

Technostress and Mental Health among Physical Education Students: The Mediating Role of Sleep Quality and a Latent Profile Analysis

Han Yuan*

Department of Physical Education, Xiangtan University, Xiangtan, Hunan, China

Corresponding Author Email: yuanhan202104@163.com

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Abstract

Digital learning environments have made technostress an emerging health risk for college students. Using cross-sectional survey data from 1,035 undergraduate and postgraduate students in physical education–related majors in China, this study examined whether sleep quality mediates the associations of technostress with depression, anxiety, and life satisfaction, and used latent profile analysis to identify subgroups with different health risks. Overall, 52.9% of students reported poor sleep quality, and 17.8% and 9.0% reached the clinical cut-offs for depression and anxiety, respectively. Sleep quality partially mediated the effects of technostress on depression (48.4% mediated) and anxiety (41.3% mediated), and showed a suppression effect on life satisfaction. Four profiles were identified: healthy adaptation (24.7%), subclinical digital fatigue (55.6%), sedentary behavioral inhibition (10.4%), and resource-depleted psychological distress (9.3%). These findings suggest that technostress harms students' mental health mainly by impairing sleep, and that health risks vary considerably across students. Universities should adopt tiered interventions and redefine the boundaries of digital learning.

Keywords: Technostress, Sleep Quality, Mental Health, Sedentary Behavior, Latent Profile Analysis

Introduction

The rapid digitalization of higher education is profoundly changing how college students learn. Online course platforms, video conferencing systems, and academic databases have become part of daily study, and together with heavy academic workloads and training assessments, technostress is becoming an emerging public health risk for students in physical education (PE)–related majors. Technostress was first defined as “a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner” (Brod, 1984). Ragu-Nathan, Tarafdar, Ragu-Nathan, and Tu (2008) operationalized it into five dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. More recently, researchers have shown that university students also experience technostress in technology-enhanced learning when there is a misfit between themselves and the technological environment (Wang, Tan, & Li, 2020).

However, two gaps remain in the literature. First, the specific pathways through which technostress develops into mental health risks, especially the role of sleep quality, have not been systematically tested among college students. Second, most previous studies have adopted a variable-centred approach that treats students as a homogeneous group, which makes it difficult to reveal different combinations of technostress, sedentary behavior, sleep, and mental health among students. Students in PE-related majors face both the demands of digital learning and the requirements of specialized training and assessment, making them an important group in which to examine these questions.

Beyond this combination of demands, PE-related students differ from general university populations in several theoretically and empirically important ways. First, their daily schedules are organized around early-morning and evening training sessions, practical courses, and competitions, which compress the time available for sleep and make their sleep–wake patterns less regular than those of other students. When digital learning tasks such as online coursework and platform-based assignments are added to these fixed commitments, technology use is more likely to be pushed into late-night hours and to directly displace sleep. Second, sleep carries particular significance for this group. According to the effort–recovery model (Meijman & Mulder, 1998), recovery after exertion is essential for maintaining health, and for PE students sleep is the main recovery process not only after cognitive effort but also after intensive physical training. Stress-related sleep impairment (Åkerstedt, 2006) therefore threatens both their mental health and their physical recovery and training performance, making the sleep pathway especially consequential in this population. Third, from the perspective of COR theory (Hobfoll, 1989), PE students must continuously invest physical, cognitive, and emotional resources in training while simultaneously meeting academic and digital learning demands. This dual investment leaves fewer reserves for coping with technostress and makes them more vulnerable to loss spirals, in which technostress erodes sleep and sleep loss further depletes the resources needed for psychological well-being. Fourth, PE students are commonly assumed to be physically active and psychologically resilient, so their exposure to digital learning stress and the associated health risks has received little research attention. This assumption may also conceal heterogeneity within the group: some students may adapt well, whereas others may develop sedentary, energy-saving behavior or psychological distress despite their sport-oriented training, which calls for a person-centred approach. Studying PE-related students in China therefore allows a test of whether the sleep pathway holds in a population with high physical demands and distinctive daily rhythms, and provides evidence for targeted interventions in physical education and sport institutions.

The transactional model of stress (Lazarus & Folkman, 1984) holds that stress responses depend on an individual's cognitive appraisal of environmental demands relative to available coping resources. When students appraise constantly updated digital learning tools as exceeding their coping capacity, stress responses are persistently activated. Conservation of resources (COR) theory (Hobfoll, 1989; Hobfoll, Halbesleben, Neveu, & Westman, 2018) further proposes that individuals facing continuous resource loss tend to adopt energy-saving behavioral strategies to protect their remaining resources and may fall into a loss spiral. The effort–recovery model (Meijman & Mulder, 1998) emphasizes that workload does not necessarily damage health; the key is whether individuals can recover sufficiently after exertion, and sleep is the most important recovery process.

All five dimensions of technostress continuously drain individuals' cognitive and emotional resources (Ragu-Nathan et al., 2008). Among university students, misfit between technological demands and personal abilities or needs produces notable stress experiences (Wang et al., 2020). Prolonged exposure to stress increases negative emotions such as depression and anxiety and lowers individuals' overall evaluation of their lives. Thus, the following hypothesis is proposed:

H1: Technostress positively predicts depressive symptoms (H1a) and anxiety symptoms (H1b), and negatively predicts life satisfaction (H1c).

Stress and sleep are closely related, and individuals with higher stress levels tend to have poorer sleep quality (Åkerstedt, 2006). The perseverative cognition hypothesis suggests that repetitive thinking after a stressful event prolongs physiological activation (Brosschot, Gerin, & Thayer, 2006). Techno-invasion blurs the boundary between study time and rest time, making it difficult for students to psychologically detach from their studies (Sonnentag & Fritz, 2007), which in turn hinders sleep onset and recovery. Impaired sleep then reduces the resources available for coping with stress the next day, increasing the risk of depression and anxiety and lowering life satisfaction. Thus, the following hypothesis is proposed:

H2: Sleep quality mediates the associations of technostress with depressive symptoms (H2a), anxiety symptoms (H2b), and life satisfaction (H2c).

Latent profile analysis (LPA) is a person-centred method that identifies unobserved subpopulations based on a set of indicators (Spurk, Hirschi, Wang, Valero, & Kauffeld, 2020). According to COR theory, students facing the same level of technostress may show different adaptation patterns depending on their resource reserves: some remain healthy, some develop subclinical distress, some adopt energy-saving sedentary behavior, and others develop severe psychological distress. Therefore, this study addressed the following research question: Are there latent subgroups of students in PE-related majors with distinct patterns of technostress, sedentary behavior, sleep quality, and mental health?

Therefore, this study examined the mediating role of sleep quality in the associations of technostress with depression, anxiety, and life satisfaction among students in PE-related majors (H1 and H2), and used LPA to identify subgroups of students with different patterns of technostress, sedentary behavior, and health risks, in order to provide empirical evidence for promoting college students' mental health in digital learning environments.

Methods

Design and Participants

This study used a cross-sectional survey design. Data were collected through self-administered online questionnaires from students in PE-related majors at multiple universities in China between February and March 2026. The inclusion criteria were: (1) enrolment in a PE-related major, such as physical education or sports training, at the undergraduate, master's, or doctoral level; (2) at least three months since enrolment; (3) use of information and communication technology in daily study (e.g., online course platforms, video conferencing systems, and academic databases); and (4) informed and voluntary consent. Part-time students, students with a diagnosed severe mental illness, and questionnaires completed in less than five minutes or showing obvious patterned responding

were excluded. Of the 1,079 questionnaires returned, 44 incomplete questionnaires were removed, leaving a valid sample of 1,035 (valid response rate = 95.9%).

Of the participants, 55.8% were female, the largest age group was 21–25 years (44.6%), 59.0% were undergraduates, the largest major category was physical education (39.8%), 56.3% had been enrolled for three years or less, and 52.1% took 25%–50% of their courses online (Table 1).

Table 1

Demographic Characteristics of Participants (N = 1,035)

Characteristic	Category	<i>n</i>	%
Gender	Male	457	44.2
	Female	578	55.8
Age (years)	≤ 20	268	25.9
	21–25	462	44.6
	26–30	213	20.6
	> 30	92	8.9
Degree level	Undergraduate	611	59.0
	Master's	320	30.9
	Doctoral	104	10.1
Major	Physical education	412	39.8
	Sports training	298	28.8
	Other PE-related majors	325	31.4
Years enrolled	≤ 3	583	56.3
	> 3	452	43.7
Proportion of online courses	< 25%	237	22.9
	25%–50%	539	52.1
	50%–75%	155	15.0
	> 75%	104	10.0
Frequency of studying at home/dormitory	Never	143	13.8
	Occasionally	596	57.6
	Often	254	24.5
	Almost every day	42	4.1

Note. The sample includes undergraduate, master's, and doctoral students in physical education, sports training, and other PE-related majors.

Measures

Technostress. Technostress was measured with a Chinese version of the technostress creators scale based on Ragu-Nathan et al. (2008). The scale includes 23 items across five dimensions (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty), rated on a 5-point scale, with higher scores indicating greater technostress.

Sleep quality. Sleep quality was measured with the Chinese version of the Pittsburgh Sleep Quality Index (PSQI; Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). Its 19 self-rated items form seven component scores, with a total score ranging from 0 to 21. Higher scores indicate poorer sleep quality, and a total score above 5 indicates poor sleep quality.

Depressive and anxiety symptoms. Depressive and anxiety symptoms were measured with the Chinese versions of the Patient Health Questionnaire-9 (PHQ-9; Kroenke, Spitzer, & Williams, 2001) and the Generalized Anxiety Disorder-7 (GAD-7; Spitzer, Kroenke, Williams, & Löwe, 2006), which assess the frequency of symptoms over the past two weeks. A total score of 10 or above was used as the clinical cut-off for both measures.

Life satisfaction. Life satisfaction was measured with the Satisfaction With Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985), which contains five items rated on a 7-point scale, with higher scores indicating greater life satisfaction.

Physical activity and sedentary behavior. Physical activity and sedentary behavior were measured with the Chinese version of the International Physical Activity Questionnaire–Short Form (IPAQ-SF; Craig et al., 2003), which uses a 7-day recall to assess time spent in vigorous activity, moderate activity, walking, and sitting on weekdays. Physical activity was converted into metabolic equivalent (MET) minutes per week and classified as low, moderate, or high according to the IPAQ scoring protocol.

In this sample, Cronbach's α values for the scales ranged from .632 to .929.

Procedure and Ethics

The questionnaire was completed anonymously. Each questionnaire link contained a unique identification code, and each device or account could submit only once to prevent duplicate responses. Before answering, participants read an informed consent form describing the purpose of the study, data confidentiality measures, and their right to withdraw at any time, and they entered the questionnaire only after clicking "agree to participate." The average completion time was 15–20 minutes. The study was approved by the institutional ethics committee (approval number: GUES2026011801), and all participants provided electronic informed consent.

Data Analysis

Data were analyzed in Python (scipy and scikit-learn), with the significance level set at two-tailed $p < .05$. First, descriptive statistics and reliability were calculated, and Harman's single-factor test was used to assess common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Second, Pearson correlation analysis was conducted. Third, mediation effects were tested with ordinary least squares (OLS) regression controlling for gender, age, degree level, and years of enrolment, and bias-corrected 95% confidence intervals (CIs) were estimated with 5,000 bootstrap resamples (Preacher & Hayes, 2008); when the indirect and direct effects had opposite signs, the result was interpreted as a suppression effect (MacKinnon, Krull, & Lockwood, 2000). Fourth, LPA was conducted by fitting Gaussian mixture models with two to five classes, using technostress, sedentary time, sleep quality, depression, anxiety, and life satisfaction as indicators. The optimal number of profiles was determined using the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the sample-size adjusted

BIC (aBIC), and entropy ($\geq .80$; Nylund, Asparouhov, & Muthén, 2007; Spurk et al., 2020). Differences between profiles were tested with one-way analysis of variance (ANOVA), with η^2 reported as the effect size.

Results

Common Method Bias and Descriptive Statistics

Harman's single-factor test showed that the first unrotated principal component explained 41.2% of the total variance, below the 50% criterion, indicating that common method bias was not a serious threat. Cronbach's α values ranged from .632 to .929, indicating generally good reliability. Descriptive statistics are presented in Table 2.

Table 2

Descriptive Statistics and Reliability (N = 1,035)

Variable	M	SD	Min	Max	Skewness	Kurtosis	α
Technostress (total)	3.28	0.58	1	5	0.33	2.05	.929
Techno-overload	3.36	0.70	1	5	0.07	0.85	.804
Techno-invasion	3.20	0.77	1	5	0.10	0.70	.821
Techno-complexity	3.18	0.77	1	5	0.02	0.67	.894
Techno-insecurity	3.24	0.72	1	5	-0.02	1.01	.801
Techno-uncertainty	3.43	0.70	1	5	0.10	0.89	.823
Sedentary time (h/weekday)	5.59	3.53	0.50	12.00	0.26	-0.83	—
Total MET-min/week	1779	1773	0	19278	5.01	38.21	—
PSQI total	5.99	3.09	0	21	0.60	0.64	.632
PHQ-9 total	6.40	4.38	0	27	0.88	1.75	.881
GAD-7 total	4.29	3.91	0	21	0.98	1.24	.920
SWLS total	21.91	5.78	5	35	0.40	0.16	.897

Note. Higher PSQI scores indicate poorer sleep quality.

Physical Activity and Sedentary Behavior

In total, 109 students (10.5%) had low physical activity, 804 (77.7%) had moderate physical activity, and 122 (11.8%) had high physical activity, indicating that most of the sample was moderately active. The mean weekday sedentary time was 5.59 hours ($SD = 3.53$), and 14.3% of students ($n = 148$) sat for 10 hours or more per day. Both correlation and bootstrap mediation analyses showed that weekday sedentary time was almost unrelated to technostress ($r = .019$, $p = .533$) and to the mental health indicators, and all confidence intervals for the mediation effects included zero. This may reflect a ceiling effect of study-related sitting in this sample. Therefore, sedentary time was reported separately as an independent health behavior indicator and was not included in the mediation model; its differentiation across subgroups is presented in the LPA.

Sleep Quality and Mental Health

The mean PSQI score was 5.99 ($SD = 3.09$), and 52.9% of students ($n = 547$) scored above 5, indicating poor sleep quality; the subjective sleep quality and sleep disturbance components had the highest scores. The mean PHQ-9 score was 6.40 ($SD = 4.38$), and 17.8% of students ($n = 184$) reached the clinical cut-off for depressive symptoms. The mean GAD-7 score was 4.29

($SD = 3.91$), and 9.0% of students ($n = 93$) reached the clinical cut-off for anxiety symptoms. The mean SWLS score was 21.91 ($SD = 5.78$), within the “slightly satisfied” range, and 15.1% of students ($n = 156$) reported some degree of dissatisfaction.

Correlation Analysis

Technostress was significantly and positively correlated with sleep quality scores ($r = .181$), depression ($r = .201$), and anxiety ($r = .203$; all $p < .001$), but not with life satisfaction ($r = .059$, $p = .056$). Sleep quality scores were significantly and positively correlated with depression ($r = .554$) and anxiety ($r = .483$), and negatively correlated with life satisfaction ($r = -.275$), providing preliminary support for the mediating role of sleep quality (Table 3).

Table 3

Pearson Correlations among Main Variables (N = 1,035)

Variable	1	2	3	4	5	6
1. Technostress	—					
2. Sedentary time	.019	—				
3. Sleep quality (PSQI)	.181***	.068*	—			
4. Depression (PHQ-9)	.201***	.040	.554***	—		
5. Anxiety (GAD-7)	.203***	.069*	.483***	.781***	—	
6. Life satisfaction (SWLS)	.059	-.055	-.275***	-.353***	-.313***	—

Note. * $p < .05$. *** $p < .001$.

Mediating Role of Sleep Quality

After controlling for gender, age, degree level, and years of enrolment, the bootstrap analysis showed (Table 4, Figure 1) that technostress significantly and positively predicted PSQI scores ($\beta = 0.177$, $p < .001$); that is, higher technostress was associated with poorer sleep quality. The total effects of technostress on depression ($\beta = 0.196$, $p < .001$) and anxiety ($\beta = 0.198$, $p < .001$) were significant, supporting H1a and H1b, whereas the total effect on life satisfaction was not significant ($\beta = 0.060$, $p = .057$), so H1c was not supported. The indirect effect of technostress on depression through sleep quality was significant ($\beta = 0.095$, 95% CI [0.060, 0.132]), accounting for 48.4% of the total effect, and the indirect effect on anxiety was also significant ($\beta = 0.082$, 95% CI [0.052, 0.114]), accounting for 41.3% of the total effect. Both were partial mediation effects, supporting H2a and H2b. For life satisfaction, the indirect effect was significantly negative ($\beta = -0.052$, 95% CI [-0.075, -0.032]), while the direct effect was significantly positive ($\beta = 0.112$, $p < .001$). The two effects had opposite signs and offset each other, bringing the total effect close to zero, which indicates a suppression effect; thus, H2c was supported.

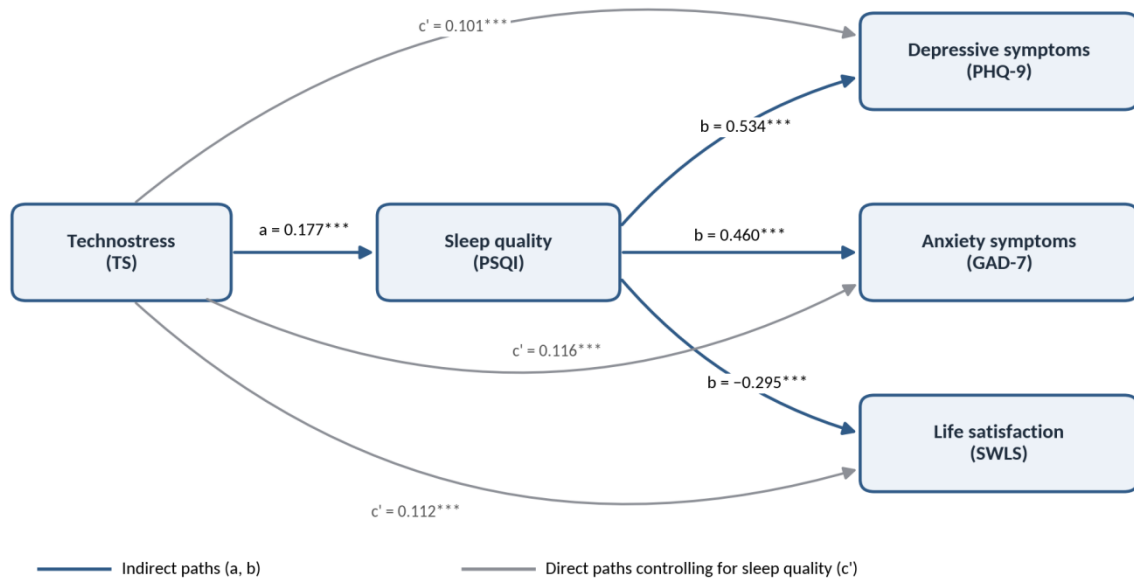


Figure 1. Mediating Role of Sleep Quality in the Associations between Technostress and Mental Health Outcomes

Note. a and b are the mediation path coefficients; c' is the direct effect after controlling for sleep quality. *** $p < .001$. Indirect effects: depression $\beta = 0.095$ (48.4% mediated), anxiety $\beta = 0.082$ (41.3% mediated), life satisfaction $\beta = -0.052$ (suppression effect).

Table 4

Bootstrap Tests of the Mediating Effect of Sleep Quality (N = 1,035)

Outcome	Path	β	p	95% CI
Depression (PHQ-9)	a Technostress $\rightarrow$ sleep quality	0.177	< .001	—
	b Sleep quality $\rightarrow$ depression	0.534	< .001	—
	c Total effect	0.196	< .001	—
	c' Direct effect	0.101	< .001	—
	a $\times$ b Indirect effect (48.4% mediated)	0.095	—	[0.060, 0.132]
Anxiety (GAD-7)	a Technostress $\rightarrow$ sleep quality	0.177	< .001	—
	b Sleep quality $\rightarrow$ anxiety	0.460	< .001	—
	c Total effect	0.198	< .001	—
	c' Direct effect	0.116	< .001	—
	a $\times$ b Indirect effect (41.3% mediated)	0.082	—	[0.052, 0.114]
Life satisfaction (SWLS)	a Technostress $\rightarrow$ sleep quality	0.177	< .001	—
	b Sleep quality $\rightarrow$ life satisfaction	-0.295	< .001	—
	c Total effect	0.060	.057	—
	c' Direct effect	0.112	< .001	—
	a $\times$ b Indirect effect (suppression)	-0.052	—	[-0.075, -0.032]

Note. Control variables were gender, age, degree level, and years of enrolment. Path b is the effect of sleep quality on the outcome controlling for technostress. Bias-corrected 95% CIs were based on 5,000 bootstrap resamples.

Latent Profile Analysis

Gaussian mixture models were fitted using technostress, sedentary time, PSQI, PHQ-9, GAD-7, and SWLS scores as indicators (Table 5). Among the two- to four-profile solutions, the four-profile solution had the lowest AIC and aBIC and the highest entropy (0.921, above the .80 criterion), whereas the three-profile solution had a slightly lower BIC. The five-profile solution had an entropy of 0.794, below the .80 criterion, indicating insufficient classification accuracy, and was therefore not retained. The four-profile solution also identified a sedentary subgroup with distinct theoretical meaning. Considering both statistical indices and theoretical interpretability, the four-profile solution was selected as optimal.

Table 5

Fit Indices of Latent Profile Models (K = 2–4)

K	AIC	BIC	aBIC	Entropy	Selected
2	15612.78	15884.60	15709.91	0.634	
3	12751.23	13161.43	12897.81	0.850	
4	12635.13	13183.71	12831.16	0.921	✓

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = sample-size adjusted BIC; ✓ = selected model. The five-profile solution (entropy = 0.794) was not retained because its entropy was below .80.

The characteristics of the four profiles are shown in Table 6. The *healthy adaptation* profile ($n = 256$, 24.7%) had the lowest technostress ($M = 3.14$), the best sleep quality (PSQI = 4.03, below the clinical cut-off), minimal depressive symptoms (PHQ-9 = 2.02), a GAD-7 score of 0 for all members, and the highest life satisfaction (SWLS = 25.17), serving as the low-risk reference group in the digital learning environment. The *subclinical digital fatigue* profile ($n = 575$, 55.6%) was the largest group. It showed moderate technostress ($M = 3.21$), the shortest sedentary time (4.66 hours), mildly impaired sleep quality (PSQI = 6.24), 14.8% above the depression cut-off, 4.7% above the anxiety cut-off, and relatively low life satisfaction (SWLS = 20.78). This group was in a transitional state in which technostress continued to accumulate but clear clinical symptoms had not yet appeared, making it a key target for primary prevention.

The *sedentary behavioral inhibition* profile ($n = 108$, 10.4%) had the most distinctive behavioral features: an average of 11.67 hours of sitting per day, with all members sitting for 10 hours or more per day, far more than the other three groups (4.66–5.39 hours). It also showed moderately high technostress ($M = 3.32$), impaired sleep quality (PSQI = 6.76), a depression positive rate of 23.1%, and an anxiety positive rate of 7.4%. This pattern is consistent with the predictions of COR theory: when technostress continuously consumes cognitive and emotional resources, students adopt energy-saving sedentary behavior as a passive coping strategy. The *resource-depleted psychological distress* profile ($n = 96$, 9.3%) had the highest technostress ($M = 4.00$), the poorest sleep quality (PSQI = 8.89), and positive rates of 76.0% for depression, 60.4% for anxiety, and 85.4% for poor sleep, making it the high-risk group most in need of priority clinical intervention.

One-way ANOVA showed that all six indicators differed significantly across the four profiles ($F = 40.35\text{--}412.71$, $\eta^2 = .105\text{--}.546$, all $p < .001$), with medium to large effect sizes, indicating good discrimination between profiles.

Table 6

Characteristics of the Four Latent Profiles (N = 1,035)

Variable	Healthy adaptation (n = 256, 24.7%)	Subclinical digital fatigue (n = 575, 55.6%)	Sedentary behavioral inhibition (n = 108, 10.4%)	Resource-depleted distress (n = 96, 9.3%)
Technostress	3.14 (0.48)	3.21 (0.51)	3.32 (0.59)	4.00 (0.51)
Sedentary time (h/weekday)	5.20 (3.50)	4.66 (2.71)	11.67 (1.29)	5.39 (3.39)
Sleep quality (PSQI)	4.03 (2.77)	6.24 (2.85)	6.76 (3.00)	8.89 (3.14)
Depression (PHQ-9)	2.02 (2.12)	6.96 (3.11)	7.19 (4.64)	13.78 (4.32)
Anxiety (GAD-7)	0.00 (0.00)	4.99 (2.72)	5.30 (3.87)	10.36 (3.89)
Life satisfaction (SWLS)	25.17 (4.96)	20.78 (5.42)	20.85 (6.05)	21.21 (6.06)
PHQ-9 ≥ 10 (%)	0.4	14.8	23.1	76.0
GAD-7 ≥ 10 (%)	0.0	4.7	7.4	60.4
PSQI > 5 (%)	24.2	57.4	67.6	85.4
Sitting ≥ 10 h/day (%)	10.9	0.0	100.0	12.5

Note. Values are means (standard deviations) or percentages. One-way ANOVA for the six indicators: $F = 40.35\text{--}412.71$, $\eta^2 = .105\text{--}.546$, all $p < .001$.

Discussion

This study found that technostress may persist as a chronic health exposure in digital educational environments rather than being a temporary problem of technological adaptation. The mean technostress score was 3.28, all five dimensions were at moderate-to-high levels, and more than half of the students reported poor sleep quality. From the perspective of the transactional model of stress (Lazarus & Folkman, 1984), students must repeatedly appraise constantly updated digital learning tools, and when technological demands are appraised as exceeding their coping capacity, stress responses become chronically activated. In this study, techno-uncertainty had the highest score, which is consistent with the rapid iteration of educational technologies and the constant demand on students to learn new platforms and tools (Ragu-Nathan et al., 2008; Wang et al., 2020).

Impaired sleep recovery is the core mechanism through which technostress translates into psychological distress. Sleep quality partially mediated the effects of technostress on depression (48.4%) and anxiety (41.3%), which is consistent with the effort–recovery model (Meijman & Mulder, 1998). Techno-invasion blurs the boundary between study and non-study time, so students continue to receive course and task information before bed and at night, making psychological detachment difficult (Sonnentag & Fritz, 2007). The persistent cognitive activation caused by technostress makes it hard for the nervous system to relax even when the body is at rest (Brosschot et al., 2006), leading to difficulty falling asleep and poorer sleep quality, in line with existing evidence on the close link between stress and sleep (Åkerstedt, 2006). Impaired sleep further reduces the cognitive resources needed to cope

with technostress the next day, forming the loss spiral described by COR theory (Hobfoll et al., 2018).

The suppression effect found for life satisfaction deserves particular attention. The negative indirect path through impaired sleep and the positive direct path, which may reflect a sense of competence derived from technological mastery, offset each other, bringing the total effect close to zero (MacKinnon et al., 2000). This suggests that interventions should both reduce technological burden and enhance students' sense of control over technology. This finding may also explain why the resource-depleted psychological distress profile, despite having the most severe depressive and anxiety symptoms, did not report clearly lower life satisfaction than the other two at-risk profiles.

The LPA represents an important methodological and substantive contribution of this study (Spurk et al., 2020). The existence of the healthy adaptation profile (24.7%) shows that digital environments do not necessarily damage health, and that protective factors may exist in individual resource reserves, institutional support, or coping strategies. The subclinical digital fatigue profile (55.6%) is the finding with the greatest public health significance: this largest subgroup had not reached any clinical cut-off but already showed signs of mildly impaired sleep, and without intervention it may progress to more serious health problems over time. The sedentary behavioral inhibition profile (10.4%) has considerable theoretical value. Its sedentary behavior does not simply reflect a lack of exercise awareness but may be a behavioral manifestation of digital resource depletion, consistent with the COR prediction of energy-saving behavior under resource loss (Hobfoll, 1989). This finding also shows that variable-centred analyses of the whole sample can mask the role of sedentary behavior in specific subgroups. The high comorbidity of the three mental health indicators in the resource-depleted psychological distress profile (9.3%) suggests systemic distress following resource depletion rather than an isolated symptom, calling for responses at the institutional and policy levels.

Students' psychological state, sleep quality, and life satisfaction directly affect their academic performance and long-term professional development. Previous research has highlighted the importance of competency and job satisfaction for the career development of PE teachers (Yan, Teo, Lim, & Lin, 2022). The present findings on the heterogeneity of digital health risks among students in PE-related majors can therefore inform mental health education and the development of intervention competence in pre-service PE teacher education.

This study has several limitations. First, the cross-sectional design limits causal inference, and the temporal order between technostress and mental health outcomes needs to be verified in longitudinal studies. Second, the internal consistency of the PSQI ($\alpha = .632$), calculated from its seven component scores, was below conventional standards, so the sleep quality results should be interpreted with caution. Third, all data were self-reported; although Harman's single-factor test did not indicate serious common method bias, its influence cannot be completely ruled out (Podsakoff et al., 2003). Fourth, academic workload variables such as course load and the intensity of professional training were not measured and could be controlled in future studies. Fifth, although the LPA solution considered both statistical and theoretical criteria, different software and random seeds may produce slightly different classifications, and the results should be interpreted with caution. Future research could

adopt longitudinal designs to examine transitions between profiles and evaluate the effectiveness of tiered interventions.

Conclusion

Based on cross-sectional survey data from 1,035 students in PE-related majors in China, this study shows that technostress acts as a chronic health exposure in digital learning environments. Its core harmful pathway is the erosion of sleep recovery, and impaired sleep further aggravates depressive and anxiety symptoms. More than half of the students were in a state of subclinical distress characterized by impaired sleep. The LPA further revealed four distinct health risk patterns within the student population: the sedentary behavioral inhibition profile, characterized by extreme sitting time, provides empirical support for the behavioral mechanism proposed by COR theory, while the resource-depleted psychological distress profile, with the highest technostress and the most severe psychological symptoms, suggests that digital health inequalities have already emerged among students.

Author Contributions

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the institutional ethics committee (approval number: GUES2026011801).

Informed Consent Statement

Informed consent was obtained from all participants involved in the study.

Conflicts of Interest

The author declares no conflicts of interest.

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