and the present estimates give that argument a numerical form (*Kardefelt-Winther, 2014; Kuss & Griffiths, 2017*).

Why Burnout Dominates the Transmission

Exactly half the total effect passes through the two mediators, and the burnout route carries more than twice as much as either route involving emotion regulation. The bootstrap contrasts confirm that this ordering is not an artefact of sampling, since the burnout route significantly exceeds both alternatives while the two smaller routes do not differ from one another. Conservation of resources theory offers a coherent reading, because burnout represents accumulated depletion rather than momentary distress, and depletion of that kind is what disrupts sleep across nights rather than on a single occasion (*Hobfoll, 1989; Edú-Valsania et al., 2022*).

The path from burnout to sleep quality at minus 0.398 is the strongest in the model, which places the academic pathway rather than the technological one closest to the outcome. Experimental reviews of how emotional states affect sleep support this positioning, since sustained negative affect lengthens sleep onset and fragments continuity through mechanisms that operate at bedtime (*Krizan et al., 2024*). Bedtime procrastination supplies a behavioural counterpart, in which depleted students reclaim discretionary time by delaying sleep and then face the next day with fewer resources still (*Kroese et al., 2014*). The behavioural indicators in this study fit that account, since burnout predicted shorter duration, longer latency, and more frequent late bedtimes.

The serial route deserves separate comment despite being the smallest of the three. Its magnitude of minus 0.045 is modest, yet it is estimated precisely and its confidence interval is comfortably distant from zero. Its theoretical value lies in specifying a sequence rather than in its size, because it shows that part of the burnout produced by compulsive viewing arrives through weakened regulatory capacity rather than through workload alone. Previous chain models in this area have linked short-video addiction to sleep through physical activity and procrastination, which are behavioural intermediaries (*Zhao & Kou, 2024*). Adding an affective-regulatory intermediary upstream of an academic one extends that work rather than duplicating it.

A Mediator, Not a Buffer

Emotion regulation is routinely described as a protective factor, and the present results support that description while sharply qualifying what the protection consists of. Regulation predicts lower burnout and better sleep, and it transmits part of the effect of compulsive viewing, so students with stronger regulatory capacity do fare better. What it does not do is weaken the association between short-video addiction and burnout. The interaction between the two variables produced a coefficient of 0.003 with a probability value of 0.941 and an increment in explained variance too small to report meaningfully, which is about as unambiguous a null result as this kind of test produces.

The distinction matters because the two roles imply different interventions. If regulation buffered the effect, then strengthening it would allow students to continue heavy viewing at reduced cost, and a resilience-building programme would be a sufficient response. Because regulation instead sits on the causal path, strengthening it addresses only the portion of the effect that travels through it, which these estimates place at roughly one fifth of the indirect transmission. Compulsive viewing continues to damage sleep through burnout and through the direct route regardless of how well a student regulates. Compensatory accounts of problematic

use anticipate exactly this configuration, since they treat absorbing digital content as a substitute for regulation rather than as a stressor that regulation neutralises (*Kardefelt-Winther, 2014; Brand et al., 2019*).

A related asymmetry appears in the behavioural analyses. Emotion regulation predicted sleep duration but not sleep latency or the frequency of late bedtimes, whereas short-video addiction and burnout predicted all three. Regulation therefore appears to influence how restorative sleep is rather than when sleep begins, which is consistent with its role as an affective rather than a scheduling resource. A student who regulates well may still go to bed at two in the morning, but the sleep obtained after that point appears to be more restorative than it would otherwise have been. Reviews of regulation strategies reach compatible conclusions, since reappraisal and suppression alter emotional experience without necessarily altering the behaviour that produced the emotion (*Aldao et al., 2010; Dryman & Heimberg, 2018; Gross & John, 2003*).

Convergence Across Measurement Sources

A recurring weakness of research in this area is that predictor and outcome are both self-reported on adjacent pages of the same questionnaire, which makes common method variance a live concern. The present study addressed this in two ways and both were reassuring. Harman's test and the full collinearity procedure produced values comfortably inside acceptable limits, and more importantly the conclusions replicated when the subjective sleep scale was replaced with duration, latency, and late bedtime frequency (*Podsakoff et al., 2003; Kock, 2015*). Explained variance in those behavioural models ranged from 32.7 to 36.7 per cent, which is close to the 39.6 per cent obtained with the scale.

The graded pattern across nighttime use categories adds a further piece of convergent evidence. Short-video addiction rose steadily from 2.68 among students who rarely view near bedtime to 3.21 among those who do so very often, and sleep latency rose in parallel from 21.13 to 28.12 minutes. Because nighttime use was reported as a frequency category rather than as part of any scale, this gradient cannot be attributed to a shared response tendency. Studies of bedtime media use report the same timing-specific pattern and attribute it to a combination of cognitive arousal and delayed sleep onset (*Exelmans & Van den Bulck, 2016; Cain & Gradisar, 2010*).

What the Model Contributes Theoretically

Taken together the estimates support what may be called a dual-route depletion account. Compulsive viewing damages sleep partly through an affective route in which regulatory capacity is eroded, and partly through an academic route in which accumulated exhaustion disturbs rest, with the second route carrying roughly two and a half times the weight of the first. The serial path joins the two by showing that some of the exhaustion originates in weakened regulation rather than in workload alone. Neither the compensatory use literature nor the resource depletion literature generates this configuration on its own, since the first stops at affect and the second begins at demand (*Kardefelt-Winther, 2014; Hobfoll, 1989*).

The account also clarifies why the direct path survives at minus 0.228 after both mediators enter the model. Roughly half the total association remains unexplained by regulation and burnout

together, which leaves room for the mechanisms this design did not measure. Displacement of sleep time, cognitive arousal from rapidly changing content in the hour before bed, and light exposure are the most obvious candidates, and each has independent support in the sleep literature (*Cain & Gradisar, 2010; Exelmans & Van den Bulck, 2016*). Specifying those mechanisms alongside the psychological routes tested here would produce a more complete model than either tradition currently offers.

Implications for Practice

Three consequences follow for institutions that wish to act on these findings. The first concerns screening, since the results indicate that campus wellbeing services should assess loss of control rather than hours of use. A short instrument covering difficulty stopping, exceeding intended time, and unsuccessful attempts to cut down would identify at-risk students far more accurately than any measure of duration, and it can be administered in a few minutes during routine health or academic advising. Screening on duration alone would also generate false positives among students who view a great deal without any loss of control, which wastes limited counselling capacity on people who do not need it. Screening of this kind depends on staff able to interpret digital behaviour rather than merely record it, and evidence from Islamic schools indicates that student digital literacy improves where teacher professionalism mediates the use of institutional technology resources (*Ariyani et al., 2026*). Gathering such information also creates an obligation to act on it, which is a matter of ethical leadership rather than of instrument design (*Che Noh et al., 2026*).

The second consequence concerns where intervention effort should be directed. Because academic burnout carries the largest share of the indirect effect and sits closest to the outcome, workload management, assessment scheduling, and early identification of exhaustion are likely to protect sleep more efficiently than any programme aimed at viewing behaviour alone. Systems able to flag exhaustion early are already described in prototype form, since reviews of deep learning in curriculum management list predictive analytics of student outcomes among the more developed applications (*Idham et al., 2026*), although their usefulness depends on adoption conditions among lecturers and students that institutions seldom examine before procurement (*Novita et al., 2026*). Decisions about workload sit with institutional leaders rather than with counselling staff, and studies of Indonesian pesantren indicate that collegial professional structures determine whether such decisions reach the classroom at all (*Listyasari et al., 2026*). This does not make regulation training worthless, since regulation predicts burnout strongly and contributes its own route, but it does mean that a strategy addressing only the individual student while leaving academic demands unchanged is working on the smaller half of the problem (*Schaufeli et al., 2002; Mao et al., 2024*).

The third consequence concerns the timing of viewing behaviour. The gradient across nighttime use categories and the association with sleep latency both point to the hour before sleep as the period where the behaviour does most damage. Sleep hygiene guidance for students should therefore be specific about when viewing occurs rather than general about how much, and institutional measures such as avoiding assessment deadlines set at midnight would remove one

incentive for students to remain awake and connected (*Tandon et al., 2020*). Hybrid literacy frameworks that pair technical skill with digital etiquette and self-regulated use show one practical way to deliver guidance at that level of specificity (*Andriana & Khalid, 2026*).

V. CONCLUSION

This study tested a serial mediation model linking short-video addiction to sleep quality through emotion regulation and academic burnout among 375 undergraduate students. Nine answers emerged from the analysis reported in this article. The first six confirm every hypothesised direct path, since short-video addiction predicted poorer sleep quality at minus 0.228, weaker emotion regulation at minus 0.339, and higher academic burnout at 0.331, while emotion regulation predicted lower burnout at minus 0.331 and better sleep at 0.158, and burnout predicted poorer sleep at minus 0.398. The remaining three confirm indirect transmission through emotion regulation at minus 0.053, through academic burnout at minus 0.132, and through the serial chain at minus 0.045, with every bootstrap interval excluding zero.

Two findings extend beyond the hypothesis set and deserve emphasis in any summary. Emotion regulation operated as a mediator rather than as a buffer, since its interaction with short-video addiction was entirely non-significant, which means that strengthening regulatory capacity addresses one route rather than neutralising the behaviour. The compulsive quality of viewing also proved far more informative than its duration, since the addiction construct correlated with sleep quality at minus 0.458 while daily viewing hours correlated at only minus 0.208 and the structural estimates survived the inclusion of viewing hours as a covariate. Taken together these results indicate that interventions should target how students view rather than how long, and that academic workload deserves as much attention as the technology itself.

Several limitations qualify the conclusions drawn in the preceding paragraphs. The design is cross-sectional, so the ordering of the two mediators rests on theory rather than on observed temporal precedence, and the indirect effects should be read as statistical mediation rather than as evidence of causation. Reverse and reciprocal pathways are plausible, since poor sleep may itself increase evening viewing and deplete regulatory capacity. All four constructs rely on self-report, and although the behavioural indicators and the method variance tests reduce this concern they do not eliminate it, since duration and latency were also self-estimated rather than measured objectively. Sampling was purposive and confined to undergraduates who use short-video platforms, which limits generalisation to non-users, to secondary school students, and to working adults. The model also explains 11.5 per cent of the variance in emotion regulation, which indicates that most variation in regulatory capacity arises from sources the model does not contain.

Future research should proceed in four directions that follow from these limitations. Longitudinal designs with at least three measurement waves would allow cross-lagged estimation and would test whether the proposed sequence holds over time or whether reciprocal effects dominate. Objective sleep measurement through actigraphy or validated sleep diaries would remove the shared-method concern that self-estimated duration and latency cannot fully resolve. Experimental or quasi-experimental evaluation of a combined intervention addressing both

regulatory skills and academic workload would test the practical implication that follows from the relative weight of the two routes. Finally, replication in secondary school samples would establish whether the same architecture holds at an age when regulatory capacity is still developing and when the academic pathway takes a different form.

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