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Understanding the Impact of Social Media Fatigue on the Decline in Academic Performance among University Students—From a Stressor–Strain–Outcome Perspective

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Keywords: Social media fatigue; University students; Stressor–strain–outcome model; Compulsive use; Information overload; Life intrusion

Abstract: Based on the stressor–strain–outcome (SSO) model, this study examines the effects of compulsive use, information overload, and life intrusion on the decline in academic performance among university students, and tests the mediating role of social media fatigue. Using a sample of 360 undergraduate students from universities in Shanghai, structural equation modeling (SEM) and the Bootstrap method were employed for data analysis. The results indicate that all three categories of stressors significantly and positively predict both social media fatigue and declines in academic performance. Social media fatigue partially mediates the relationship between stressors and academic performance decline, with the total indirect effect accounting for 22.4% of the total effect. These findings provide empirical support for the development of digital literacy education, academic support systems, and psychological intervention strategies in higher education institutions.

1. Introduction

With the rapid development of mobile Internet, smart terminals, and algorithmic recommendation systems, social media has become deeply embedded in university students' learning, social interaction, and daily lives. It serves not only as an important medium for information acquisition and relationship maintenance but also as a commonly used tool for learning support[1-2]. As of December 2025, the number of social network users in China had reached 1.114 billion, with mobile Internet users totaling 1.121 billion; globally, active social media users had reached 5.24 billion in 2025[1-2]. However, continuous connectivity, instant feedback, and frequent task-switching may also lead to problems such as attention fragmentation, increased procrastination, and the depletion of psychological resources[3-6].

Regarding the negative effects of social media use, existing studies have explored this issue from the perspectives of stress, overload, and behavioral outcomes. Edwards and Cooper explain the formation of stress from the perspective of person–environment fit, while Cheung and Tang suggest that external stressors can influence behavioral and performance outcomes through individual stress responses[7-8]. In digital media contexts, information and communication technology (ICT) overload, frequent switching, and persistent connectivity have been shown to significantly induce social

media fatigue and impair attention[4-6]. In the field of education, excessive use, dependence, and addiction to social media are also associated with increased academic procrastination, reduced learning engagement, and impaired academic performance[9-10].

Accordingly, this study adopts a stressor–strain–outcome (SSO) perspective and focuses on university students. It conceptualizes compulsive use, information overload, and life intrusion as stressors; social media fatigue as the strain response; and decline in academic performance as the outcome variable. Using questionnaire surveys, structural equation modeling (SEM), and the Bootstrap method, this study systematically examines the relationships among these variables. This study aims to address three key questions: 1. Do multidimensional digital stressors jointly contribute to social media fatigue? 2. Can social media fatigue explain the transmission mechanism between stressors and academic performance decline? 3. How can the explanatory boundaries of the SSO model be further extended in the context of university students' social media use?

2. Literature Review and Research Hypotheses

2.1. Stressor–Strain–Outcome Theory

The SSO theory posits that individuals are first exposed to external stimuli or environmental demands. When these demands exceed their available resources and coping capacities, stress responses such as tension, exhaustion, or fatigue emerge, which subsequently manifest in changes in attitudes, behaviors, and performance[7-8]. This framework has been widely applied to explain the negative consequences of digital media use, including the effects of excessive social media use, social media overload, and learning burnout on academic performance[5-6]. Based on this framework, the present study conceptualizes compulsive use, information overload, and life intrusion as stressors; social media fatigue as the strain response; and decline in academic performance as the outcome variable.

2.2. Antecedents of Social Media Fatigue

2.2.1. Compulsive Use and Social Media Fatigue

Compulsive use refers to individuals' persistent, high-frequency, and difficult-to-control engagement with social media even in the absence of clear functional needs. Its core characteristics include repetitive checking, continuous online presence, and difficulty disengaging. Within the SSO framework, compulsive use consumes cognitive and emotional resources through persistent connectivity and frequent task switching, thereby inducing fatigue experiences [11-12]. Existing studies indicate that problematic social media use not only increases fatigue levels but also weakens academic engagement and learning involvement[12]. Accordingly, the following hypothesis is proposed:

H1: Compulsive use has a significant positive effect on social media fatigue.

2.2.2. Information Overload and Social Media Fatigue

Information overload refers to a condition in which the quantity, update frequency, or complexity of information received within a given time exceeds an individual's cognitive processing capacity, resulting in comprehension difficulties, delayed judgment, and psychological burden [4]. In social media environments, algorithmic recommendations, fragmented content, and high-frequency interactions continuously amplify the intensity of information input, making university students more susceptible to a state of "excess information that cannot be processed in time." Relevant studies suggest that information overload and communication overload

significantly exacerbate social media fatigue and reinforce negative responses through emotional exhaustion[13-14]. Accordingly, the following hypothesis is proposed:

H2: Information overload has a significant positive effect on social media fatigue.

2.2.3. Life Intrusion and Social Media Fatigue

Life intrusion refers to the extent to which social media use penetrates the boundaries of individuals' study, rest, and private life, placing them in a state of constant connectivity and immediate responsiveness[15]. Compared with general usage frequency, life intrusion emphasizes the continuous encroachment of digital technologies on time allocation, attention distribution, and personal boundaries. Existing studies indicate that when learning tasks and social media interactions increasingly intrude into private time, individuals are more likely to experience technostress, emotional exhaustion, and fatigue responses[15-17]. Accordingly, the following hypothesis is proposed:

H3: Life intrusion has a significant positive effect on social media fatigue.

2.3. Social Media Fatigue and Academic Performance Decline

Social media fatigue refers to multidimensional negative experiences—including physical and psychological exhaustion, negative emotions, and reduced interest and motivation—resulting from intensive social media interaction[18-19]. Academic performance decline is manifested in sustained negative changes such as reduced learning efficiency, lower task completion quality, insufficient classroom participation, and deteriorating academic outcomes. Existing research suggests that social media fatigue weakens learning engagement, reinforces procrastination behaviors, and ultimately undermines academic performance[5,20-21]. Accordingly, the following hypothesis is proposed:

H4: Social media fatigue has a significant positive effect on academic performance decline.

2.4. Stressors and Academic Performance Decline: Direct Effects

Existing studies indicate that compulsive use, information overload, and life intrusion not only induce social media fatigue but may also directly impair university students' academic performance. Specifically, compulsive use encroaches upon study time and weakens concentration; information overload leads to cognitive congestion and reduced processing efficiency; and life intrusion blurs the boundaries between study and rest, thereby disrupting learning rhythms[5,22-23,25]. Accordingly, the following hypotheses are proposed:

H5: Compulsive use has a significant positive effect on academic performance decline.

H6: Information overload has a significant positive effect on academic performance decline.

H7: Life intrusion has a significant positive effect on academic performance decline.

2.5. The Mediating Role of Social Media Fatigue

According to the stressor–strain–outcome (SSO) model, stressors influence outcome variables through internal responses such as fatigue and exhaustion. Prior research has confirmed that compulsive use, information overload, and social overload can weaken university students' learning conditions and academic performance through social media fatigue or cognitive exhaustion[20,24-25]. Accordingly, the following hypotheses are proposed:

H8: Social media fatigue mediates the relationship between compulsive use and academic performance decline.

H9: Social media fatigue mediates the relationship between information overload and academic performance decline.

H10: Social media fatigue mediates the relationship between life intrusion and academic performance decline.

Based on the SSO model, compulsive use keeps individuals continuously connected; information overload occupies cognitive resources; and life intrusion blurs the boundary between study and rest. These stressors manifest as fatigue and emotional exhaustion, which weaken learning engagement and execution capacity, ultimately leading to a decline in academic performance.

In summary, the research model of this study is presented in Figure 1.

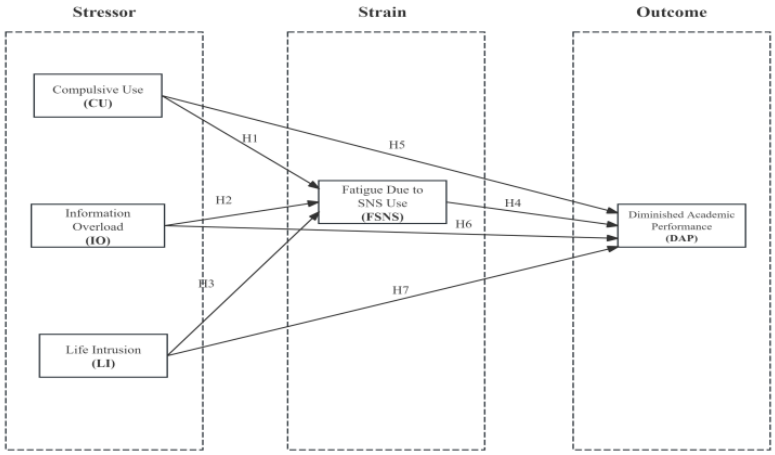

Figure 1: Research Model.

3. Research Methods

3.1. Participants and Procedure

This study employed a questionnaire survey method, targeting undergraduate students from freshman to senior years in Shanghai. A total of 375 questionnaires were collected, of which 360 valid responses remained after excluding invalid entries, yielding a valid response rate of 96%. In the sample, females accounted for 54.44% and males for 45.56%. Students aged 19–20 and 21–22 accounted for 49.72% and 50.28%, respectively. Sophomores constituted the largest proportion (36.39%). Approximately 95% of respondents had more than three years of social media experience. In terms of daily usage, 56.94% reported 1–2 hours, and 36.11% reported 3–4 hours of use. The basic demographic characteristics of the sample are presented in Table 1.

Table 1: Sample Characteristics

Variable	Category	Frequency	Percentage (%)
Gender	Male	164	45.56%
	Female	196	54.44%
Grade	Freshman	64	17.78%
	Sophomore	131	36.39%
	Junior	76	21.11%
	Senior	89	24.72%
Age	19–20	179	49.72%
	21–22	181	50.28%
Years of Social Media Use	<1 year	7	1.94%
	1–2 years	11	3.06%
	3–4 years	67	18.61%
	>5 years	275	76.39%
Daily Usage	<1 hour	14	3.89%
	1–2 hours	205	56.94%
	3–4 hours	130	36.11%
	>5 hours	11	3.06%

3.2. Measurement of Variables

To ensure the validity of the measurement instruments, this study adopted well-established international scales and made minor modifications based on the research context, thereby ensuring reliability and validity.

3.2.1. Compulsive Use (CU)

This variable was measured using the scale developed by Malik et al.[24], consisting of four items. A five-point Likert scale was used (5 = always, 4 = often, 3 = sometimes, 2 = occasionally, 1 = never), with higher scores indicating a higher frequency of compulsive social media use. The Cronbach's α for this scale in the present study was 0.826.

3.2.2. Information Overload (IO)

This variable was measured using the scale developed by Shi et al.[25], consisting of three items. A five-point Likert scale was employed (5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, 1 = strongly disagree), with higher scores indicating a higher perceived level of information overload. The Cronbach's α for this scale in the present study was 0.826.

3.2.3. Life Intrusion (LI)

This variable was measured using the scale developed by Xiao et al.[15], consisting of three items. A five-point Likert scale was employed (5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, 1 = strongly disagree), with higher scores indicating a greater degree of life intrusion caused by social media use. In this study, the Cronbach's α for this scale was 0.804.

3.2.4. Fatigue Due to SNS Use (FSNS)

This variable was measured using the scale developed by Malik et al.[24], consisting of three items. A five-point Likert scale was used (5 = always, 4 = often, 3 = sometimes, 2 = occasionally, 1 = never), with higher scores indicating a higher level of fatigue caused by social networking service (SNS) use. In this study, the Cronbach's α for this scale was 0.812.

3.2.5. Diminished Academic Performance (DAP)

This variable was measured using the scale developed by Malik et al.[24], consisting of four items. A five-point Likert scale was adopted (5 = always, 4 = often, 3 = sometimes, 2 = occasionally, 1 = never), with higher scores indicating greater declines in academic performance due to social media use. In this study, the Cronbach's α for this scale was 0.824.

3.3. Common Method Bias Test

The test for common method bias showed that, in Harman's single-factor test, the variance explained by the first unrotated factor was 37.15%, which is below the critical threshold of 50%. Further confirmation was conducted using the confirmatory factor analysis (CFA) comparison method with Mplus 8.3. The results indicated that $\Delta\chi^2 = 847.493$ and $\Delta df = 10$, with a significant difference between the two models ($p < 0.001$), suggesting that no serious common method bias was present (see Table 2).

Table 2: CFA Comparison between Model 1 and Model 2.

Model	χ^2	DF	$\triangle\chi^2$	$\triangle$DF	P
Single-factor	972.590	119	847.493	10	0.000
Multi-factor	125.097	109			

4. Data Analysis

4.1. Reliability and Validity of the Measurement Scales

Confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the measurement scales. For reliability, the composite reliability (CR) and Cronbach's α values for all constructs exceeded 0.7, indicating satisfactory internal consistency. For convergent validity, all factor loadings exceeded 0.7, and the average variance extracted (AVE) values were above 0.5, demonstrating adequate convergent validity. Detailed results are presented in Table 3.

Table 3: Reliability and Validity of the Measurement Scales.

Dimension	Item	Unstandardized Coefficient	Standard Error	Z-value	p-value	Standardized Coefficient	Reliability (Cronbach's α)	Composite Reliability (CR)	Convergent Validity (AVE)
CU	CU1	1.000	-	-	-	Standardized Coefficient	0.826	0.826	0.543
	CU2	1.012	0.079	12.758	***	0.737			
	CU3	0.974	0.076	12.805	***	0.729			
	CU4	1.011	0.081	12.523	***	0.733			
IO	IO1	1.000	-	-	-	0.781	0.826	0.827	0.614
	IO2	1.033	0.073	14.101	***	0.801			
	IO3	0.967	0.071	13.659	***	0.768			
LI	LI1	1.000	-	-	-	0.758	0.804	0.805	0.579
	LI2	1.055	0.083	12.679	***	0.757			
	LI3	1.063	0.083	12.833	***	0.767			
FSNS	FSNS1	1.000	-	-	-	0.742	0.812	0.813	0.593
	FSNS2	1.083	0.081	13.376	***	0.803			
	FSNS3	1.001	0.079	12.697	***	0.763			
DAP	DAP1	1.000	-	-	-	0.730	0.824	0.824	0.540
	DAP2	1.066	0.085	12.516	***	0.755			
	DAP3	1.010	0.080	12.656	***	0.722			
	DAP4	0.971	0.079	12.226	***	0.731			

4.2. Confirmatory Factor Analysis

To assess construct validity, confirmatory factor analysis was conducted using Mplus 8.3. As shown in Table 4, the five-factor model demonstrated superior fit indices ($\chi^2/df = 1.148$, RMSEA = 0.020, SRMR = 0.029, CFI = 0.994, TLI = 0.992) compared to alternative models, indicating good discriminant validity among the constructs.

Table 4: Confirmatory Factor Analysis Results.

Fit Indices	χ^2	df	χ^2/df	RMSEA	SRMR	CFI	TLI	Model Comparison Test			
								Model Comparison	$\Delta\chi^2$	Δdf	P
Baseline Model (Five-Factor Model)	125.097	109	1.148	0.020	0.029	0.994	0.992				
Four-Factor Model	406.214	113	3.595	0.085	0.062	0.883	0.859	2 vs.1	281.117	4	***
Three-Factor Model	599.908	116	5.172	0.108	0.073	0.807	0.774	3 vs.1	474.811	7	***
Two-Factor Model	840.166	118	7.120	0.130	0.087	0.712	0.669	4 vs.1	715.069	9	***
Single-Factor Model	972.590	119	8.173	0.141	0.094	0.660	0.612	5 vs.1	847.493	10	***

Note: (1) n = 360. (2) *** $p < 0.001$ (two-tailed test). Baseline model: Compulsive use, information overload, life intrusion, fatigue due to SNS use, and diminished academic performance. Four-factor model: Based on the baseline model, information overload and life intrusion are combined into a single factor. Three-factor model: Based on the baseline model, information overload and life intrusion are combined into one factor, and fatigue due to SNS use and diminished academic performance are combined into another factor. Two-factor model: Compulsive use, information overload, and life intrusion are combined into one factor, while fatigue due to SNS use and diminished academic performance are combined into another factor. Single-factor model: Compulsive use, information overload, life intrusion, fatigue due to SNS use, and diminished academic performance are all combined into a single factor.

Table 5: Means, Standard Deviations, and Correlation Coefficients.

Variables	M	SD	1	2	3	4	5	6	7	8	9	10
1 Gender	1.540	0.499	1	-0.087	-0.073	0.053	-0.019	-0.085	-0.003	-0.050	-0.064	-0.063
2 Grade Level	2.530	1.050	-0.087	1	0.813***	-0.169***	-0.034	0.060	0.005	0.017	0.045	-0.042
3 Age	1.500	0.501	-0.073	0.813***	1	-0.814***	-0.022	0.042	-0.012	-0.033	0.043	0.004
4 Duration of Social Media Use	3.690	0.625	0.053	-0.169***	-0.814***	1	0.030	-0.026	-0.082	-0.104*	-0.022	-0.085
5 Daily Social Media Usage	2.380	0.613	-0.019	-0.034	-0.022	0.030	1	-0.01	0.032	-0.020	-0.005	0.032
6 Compulsive Use	3.367	0.905	-0.085	0.060	0.042	-0.026	-0.01	1	0.368***	0.381***	0.372***	0.473***
7 Information Overload	3.430	0.997	-0.003	0.005	-0.012	-0.082	0.032	0.368***	1	0.347***	0.401***	0.450***
8 Life Intrusion	3.435	0.920	-0.050	0.017	-0.033	-0.104*	-0.020	0.381***	0.347***	1	0.391***	0.453***
9 Fatigue Due to SNS Use	3.416	0.919	-0.064	0.045	0.043	-0.022	-0.005	0.372***	0.401***	0.391***	1	0.483***
10 Diminished Academic Performance	3.205	0.951	-0.063	-0.042	0.004	-0.085	0.032	0.473***	0.450***	0.453***	0.483***	1

Note: * indicates $p < 0.05$; ** indicates $p < 0.01$; *** indicates $p < 0.001$.

4.3. Descriptive Statistical Analysis

SPSS 27.0 was used to calculate the means, standard deviations, and correlation coefficients among the variables (see Table 5). The results indicate that compulsive use, information overload, life intrusion, fatigue due to SNS use, and diminished academic performance are all significantly positively correlated with each other ($p < 0.001$). In addition, diminished academic performance is also significantly positively correlated with academic performance decline.

4.4. Structural Model Testing

The results of the structural model testing indicate that the model demonstrates satisfactory fit, with the following indices: $\chi^2/df = 1.681$, TLI = 0.963, CFI = 0.970, RMSEA = 0.043, and SRMR = 0.065. Overall, the model constructed in this study exhibits good goodness-of-fit, and detailed results are presented in Table 6. The standardized path coefficients show that compulsive use, information overload, and life intrusion have significant positive effects on social media fatigue, with coefficients of 0.196, 0.284, and 0.273, respectively. Social media fatigue, in turn, has a significant positive effect on diminished academic performance ($\beta = 0.264$). Moreover, the direct effects of the three stressors on diminished academic performance are 0.259, 0.207, and 0.220, respectively, all of which are statistically significant. Therefore, hypotheses H1–H7 are supported (see Table 7 and Figure 2 for details).

Table 6: Model Fit Indices.

Fit Index	χ^2	df	χ^2/df	TLI	CFI	RMSEA	SRMR
Recommended Value	—	—	<3	>0.900	>0.900	<0.080	<0.080
Observed Value	125.097	109	1.148	0.992	0.994	0.020	0.029

Note: χ^2/df = chi-square/degrees of freedom; TLI = Tucker–Lewis Index; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual.

Table 7: Path Analysis Results.

Hypotheses	Path	Unstandardized Coefficient	Standard Error	Z-value	p-value	Standardized Coefficient	Result
H1	Compulsive Use → Fatigue Due to SNS Use	0.192	0.071	2.717	0.007**	0.196	Supported
H2	Information Overload → Fatigue Due to SNS Use	0.253	0.062	4.049	0.000***	0.284	Strongly Supported
H3	Life Intrusion → Fatigue Due to SNS Use	0.277	0.073	3.790	0.000***	0.273	Strongly Supported
H4	Fatigue Due to SNS Use → Diminished Academic Performance	0.279	0.074	3.789	0.000***	0.264	Strongly Supported
H5	Compulsive Use → Diminished Academic Performance	0.269	0.069	3.891	0.000***	0.259	Strongly Supported
H6	Information Overload → Diminished Academic Performance	0.195	0.062	3.145	0.002**	0.207	Supported
H7	Life Intrusion → Diminished Academic Performance	0.237	0.072	3.274	0.001***	0.220	Strongly Supported

Note: * indicates p < 0.05; ** indicates p < 0.01; *** indicates p < 0.001.

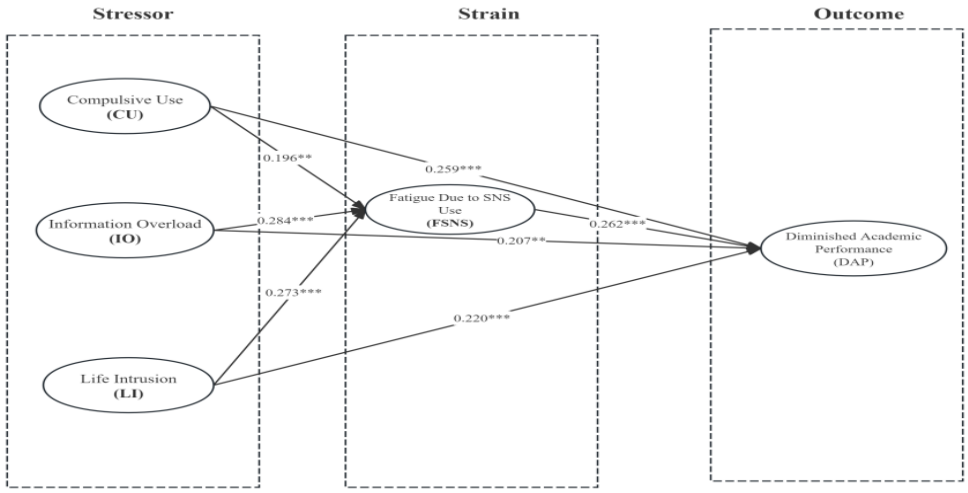

Figure 2: Schematic Diagram of Structural Equation Model Analysis Results

4.5. Mediation Effect Testing

As shown in Table 8, The Bootstrap mediation analysis indicates that all three specific indirect paths are significant: CU → FSNS → DAP: indirect effect = 0.054; IO → FSNS → DAP: indirect effect = 0.071; LI → FSNS → DAP: indirect effect = 0.077. The total indirect effect is 0.202, accounting for 22.4% of the total effect, indicating that social media fatigue plays a partial mediating role between the three stressors and diminished academic performance. Therefore,

hypotheses H8–H10 are supported.

Table 8: Bootstrapping Mediation Effects.

Path		Estimate	Product of Coefficients		P	Bootstrapping			
						Bias-Corrected 95% CI		Percentile 95% CI	
			Standard Error	Z		Lower	Upper	Lower	Upper
Mediating Effects									
IND1	CU→FSNS→DAP	0.054	0.025	2.173	0.030	0.016	0.119	0.012	0.108
IND2	I0→FSNS→DAP	0.071	0.027	2.661	0.008	0.032	0.139	0.028	0.13
IND3	LI→FSNS→DAP	0.077	0.033	2.376	0.018	0.029	0.158	0.025	0.15
Direct Effects									
DE1	CU→DAP	0.269	0.074	3.625	0.000	0.127	0.419	0.128	0.419
DE2	I0→DAP	0.195	0.065	3.01	0.003	0.072	0.325	0.074	0.329
DE3	LI→DAP	0.237	0.069	3.439	0.001	0.096	0.37	0.1	0.376
Total Mediating and Total Effects									
IETOTAL	IND1+IND2+IND3	0.202	0.057	3.534	0.000	0.102	0.328	0.096	0.321
TOTAL	IETOTAL+DE1+DE2+DE3	0.902	0.081	11.068	0.000	0.739	1.063	0.751	1.076
Comparison of Mediating Effects									
COM1	IND1vs.IND2	-0.017	0.033	-0.515	0.606	-0.092	0.04	-0.089	0.042
COM2	IND1vs.IND3	-0.024	0.04	-0.603	0.546	-0.111	0.045	-0.109	0.047
COM3	IND2vs.IND	-0.007	0.035	-0.196	0.845	-0.081	0.059	-0.079	0.062
Proportion of Mediation Effects									
P1	IND1/IETOTAL	0.266	0.098	2.702	0.007	0.074	0.466	0.069	0.459
P2	IND2/IETOTAL	0.350	0.088	3.984	0.000	0.191	0.534	0.193	0.535
P3	IND3/IETOTAL	0.384	0.103	3.735	0.000	0.181	0.584	0.181	0.584
R	IETOTAL/TOTAL	0.224	0.064	3.484	0.000	0.112	0.364	0.106	0.357

5. Discussion and Implications

The findings indicate that the decline in college students' academic performance is not attributable to a single factor, but rather results from the combined effects of multiple digital stressors, including compulsive use, information overload, and life intrusion. These stressors not only directly undermine time management, cognitive focus, and boundary control, but also indirectly exacerbate academic impairment through social media fatigue. This suggests that social media fatigue functions as a key psychological mechanism linking digital stress to academic outcomes. From a practical perspective, higher education institutions should incorporate digital literacy education into student development systems to help students recognize the risks associated with compulsive use and information overload. In addition, instructors and administrative departments should optimize the management of course groups, class communication channels, and platform notifications to reduce excessive information accumulation and boundary intrusion. Psychological counseling services may also integrate social media fatigue into screening and intervention frameworks, guiding students to mitigate risks through strategies such as setting usage schedules, activating focus modes, and establishing clear digital boundaries.

This study has several limitations. First, the sample is limited to undergraduate students in

Shanghai, and the representativeness of the findings requires further expansion. Second, the cross-sectional design constrains the ability to rigorously establish causal relationships among variables. Third, although social media fatigue demonstrates a partial mediating effect, it does not fully account for the observed relationships. Future research may adopt longitudinal or quasi-experimental designs and incorporate additional variables—such as self-control, fear of missing out (FoMO), and academic self-efficacy—to further refine and extend the explanatory framework.

References

[1] China Internet Network Information Center (CNNIC). The 57th Statistical Report on China's Internet Development. Beijing: CNNIC; 2026.

[2] Kemp S. Digital 2025: The state of social media in 2025. 2025; Retrieved from https://datareportal.com/reports/digital-2025-global-overview-report

[3] Ayyagari R, Grover V, Purvis R. Technostress: Technological antecedents and implications. MIS Quarterly 2011; 35(4): 831-858.

[4] Lee AR, Son SM, Kim KK. Information and communication technology overload and social networking service fatigue: A stress perspective. Computers in Human Behavior 2016; 55: 51-61.

[5] Ma X, Liu Y, Zhang W. The impact of multidimensional excessive social media use on academic performance: The moderating role of mindfulness. Frontiers in Psychology 2025; 16: 1579509.

[6] Duan N, Li L, Kanchanapoom K, et al. The impact of social media overload on learning engagement: A moderated mediation model. BMC Psychology 2025; 13(1): 1322.

[7] Edwards JR, Cooper CL. The person-environment fit approach to stress: Recurring problems and some suggested solutions. Journal of Organizational Behavior 1990; 11(4): 293-307.

[8] Cheung F, Tang C. The influence of emotional dissonance on subjective health and job satisfaction: Testing the stress-strain-outcome model. Journal of Applied Social Psychology 2010; 40(12): 3192-3217.

[9] Ren G and Chen Y. Does social media use enhance or impair learning performance? China Distance Education 2020; (9): 44-52.

[10] Wu H. A study on social media dependence and academic procrastination among college students. Journal of Anshan Normal University 2023; 25(5): 92-95.

[11] Qin C, Yan X, Li Y, et al. Too much social media? Unveiling the effects of determinants in social media fatigue. Frontiers in Psychology 2024; 15: 1277846.

[12] Khalaf MAA, Ali OA, Mohamed AA, et al. Social media addiction and academic engagement: the mediating roles of sleep quality and fatigue. Frontiers in Education 2025; 10: 1614746.

[13] Pang H, Ji M, Hu X. How differential dimensions of social media overload influences young people's fatigue and negative coping during prolonged COVID-19 pandemic? Insights from a technostress perspective. Healthcare 2023; 11(1): 6.

[14] Sheng N, Yang C, Han L, et al. Too much overload and concerns: Antecedents of social media fatigue and the mediating role of emotional exhaustion. Computers in Human Behavior 2023; 139: 107500.

[15] Xiao L, Mou J. Social media fatigue - Technological antecedents and the moderating roles of personality traits: The case of WeChat. Computers in Human Behavior 2019; 101: 297-310.

[16] Loh XK, Lee VH, Loh XM, et al. The dark side of mobile learning via social media: How bad can it get? Information Systems Frontiers 2022; 24(6): 1887-1904.

[17] Nayak S, Budhwar P. Negative effects of enterprise social networks (ESNs) and technostress: Empirical evidence from R&D centres operating in India. Aslib Journal of Information Management 2022; 74(5): 956-988.

[18] Ravindran T, Chua AYK, Goh DH. Antecedents and effects of social network fatigue. Journal of the Association for Information Science and Technology 2014; 65(11): 2306-2320. http://dx.doi.org/10.1002/asi.23122.

[19] Bright LF, Kleiser SB, Grau SL. Too much Facebook? An exploratory examination of social media fatigue. Computers in Human Behavior 2015; 44: 148-155. http://dx.doi.org/10.1016/j.chb.2014.11.048.

[20] Dhir A, Yossatorn Y, Kaur P, et al. Online social media fatigue and psychological wellbeing—A study of compulsive use, fear of missing out, fatigue, anxiety and depression. International Journal of Information Management 2018; 40: 141-152. http://dx.doi.org/10.1016/j.ijinfomgt.2018.01.012.

[21] Ning W, Inan FA. Impact of social media addiction on college students' academic performance: An interdisciplinary perspective. Journal of Research on Technology in Education 2024; 56(5): 616-631. http://dx.doi.org/10.1080/15391523.2023.2196456.

[22] Junco R. Too much face and not enough books: The relationship between multiple indices of Facebook use and academic performance. Computers in Human Behavior 2012; 28(1): 187-198.

[23] Li Z, Song X. The impact of compulsive WeChat use on college students' learning engagement: A four-year longitudinal study. Chinese Journal of Health Psychology 2023; 31(8): 1217-1223. http://dx.doi.org/10.13342/j.cnki.cjhp.2023.08.020.
[24] Malik A, Dhir A, Kaur P, et al. Correlates of social media fatigue and academic performance decrement: A large cross-sectional study. Information Technology & People 2020; 34(2): 557-580. http://dx.doi.org/10.1108/ITP-06-2019-0289.
[25] Shi C, Yu L, Wang N, et al. Effects of social media overload on academic performance: A stressor–strain–outcome perspective. Asian Journal of Communication 2020; 30(2): 179-197. http://dx.doi.org/10.1080/01292986.2020.1748073.