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# Digital Distraction and Sleep: Distinct Pathways from Phubbing Dimensions to Teachers' Insomnia through Psychological Distress

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**ABSTRACT: Backgrounds:** In the digital era, smartphone-driven phubbing behavior has become increasingly prevalent among teachers and may contribute to insomnia. Psychological distress has been identified as a potential mechanism linking maladaptive technology use to sleep problems; however, this mediating pathway has not been examined longitudinally. Furthermore, gender differences in these associations remain unclear. This study aimed to examine the longitudinal relationship between phubbing behavior and insomnia, the mediating role of psychological distress, and the moderating role of gender. **Methods:** A two-wave longitudinal design with a four-month interval was employed. At Time 1 (T1), 1061 teachers participated, with 632 teachers successfully matched at Time 2 (T2), yielding a 59.6% retention/matching rate. The Insomnia Severity Index (McDonald's  $\omega = 0.91$ ), Depression Anxiety Stress Scales-21 ( $\omega = 0.96$ ), and Phubbing Scale ( $\omega = 0.84-0.87$ ) were administered to assess insomnia symptoms, psychological distress, and phubbing behavior, respectively. **Results:** Structural equation modeling revealed divergent pathways for the two phubbing dimensions. T1 phone obsession directly predicted T2 insomnia ( $b = 0.14$ ,  $SE = 0.07$ ,  $z = 2.09$ ,  $\beta = 0.12$ ,  $p = 0.036$ , bootstrap CI [0.011, 0.248]), whereas T1 communication disturbance did not. Instead, psychological distress significantly mediated the relationship between T1 communication disturbance and T2 insomnia (indirect effect = 0.16,  $p = 0.001$ , 95% CI [0.047, 0.312];  $\beta = 0.11$ ). Regarding moderation, multi-group chi-square difference tests indicated that gender did not significantly moderate any of the structural paths, despite descriptive variations in group-level patterns. **Conclusions:** The two phubbing dimensions uniquely contribute to teachers' insomnia through distinct pathways: phone obsession directly predicted subsequent insomnia, whereas communication disturbance indirectly contributed to insomnia by elevating psychological distress. These findings support implementing universal, dimension-specific interventions targeting both compulsive smartphone habits and psychological distress. Although multi-group analyses did not indicate statistically significant gender moderation, future research with larger and more balanced gender subsamples is needed to further investigate this question.

**KEYWORDS:** Insomnia; phubbing; psychological distress; gender; school teachers

## 1 Introduction

Insomnia, characterized by difficulties initiating sleep, maintaining sleep, or experiencing early morning awakening [1], represents a significant health concern particularly prevalent among teachers, who exhibit higher insomnia rates compared to many other professions [2]. While previous research has identified various risk factors including Type D personality traits [3], excessive workload [4,5], low job satisfaction [6],

work rumination [7], and emotional disorders [8], limited research has examined how technology-related behaviors, specifically phubbing, contribute to teachers' sleep disturbances.

Though phubbing traditionally refers to phone-snubbing during face-to-face interactions [9], the construct also encompasses a broader pattern of problematic smartphone dependency, as evidenced by research identifying phone obsession as a core determinant of phubbing behavior [10]. It is therefore reasonable to speculate that individuals who exhibit high phubbing tendencies may also demonstrate similar compulsive phone-checking behaviors at bedtime, potentially bringing work-related content into their sleep environment. This underexplored link is particularly concerning given the digital transformation of education, where smartphones have become indispensable for managing classroom activities, parent communication, and administrative tasks [11], creating conditions for chronic hyperconnectivity that disrupts sleep through both physiological mechanisms (blue light exposure) and psychological pathways (cognitive arousal) [12].

Moreover, the relationship between phubbing and insomnia is unlikely to be direct. Phubbing may elevate psychological distress, including symptoms of depression, anxiety, and stress, which in turn compromises sleep quality [13]. This pathway may also manifest differently across genders, with female teachers potentially facing greater expectations for digital responsiveness while experiencing higher baseline insomnia risk [14]. To address these gaps, the present study employs a longitudinal design to examine the relationships among phubbing, psychological distress (as indexed by depression, anxiety, and stress), and insomnia among school teachers. Two objectives are pursued: (a) to test whether psychological distress mediates the association between phubbing and insomnia, and (b) to determine whether gender moderates these direct and indirect pathways. The findings are expected to inform targeted interventions for promoting sleep health among teachers in an increasingly hyperconnected educational landscape.

### **1.1 School Teachers' Insomnia and Risk Factors**

Stress is recognized as a critical risk factor for insomnia [15], making it unsurprising that school teachers, who work in a notably high-stress occupation, represent a particularly vulnerable population. Recent systematic reviews have confirmed this vulnerability through striking prevalence comparisons. While the worldwide prevalence of insomnia in the general adult population is estimated at 16.2%, with severe insomnia affecting 7.9% of individuals [16], teachers experience dramatically higher rates. A systematic review found that insomnia symptoms among teachers range from 36.0% to 61.0%, which is more than double the general population prevalence, and notably identified teachers as having among the highest insomnia rates compared to other occupations [2]. This substantial disparity underscores the unique sleep challenges faced by educators and highlights the urgent need to understand the specific mechanisms driving their elevated insomnia risk.

Existing literature has identified multiple factors associated with teachers' insomnia, which can be categorized into demographic, occupational, and personality-related dimensions [3–6]. Regarding demographic factors, female teachers, those with less teaching experience, and married teachers demonstrate higher insomnia prevalence compared to their respective counterparts across educational levels from preschool to high school [6]. These demographic vulnerabilities suggest that certain teacher subgroups may require targeted support.

Occupational factors demonstrate strong associations with teachers' insomnia. Low job satisfaction has been linked to sleep disturbances among Portuguese school teachers [6], while excessive workload such as extended working hours and lengthy commutes significantly predicts insomnia among Japanese

educators [4,5]. Additional workplace stressors, including problematic interpersonal relationships, low job control, and inadequate rewards, further compound teachers' sleep difficulties [5].

Beyond structural workplace factors, psychological dimensions also play a crucial role. Among Polish high school teachers, those with Type D (distressed) personality, characterized by negative affectivity and social inhibition, experienced significantly higher rates of both insomnia and depression [3]. These findings suggest that individual psychological profiles may modulate vulnerability to occupational stressors and subsequent sleep disturbances. Specifically, teachers with high negative affectivity may perceive classroom challenges as more threatening, while their social inhibition prevents them from effectively coping with these demands, ultimately leading to sustained sleep difficulties.

While identifying demographic characteristics and personality traits is valuable, these factors are largely immutable. Consequently, pinpointing modifiable behavioral risk factors is essential for developing practical intervention strategies. Although traditional occupational stressors have been well documented, one increasingly pervasive behavior remains underexplored: phubbing. As smartphones become integral to educational practice [11], teachers may be particularly susceptible to developing problematic smartphone habits that extend beyond professional necessity into compulsive personal use. This oversight represents a critical gap, as phubbing constitutes a modifiable behavior with potential implications for sleep health.

### ***1.2 Phubbing as a Potential Risk Factor for Teachers' Insomnia***

A key question is whether phubbing, traditionally understood as an interpersonal phenomenon, may also have implications for behaviors beyond social settings, particularly compulsive smartphone engagement at bedtime that disrupts sleep. It is important to acknowledge that phubbing was originally conceptualized as a specific interpersonal behavior, namely ignoring a companion in favor of one's phone during face-to-face interactions [9]. However, the construct has increasingly been recognized as a behavioral manifestation of underlying compulsive smartphone dependency rather than a purely social phenomenon [17]. This broader interpretation is empirically supported by the Phubbing Scale [10], which captures two distinct dimensions: communication disturbance, reflecting the interpersonal disruption caused by phone use during social interactions, and phone obsession, reflecting an intrapsychic preoccupation with the device itself. The latter dimension, in particular, extends beyond the interpersonal context and taps into habitual, compulsive patterns of smartphone engagement that are not confined to social settings. Such behavior manifests as an inability to disengage from devices during evening hours as professional obligations, including parent communications and administrative tasks, draw attention to the screen [18]. This expanded conceptualization is particularly relevant given that smartphones have fundamentally altered the teaching profession by blurring the boundaries between professional and private life [11].

Consequently, the psychological reliance that may lead teachers to prioritize screens during the day often extends into bedtime routines. Research indicates that work-related rumination before bed significantly impairs sleep quality [7]; in this context, phubbing functions as a mechanism that perpetuates cognitive arousal. Rather than psychologically disengaging from work, teachers who compulsively check notifications maintain a state of hypervigilance regarding occupational stressors. This phenomenon is particularly pronounced in contexts with extensive information and communication technology integration, such as China, the context of the present study, where digital platforms dominate both pedagogical and administrative interactions [18]. In such environments, phubbing evolves from a personal habit into a professionally reinforced behavior, driven by implicit expectations of constant availability that significantly compromise sleep health.

Direct empirical investigation into the specific relationship between phubbing and teacher insomnia remains scarce. However, valid inferences can be drawn from the robust literature on related forms of

problematic technology use, particularly Problematic Internet Use (PIU). As phubbing is conceptualized as a specific, interpersonal manifestation of PIU [17], it shares core pathological features, such as compulsive device checking, that are known to disrupt sleep [12]. Among Hungarian high school teachers, PIU was significantly associated with burnout, depression, and notably higher insomnia prevalence, as well as diminished quality of life across all domains [19]. Similarly, a study of Japanese junior and senior high school teachers revealed that PIU was significantly correlated with alcohol addiction, insomnia, and depression, with insomnia demonstrating effect sizes comparable to those observed for depression [20]. Further evidence from a Turkish adult sample, in which teachers constituted the majority of participants, demonstrated strong correlations between PIU and insomnia [21]. Moreover, a recent meta-analysis examining nomophobia, a construct closely related to phubbing, revealed a robust association with insomnia ( $r = 0.56$ ), approaching a large effect size [12].

Recent longitudinal evidence from related constructs further supports the temporal direction of this relationship. A cross-lagged panel analysis of 1181 Chinese college students demonstrated that problematic mobile phone use unidirectionally predicted subsequent sleep quality over a 12-month interval [22]. Similarly, a three-wave longitudinal study of 2052 Korean adolescents revealed reciprocal associations between smartphone overdependence and sleep quality across a two-year period [23]. Additionally, a cross-lagged panel analysis among Chinese college students found that internet addiction longitudinally predicted insomnia over time [24]. These findings provide preliminary longitudinal support for the hypothesis that problematic digital behaviors temporally precede sleep deterioration.

Collectively, these cross-sectional and longitudinal findings suggest that problematic digital behaviors compromise sleep health, warranting specific investigation into phubbing as a distinct phenomenon. However, the existing longitudinal evidence has focused on broader constructs such as problematic mobile phone use, smartphone overdependence, and internet addiction, and no study to date has examined the prospective relationship between phubbing specifically and insomnia. Moreover, existing research has been conducted predominantly among adolescent and college student populations, leaving the temporal effects of phubbing on sleep among working adult populations, particularly teachers, entirely unexplored. As emphasized in a recent review, identifying modifiable antecedent factors through longitudinal research is essential for developing targeted interventions [2], underscoring the need for prospective studies that can establish the directional effects of phubbing on teachers' sleep outcomes.

### ***1.3 Psychological Distress as Mediator and Gender as Moderator***

This study examines psychological distress as a potential mediator linking teachers' phubbing behaviors to insomnia, while considering gender as a moderator of these relationships. Although the hyperarousal model suggests that phubbing patterns could directly affect teachers' insomnia through sustained physiological activation [15], emerging evidence indicates that phubbing may also operate through psychological pathways, specifically by elevating distress levels that subsequently compromise sleep quality.

Substantial literature documents the association between phubbing and psychological distress across diverse populations. Among Chinese primary and middle school teachers, phubbing demonstrates a significant positive relationship with depression, yielding a medium effect size even after controlling for age and gender [13]. This pattern extends beyond educational contexts to the broader population [25]. A comprehensive meta-analysis encompassing 83 studies with participants averaging 19.68 years (range: 6–74 years) revealed consistent positive associations between experiencing phubbing and various negative affect indicators, including anxiety, depression, exhaustion, and stress, with particularly notable moderate

positive associations emerging for anxiety symptoms [26]. These findings suggest that phubbing behaviors systematically undermine psychological wellbeing across developmental stages and occupational contexts.

The pathway from psychological distress to insomnia is well-established, with meta-analytic evidence demonstrating robust associations between distress components (particularly depression and anxiety) and sleep disturbances [2,26]. Among teacher populations specifically, a recent scoping review analyzing 31 studies identified psychological distress variables as the most prevalent risk factors associated with insomnia, surpassing other occupational and demographic predictors [2]. This convergent evidence supports a mediation model wherein phubbing behaviors generate psychological distress, which subsequently manifests as insomnia through established psychophysiological mechanisms, highlighting the importance of addressing both technological behaviors and their psychological consequences in interventions targeting teacher sleep health.

Furthermore, gender constitutes a crucial moderator in insomnia pathways. Beyond general prevalence differences showing higher insomnia rates in females [2,14], male and female teachers appear to exhibit distinct vulnerability profiles in response to different types of stressors. Women tend to be more susceptible to interpersonal and emotional stressors [27,28]; among Japanese educators, for example, low collegial support significantly predicted insomnia only in females [5]. Men, by contrast, appear more susceptible to structural stressors, with extended working hours predicting sleep problems exclusively among male teachers [4].

Based on the specific occupational demands of the teaching profession, gender is hypothesized to moderate all three pathways. First, the relationship between phubbing and psychological distress is expected to vary by gender. Although prior research found that gender did not moderate the phubbing-depression link among Ukrainian university students [29], the occupational context of teaching likely introduces different dynamics. Teaching is a profession characterized by high emotional labor, which falls disproportionately on female educators who often juggle a “double burden” of pedagogical responsibilities and domestic care [30]. According to Social Role Theory [31], women are socialized to prioritize relational maintenance. When female teachers engage in phubbing, this behavior contradicts their socialized role as attentive caregivers and communicators, potentially generating feelings of guilt for neglecting interpersonal responsibilities and conflict between their professional/domestic roles and their smartphone habits [32]. In contrast, male teachers may perceive their own smartphone use as a permissible recovery strategy [33]. Consequently, the same phubbing behavior may produce greater psychological distress in female teachers than in their male counterparts.

Second, the pathway from distress to insomnia is likely subject to gender-specific processing mechanisms. Extensive research indicates that female teachers consistently report higher levels of emotional exhaustion and are more prone to cognitive rumination regarding student interactions and workplace conflicts [5,34]. Unlike male teachers, who are more likely to employ externalizing or compartmentalization strategies to manage work stress, female teachers tend to engage in rumination, characterized by a repetitive internal focus on negative affect. This tendency to cognitively replay the day’s stressors is a known driver of pre-sleep physiological arousal [7], suggesting that equivalent levels of occupational distress will translate into more severe sleep onset difficulties for female educators.

Finally, the direct association between phubbing and insomnia may be moderated by gender due to differences in bedtime technology habits. Research suggests that while men often use devices for passive entertainment (e.g., gaming, news), women are more likely to use smartphones for social monitoring and maintaining social networks [35]. For teachers, this often blurs into monitoring work-related chats or parent groups. This active social monitoring requires higher cognitive load and emotional involvement

than passive consumption, creating a state of hypervigilance that specifically predisposes female teachers to greater sleep latency and reduced sleep quality.

### **1.4 Current Study**

Despite the established vulnerability of teachers to insomnia, there is a scarcity of research examining the specific mechanisms linking phubbing to sleep disturbances in this occupational group, particularly regarding the mediating role of psychological distress and the moderating influence of gender. To bridge this critical gap, the present study employs a two-wave longitudinal design to investigate the temporal influence of phubbing on teachers' subsequent insomnia symptoms.

Based on the above theoretical and empirical rationale, the following hypotheses were proposed:

**Hypothesis 1 (H1):** *T1 phubbing will be positively associated with T2 insomnia through a direct pathway.*

**Hypothesis 2 (H2):** *T1 phubbing will be indirectly associated with T2 insomnia through T2 psychological distress (i.e., psychological distress will mediate the phubbing-insomnia relationship).*

**Hypothesis 3 (H3):** *Gender will moderate the structural pathways such that the direct and indirect associations between phubbing and insomnia will be stronger among female teachers than among male teachers.*

## **2 Methods**

### **2.1 Procedure and Participants**

This longitudinal study employed a two-wave design with a four-month interval between data collection points. The baseline survey (T1) was administered in February 2024, coinciding with the beginning of the spring semester, while the second wave (T2) was conducted in June 2024, corresponding to the semester's end. The four-month interval was selected for several reasons. First, it aligns with a complete academic semester, capturing the cumulative effects of phubbing behaviors on psychological distress and insomnia as occupational demands intensify from the beginning to the end of term. Second, this four-month timeframe strikes an appropriate balance: it is long enough to allow meaningful changes in psychological distress and insomnia to emerge over a full academic semester, while being short enough to limit the influence of confounding factors such as summer break, holidays, or new semester starts that are more common in longer follow-up periods (e.g., six months or more). Third, the four-month interval is consistent with previous short-term longitudinal research on problematic smartphone behaviors and psychological outcomes, which has employed intervals ranging from approximately three months [36] and successfully detected temporal effects of problematic digital behaviors on well-being indicators. Participants were recruited through convenience sampling across multiple educational institutions in China. Assistance was first sought from school administrators, and upon obtaining their agreement, the online survey was distributed to teachers within their respective schools. At each wave, surveys were distributed to all teachers in the participating schools; participation at T2 was not restricted to T1 respondents. Responses across the two waves were subsequently matched using self-generated identification codes (described below). This open recruitment strategy reduced individual participant burden by not requiring T1 respondents to commit to a second survey, while the matched longitudinal subsample and full information maximum likelihood (FIML) estimation ensured adequate statistical power for the longitudinal analyses.

Participation was limited to in-service teachers without diagnosed clinical mental disorders. All participants provided electronic informed consent prior to the commencement of the survey, after being informed of the

study's purpose, procedures, voluntary nature, and their right to withdraw at any time without penalty. To ensure participant confidentiality, no personally identifiable information such as names or official ID numbers was collected. Instead, participants created a self-generated identification code by combining the last four digits of their phone number with their month and day of birth to link responses across the two waves. This method allowed for data matching while maintaining participant privacy throughout the study. Furthermore, participation was entirely voluntary and individuals were explicitly notified of their right to withdraw from the research at any point without penalty. Regarding data security, all electronic responses were kept in secure digital storage that was accessible only to the primary research team. The study protocol was approved by the Institutional Review Board of the Jiangxi Psychological Consultant Association (IRB Reference: JXSXL-2024-JA08).

At T1 and T2, 1061 and 812 teachers completed the online survey, with 77.0% ( $n = 817$ ) and 77.3% ( $n = 628$ ) from Jiangsu Province, respectively. Of the T1 participants, 632 (59.6%) also participated at T2 (completers), while 429 (40.4%) participated only at T1 (non-completers). Participants demonstrated similar demographic characteristics across both waves: age ranged from 24 to 61 years ( $M = 40.33$ ,  $SD = 9.32$ ) at T1 and 24 to 63 years ( $M = 41.09$ ,  $SD = 9.25$ ) at T2; female representation was 69.0% ( $n = 732$ ) at T1 and 67.9% ( $n = 551$ ) at T2; public school employment comprised 95.9% ( $n = 1017$ ) at T1 and 97.5% ( $n = 792$ ) at T2; and Chinese was the most frequently taught subject (25.4% at T1 and 26.5% at T2).

To examine potential attrition bias, completers and non-completers were compared on all demographic variables. No significant differences were found for gender ( $\chi^2 = 0.22$ ,  $p = 0.638$ ), age ( $t = 1.11$ ,  $p = 0.268$ ), school ownership ( $\chi^2 = 0.13$ ,  $p = 0.722$ ), or teaching subject ( $\chi^2 = 3.25$ ,  $p = 0.517$ ). However, a significant difference emerged for school type ( $\chi^2 = 65.26$ ,  $p < 0.001$ ), with completers including a higher proportion of junior vocational school teachers (41.0%) and non-completers including more senior high school (5.8%) and senior vocational school (8.8%) teachers (see Table 1 for detailed demographics). To assess the missing data pattern, Little's Missing Completely at Random (MCAR) test was conducted on mean scores for the study variables (insomnia, distress, and phubbing), revealing that missingness was completely at random across the studied variables ( $D^2(10) = 9.87$ ,  $p = 0.452$ ). This result, together with the largely comparable demographic profiles between completers and non-completers, supported the use of full information maximum likelihood (FIML) estimation for handling missing data in the structural analyses.

**Table 1:** Demographic Characteristics of Participants Across Study Waves and Attrition Comparison.

	T1 ( $n = 1061$ )	T2 ( $n = 812$ )	Non-Completers ( $n = 429$ )	Matched Longitudinal Sample (T1 and T2; $n = 632$ )	$t$ ( $p$ -Value) or $\chi^2$ ( $p$ -Value)
Gender: $n$ (%)					0.22 (0.638)
Male	329 (31.0%)	261 (32.1%)	137 (31.9%)	192 (30.4%)	
Female	732 (69.0%)	551 (67.9%)	292 (68.1%)	440 (69.6%)	
Age of years: mean (SD)	40.33 (9.32)	41.09 (9.25)	40.55 (9.38)	41.19 (9.13)	1.11 (0.268)
School ownership: $n$ (%)					0.13 (0.722)
Public	1017 (95.9%)	792 (97.5%)	405 (94.4%)	601 (95.1%)	
Private	44 (4.1%)	20 (2.5%)	24 (5.6%)	31 (4.9%)	
School type: $n$ (%)					65.26 (<0.001)
Senior high school	72 (6.8%)	28 (3.4%)	25 (5.8%)	8 (1.2%)	
Senior vocational school	46 (4.3%)	43 (5.3%)	38 (8.8%)	15 (2.4%)	
Junior high school	271 (25.5%)	151 (18.6%)	115 (26.9%)	143 (22.6%)	
Junior vocational school	304 (28.7%)	264 (32.5%)	99 (23.0%)	259 (41.0%)	
Primary school	368 (34.7%)	326 (40.1%)	152 (35.5%)	207 (32.8%)	

**Table 1:** *Cont.*

	T1 (n = 1061)	T2 (n = 812)	Non-Completers (n = 429)	Matched Longitudinal Sample (T1 and T2; n = 632)	t (p-Value) or $\chi^2$ (p-Value)
Teaching subject: n (%)					3.25 (0.517)
Chinese	269 (25.4%)	215 (26.5%)	103 (23.9%)	181 (28.6%)	
Mathematics	195 (18.4%)	154 (19.0%)	82 (19.1%)	107 (16.9%)	
English	132 (12.4%)	89 (11.0%)	55 (12.9%)	72 (11.4%)	
Professional subject (e.g., vocational subjects)	254 (23.9%)	196 (24.1%)	91 (21.2%)	133 (21.1%)	
Others	211 (19.9%)	158 (19.4%)	98 (22.9%)	139 (22.0%)	

Note: Statistical tests in the last column compare non-completers (n = 429) and completers (n = 632). T1: Time 1; T2: Time 2.

## 2.2 Measures

Validated Chinese versions of established scales were used to measure insomnia, psychological distress, and phubbing behavior. Each instrument is described in detail below.

### 2.2.1 Insomnia

The Insomnia Severity Index (ISI); [37] was used to assess participants' insomnia severity. This seven-item self-report measure evaluates the nature and symptoms of sleep difficulties on a 5-point Likert scale ranging from 0 (none) to 4 (very severe). The scale captures subjective sleep experiences, including symptom severity (onset, maintenance, and early morning awakening), satisfaction with sleep patterns, interference with daily functioning, noticeability of impairments to others, and overall distress. In the original validation study involving older adults, the internal consistency (Cronbach's alpha) was approximately 0.78, with acceptable concurrent validity [37]. The Chinese version has also demonstrated robust psychometric properties, reporting Cronbach's alpha coefficients ranging from 0.72 to 0.91 across clinical and control groups and known-groups validity evidenced by significantly higher scores in clinical populations [38]. In the current study, the scale demonstrated excellent internal reliability, with a McDonald's omega of 0.91 at both T1 and T2.

### 2.2.2 Psychological Distress

The Depression Anxiety Stress Scales-21 (DASS-21; [39]) was used to measure teachers' psychological distress. The DASS-21 is a shortened 21-item version of the original 42-item DASS. The items are rated on a 4-point scale ranging from 0 (did not apply to me at all) to 3 (applied to me very much or most of the time), with seven items comprising each of the three subscales: Depression, Anxiety, and Stress. The Chinese version of the DASS-21 has been widely applied in populations of Chinese school teachers (e.g., [40]) and was recently verified as a suitable instrument for cross-cultural comparison [41,42]. These recent studies suggest that the overall distress score is representative of a general factor of negative emotional states [41,42]. Consequently, in the current study, the three subscales were used as observed indicators for a latent 'Psychological Distress' variable. Internal consistency for this measure was excellent at both time points (McDonald's omega = 0.96).

### 2.2.3 Phubbing

Teachers' phubbing behavior was assessed using the Phubbing Scale [10], a 10-item self-report measure comprising two factors rated on a 5-point Likert scale ranging from 1 (never) to 5 (always). In the original

development study, the two-factor structure explained 56.19% of the variance, with all factor loadings exceeding 0.40 and internal consistency coefficients (Cronbach's alpha) approximating 0.85. A subsequent large-scale measurement invariance study across 20 countries, including China, established the scale's factorial validity only after removing Items 5 and 10 [43]. Consistent with these cross-cultural findings, the current study observed unacceptable factor loadings for these two items. Consequently, they were excluded, and the remaining eight items were retained for analysis (see the Results section for the confirmatory factor analysis). Internal consistency for the two resulting subscales was robust: McDonald's omega coefficients were 0.84 and 0.87 at T1, and 0.84 for both subscales at T2.

### **2.3 Data Analysis**

All statistical analyses were conducted using [jamovi 2.7.24]. A two-tailed  $p$ -value less than 0.05 was considered statistically significant. Prior to hypothesis testing, Harman's single-factor test was conducted to examine the potential for common method bias (CMB). An exploratory factor analysis including all study items was performed; if a single factor accounts for the majority of the variance (i.e., more than 50%), CMB is considered a concern [44]. The results indicated that the first unrotated factor explained 17.44% of the total variance, which is below the 50% threshold, suggesting that CMB was not a significant concern in the present study.

Following these preliminary diagnostics, the analytical focus shifted to the core study variables. Although all constructs were assessed at both time points, only T1 phubbing, T2 psychological distress, and T2 insomnia were included in the primary analyses to address the study hypotheses. The primary analyses proceeded in two steps. Descriptive statistics and Pearson correlations were first calculated to examine associations among these variables using composite mean scores. Subsequently, structural equation modeling (SEM) was employed to test the hypothesized relationships. The SEM analyses utilized the Robust Maximum Likelihood (MLR) estimator, which provides robust standard errors and scaled test statistics appropriate for data derived from ordinal Likert-type response scales that may not fully satisfy the assumption of continuous normal distribution. Missing data in the SEM analyses were handled using FIML, justified by Little's MCAR test results indicating that data were missing completely at random.

Prior to conducting the structural model, confirmatory factor analyses (CFAs) were performed separately at each time point to evaluate the measurement properties of all constructs, including communication disturbance, phone obsession, depression, anxiety, stress, and insomnia. Although only T1 phubbing subscales were used as predictors and T2 psychological distress subscales and insomnia were used as the mediator and outcome in the structural model, CFAs were conducted at both time points to verify the factorial validity and measurement quality of all instruments across the two assessment waves.

Within the SEM framework, the two phubbing subscales (communication disturbance and phone obsession) were specified as separate latent factors rather than indicators of a higher-order phubbing construct. This specification was adopted because the two subscales capture conceptually distinct facets of phubbing behavior: one reflecting the interpersonal disruption caused by phone use during social interactions, and the other reflecting an intrapsychic preoccupation with the device itself [10]. Empirically, the two subscales exhibited only a low-to-medium intercorrelation and demonstrated differential association patterns with the outcome variables (see the Results section), suggesting that each dimension may operate through distinct pathways in predicting psychological distress and insomnia. Collapsing them into a single higher-order factor would obscure these differential relationships and reduce the specificity of the findings. Psychological distress was modeled as a latent factor with three observed indicators (mean scores of the

depression, anxiety, and stress subscales), following a common approach in the literature (e.g., [45,46]). Insomnia was modeled as a unidimensional latent construct.

In the structural model, teacher age and school type (senior high school, senior vocational school, junior high school, junior vocational school, and primary school) were included as covariates of the mediator (psychological distress) and the dependent variable (insomnia). Age was controlled because it is inversely associated with problematic smartphone use, with usage declining markedly in middle adulthood [47], while simultaneously being positively associated with insomnia incidence due to age-related changes in sleep architecture and circadian regulation [48]. Failing to account for age could therefore confound the observed associations, as younger teachers may report higher phubbing levels while older teachers may experience greater insomnia severity for reasons unrelated to digital behavior. School type was controlled because teachers across different educational levels face distinct occupational demands (e.g., university entrance examination pressures in senior high schools vs. frequent digital parent communication in primary schools) that may independently influence psychological distress and insomnia; additionally, as noted above, the distribution of school type differed significantly between the two study waves, necessitating statistical adjustment to ensure that observed associations were not attributable to compositional differences across assessment points. The structural model estimated both the direct effects of T1 communication disturbance and T1 phone obsession on T2 insomnia and the indirect effects mediated through T2 psychological distress. The significance of indirect effects was tested using bias-corrected bootstrapping with 5000 resamples.

For both the CFA and the full structural model, model fit was evaluated using standard indices: Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI)  $\geq 0.90$ , and Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR)  $\leq 0.08$  [49]. Additionally, convergent validity of the measurement model was assessed via Average Variance Extracted (AVE), with values  $> 0.50$  indicating adequate validity [50].

In the multi-group analysis, descriptive statistics (means and standard deviations) were computed separately for male and female teachers, and independent-samples *t*-tests were conducted to examine gender differences across all study variables. Bivariate correlations among the study variables were also examined by gender. Following these preliminary analyses, measurement invariance was tested across male and female teachers using a sequential approach: configural invariance (same factor structure), metric invariance (equal factor loadings), and scalar invariance (equal item intercepts). Invariance was evaluated by comparing successive models; it was considered established if  $\Delta\text{CFI} > -0.01$ ,  $\Delta\text{RMSEA} \leq 0.015$ , and  $\Delta\text{SRMR} \leq 0.030$  for metric invariance, and  $\Delta\text{CFI} > -0.01$ ,  $\Delta\text{RMSEA} \leq 0.015$ , and  $\Delta\text{SRMR} \leq 0.010$  for scalar invariance [51,52]. These criteria were preferred over the chi-square difference test for invariance evaluation, as the latter is sensitive to large sample sizes when numerous parameters are simultaneously constrained. Once at least metric invariance was established, multi-group SEM (MG-SEM) was conducted to assess gender as a moderator. Specific structural paths were individually constrained to equality across groups, and chi-square difference tests were used to evaluate each constraint, as testing individual path constraints involves minimal degrees of freedom and is less susceptible to the sample size inflation that affects global invariance comparisons.

### 3 Results

#### 3.1 Descriptive Statistics and Zero-Order Correlations

Table 2 presents the mean scores for phubbing (including two dimensions), psychological distress (including three dimensions), and insomnia, along with their interrelationships. Skewness and kurtosis values for all study variables fell within acceptable ranges ( $|\text{skewness}| < 3.0$  and  $|\text{kurtosis}| < 10.0$ ; Kline [50]),

supporting the assumption of approximate normality. Most notably, the mean insomnia score at T2 was 8.87 ( $SD = 6.39$ ), which falls within the subthreshold insomnia range (8–14) according to established cutoff values [37], indicating that participants on average experienced subthreshold insomnia. The distribution of T2 insomnia severity ( $n = 812$ ) revealed that 45.0% of participants reported no clinically significant insomnia, 36.8% experienced subthreshold insomnia, 13.7% met criteria for moderate clinical insomnia, and 4.5% reported severe insomnia. Regarding phubbing behavior, using the suggested cutoff of 2.5 per item (corresponding to total score cutoffs of 20 for the overall scale and 10 for each subscale), participants demonstrated above mid-level phone obsession ( $M = 12.73, SD = 3.86$ ) but below mid-level communication disturbance ( $M = 7.85, SD = 2.46$ ), resulting in an overall moderate level of phubbing behavior, with 52.1% of participants scoring above 20. For psychological distress, using 16 as the suggested cutoff [53], 35.8% of participants exhibited potential clinical distress.

Correlation analyses revealed that T1 phubbing was positively associated with both T2 psychological distress ( $r = 0.19, p < 0.001$ ) and T2 insomnia ( $r = 0.25, p < 0.001$ ). Additionally, T2 psychological distress and insomnia showed a strong positive correlation ( $r = 0.58, p < 0.001$ ). Notably, the two dimensions of phubbing showed differential associations with the outcome variables. Communication disturbance demonstrated a stronger relationship with insomnia ( $r = 0.24, p < 0.001$ ) than phone obsession ( $r = 0.17, p = 0.002$ ). Similarly, communication disturbance was significantly associated with psychological distress ( $r = 0.22, p < 0.001$ ), whereas phone obsession showed no significant relationship with psychological distress. It should be noted that these zero-order correlations may differ from the SEM estimates reported below, as the latter represent partial associations adjusted for all constructs in the model simultaneously.

**Table 2:** Descriptive Statistics and Correlations for Phubbing, Psychological Distress, and Insomnia (Total Sample,  $N = 332\sim 1061$ ).

	<i>M (SD)</i>	<i>Skewness</i>	<i>Kurtosis</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>
1. Communication Disturbance (T1)	7.85 (2.46)	0.35	-0.23	—							
2. Phone Obsession (T1)	12.73 (3.86)	-0.14	-0.39	0.27***	—						
3. Phubbing Total (T1)	20.58 (5.10)	-0.22	0.03	0.68***	0.89***	—					
4. Depression (T2)	4.03 (4.66)	1.08	0.34	0.22***	0.07	0.16***	—				
5. Anxiety (T2)	4.57 (4.67)	1.03	0.41	0.21***	0.10	0.18***	0.91***	—			
6. Stress (T2)	4.98 (4.79)	0.85	-0.03	0.23***	0.14*	0.22***	0.91***	0.92***	—		
7. Psychological Distress Total (T2)	13.60 (13.69)	0.98	0.17	0.22***	0.11	0.19***	0.97***	0.97***	0.97***	—	
8. Insomnia (T2)	8.87 (6.39)	0.85	-0.03	0.24***	0.17**	0.25***	0.53***	0.58***	0.59***	0.58***	—

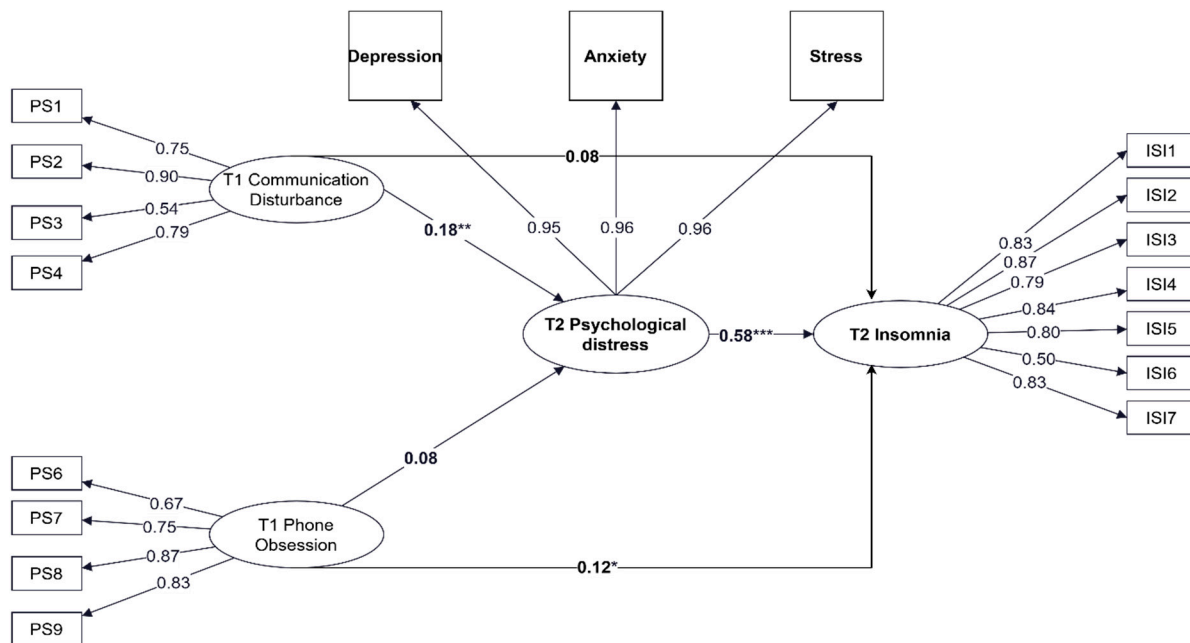
\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ . M: Mean; SD: Standard Deviation; T1: Time 1; T2: Time 2.

### 3.2 Confirmatory Factor Analysis

CFAs were conducted to evaluate the measurement properties of all constructs at both time points. Table S1 presents the model fit indices at T1 and T2. The results revealed a consistent pattern: the full 10-item Phubbing Scale failed to meet acceptable fit thresholds at both time points. However, after removing Item 5 from the Communication Disturbance subscale and Item 10 from the Phone Obsession subscale, the models achieved acceptable fit, consistent with cross-cultural findings reported by [43]. In the refined measurement model (excluding two items with poor loadings), standardized factor loadings were all greater than 0.50 (see Tables S2 and S3). AVE values for communication disturbance, phone obsession, insomnia, depression, anxiety, and stress all exceeded 0.50, supporting adequate convergent validity across all latent constructs.

### 3.3 Structural Equation Modeling Results

Table 3 displays the model fit indices for the structural equation model, which controlled for school type and teacher age; all indices fell within acceptable thresholds. Analysis of the structural paths revealed divergent effects for the two phubbing subscales (see Fig. 1). T1 communication disturbance significantly predicted T2 psychological distress ( $b = 1.40$ ,  $SE = 0.54$ ,  $z = 2.58$ ,  $\beta = 0.18$ ,  $p = 0.010$ , 95% bootstrap CI [0.141, 2.609]) but had no direct effect on T2 insomnia. In contrast, T1 phone obsession was not significantly associated with T2 psychological distress but directly predicted T2 insomnia ( $b = 0.14$ ,  $SE = 0.07$ ,  $z = 2.09$ ,  $\beta = 0.12$ ,  $p = 0.036$ , bootstrap CI [0.011, 0.248]). Additionally, T2 psychological distress was strongly associated with T2 insomnia ( $b = 0.12$ ,  $SE = 0.01$ ,  $z = 14.28$ ,  $\beta = 0.58$ ,  $p < 0.001$ , bootstrap CI [0.047, 0.312]). The indirect effect of communication disturbance on insomnia through psychological distress was statistically significant (effect = 0.16,  $SE = 0.06$ ,  $z = 2.57$ ,  $p = 0.001$ , 95% bootstrap CI [0.007, 0.103];  $\beta = 0.11$ ), whereas the indirect effect of phone obsession through psychological distress was not significant. Overall, the model explained 40.6% of the variance in T2 insomnia ( $R^2 = 0.406$ ). Taken together, H1 was partially supported: the direct pathway from phubbing to insomnia was significant only for phone obsession, not for communication disturbance. H2 was also partially supported: the indirect pathway through psychological distress was significant only for communication disturbance, not for phone obsession. These findings, with communication disturbance operating indirectly through psychological distress and phone obsession acting directly on insomnia, validate the decision to model the subscales as separate factors. The full set of covariate coefficients is presented in Table S4.



**Figure 1:** SEM results for the total sample. Note: Standardized coefficients are presented. Teacher age and school type (with primary school as the reference category) were included as covariates of both psychological distress and insomnia; their standardized coefficients ranged from  $-0.12$  to  $0.06$  (see Table S4 for full details) while not shown in the figure for clarity. \* $p < 0.05$ . \*\* $p < 0.01$ . \*\*\* $p < 0.001$ . PS: Phubbing Scale; ISI: Insomnia Severity Index; T1: Time 1; T2: Time 2.

**Table 3:** Model Fit Indices for the Total Sample and Gender Subgroups.

	$\chi^2$ (df)	CFI	NNFI	RMSEA (90 Percent Confidence Interval); RMSEA <i>p</i> -Value	SRMR
Total sample	747.24 (199)	0.947	0.933	0.042 (0.039–0.045); 0.999	0.048
Male teachers	353.03 (199)	0.954	0.942	0.040 (0.033–0.046); 0.997	0.067
Female teachers	672.74 (199)	0.937	0.920	0.048 (0.044–0.051); 0.846	0.052

CFI = Comparative fit index; NNFI = Non-normed fit index; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual.

### 3.4 Multi-Group Analysis

Tables 4 and 5 present the descriptive statistics and correlations among the study variables for male and female teachers, respectively. Regarding T1 phubbing, male teachers reported a mean communication disturbance score of 7.95 (*SD* = 2.64) and phone obsession score of 12.25 (*SD* = 3.90), while female teachers reported comparable communication disturbance (*M* = 7.81, *SD* = 2.38) but higher phone obsession (*M* = 12.95, *SD* = 3.82). For T2 psychological distress, male teachers exhibited numerically higher mean scores across all three subscales (depression: *M* = 4.59, *SD* = 4.95; anxiety: *M* = 4.95, *SD* = 4.94; stress: *M* = 5.20, *SD* = 4.98) compared to female teachers (depression: *M* = 3.78, *SD* = 4.50; anxiety: *M* = 4.39, *SD* = 4.53; stress: *M* = 4.88, *SD* = 4.71). T2 insomnia scores were similar across genders (males: *M* = 8.76, *SD* = 6.17; females: *M* = 8.92, *SD* = 6.50). Independent-samples *t*-tests revealed two statistically significant gender differences: female teachers demonstrated significantly higher phone obsession than male teachers (*t* = 2.73, *p* = 0.006, Cohen’s *d* = 0.18), whereas male teachers reported significantly higher depression scores (*t* = 2.25, *p* = 0.025, Cohen’s *d* = 0.17). Both effect sizes were small. Furthermore, correlation patterns differed by gender. Among female teachers, T1 phubbing total was positively correlated with both T2 psychological distress (*r* = 0.19, *p* = 0.030) and T2 insomnia (*r* = 0.23, *p* < 0.001). Among male teachers, T1 phubbing total was significantly associated with T2 insomnia (*r* = 0.20, *p* = 0.030) but not with T2 psychological distress.

Table S1 presents the CFA results for male and female teachers separately. Consistent with the total sample findings, the inclusion of Items 5 and 10 of the Phubbing Scale worsened model fit across both gender subgroups; conversely, removing these items yielded acceptable fit thresholds. Consequently, these two items were excluded from further analyses. For this refined measurement model, factor loadings were all greater than 0.50 (see Tables S5–S8) and AVE values exceeded 0.50 for all constructs, supporting adequate convergent validity across genders.

**Table 4:** Descriptive Statistics and Correlations for Phubbing, Psychological Distress, and Insomnia among Male Teachers (*n* = 101–329).

	<i>M</i> ( <i>SD</i> )	1	2	3	4	5	6	7	8
1. Communication Disturbance (T1)	7.95 (2.64)	—							
2. Phone Obsession (T1)	12.25 (3.90)	0.28***	—						
3. Phubbing Total (T1)	20.19 (5.29)	0.71***	0.88***	—					
4. Depression (T2)	4.59 (4.95)	0.20*	0.05	0.14	—				
5. Anxiety (T2)	4.95 (4.94)	0.20*	0.10	0.18	0.93**	—			
6. Stress (T2)	5.20 (4.98)	0.20*	0.17	0.24*	0.92***	0.93***	—		
7. Psychological Distress Total (T2)	14.74 (14.51)	0.20*	0.11	0.19	0.98***	0.98***	0.98***	—	
8. Insomnia (T2)	8.76 (6.17)	0.24*	0.20*	0.28**	0.53***	0.58***	0.59***	0.58***	—

\**p* < 0.05, \*\**p* < 0.01, \*\*\**p* < 0.001. *M*: Mean; *SD*: Standard Deviation; T1: Time 1; T2: Time 2.

**Table 5:** Descriptive Statistics and Correlations for Phubbing, Psychological Distress, and Insomnia among Female Teachers ( $n = 231\text{--}732$ ).

	<i>M (SD)</i>	1	2	3	4	5	6	7	8
1. Communication Disturbance (T1)	7.81 (2.38)	—							
2. Phone Obsession (T1)	12.95 (3.82)	0.27***	—						
3. Phubbing Total (T1)	20.75 (5.01)	0.68***	0.89***	—					
4. Depression (T2)	3.78 (4.50)	0.22***	0.08	0.17**	—				
5. Anxiety (T2)	4.39 (4.53)	0.22***	0.10	0.18**	0.90***	—			
6. Stress (T2)	4.88 (4.71)	0.24***	0.12	0.21**	0.90***	0.91***	—		
7. Psychological Distress Total (T2)	13.06 (13.28)	0.24***	0.10	0.19**	0.97***	0.97***	0.97***	—	
8. Insomnia (T2)	8.92 (6.50)	0.24***	0.15*	0.23***	0.54***	0.59***	0.59***	0.59***	—

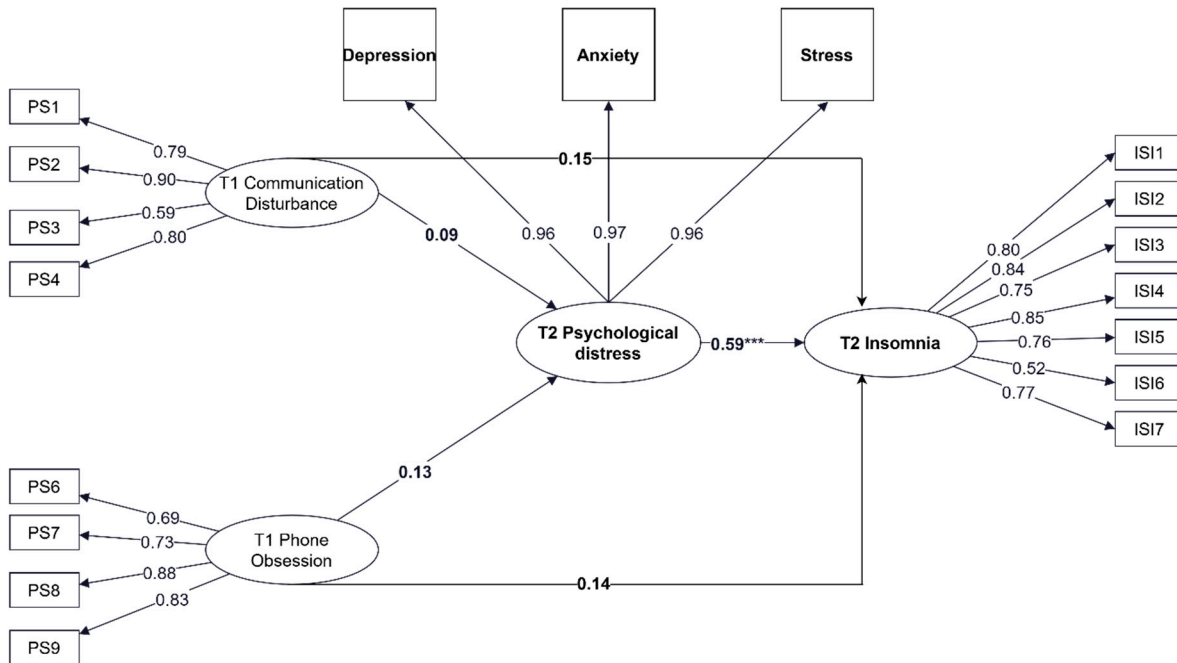
\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ . M: Mean; SD: Standard Deviation; T1: Time 1; T2: Time 2.

Prior to conducting gender-specific structural analyses, measurement invariance across male and female teachers was examined. Table S9 demonstrates that scalar invariance was achieved for all constructs at both time points, indicating that constraining factor loadings and item intercepts to equality across genders did not significantly worsen model fit. Subsequently, the structural paths revealed gender-specific patterns (see Figs. 2 and 3). For male teachers, neither communication disturbance nor phone obsession at T1 was significantly associated with T2 psychological distress, and neither subscale was directly associated with T2 insomnia. For female teachers, T1 communication disturbance was significantly associated with T2 psychological distress ( $b = 1.64$ ,  $SE = 0.61$ ,  $z = 2.68$ ,  $\beta = 0.21$ ,  $p = 0.007$ , bootstrap CI [0.484, 3.239]), whereas phone obsession was not. Neither phubbing subscale was directly associated with T2 insomnia among female teachers. The association between T2 psychological distress and T2 insomnia was significant and comparable across both genders (males:  $b = 0.10$ ,  $SE = 0.01$ ,  $z = 7.29$ ,  $\beta = 0.59$ ,  $p < 0.001$ , bootstrap CI [0.074, 0.139]; females:  $b = 0.13$ ,  $SE = 0.01$ ,  $z = 12.43$ ,  $\beta = 0.59$ ,  $p < 0.001$ , bootstrap CI [0.099, 0.144]). The indirect effect of communication disturbance on insomnia through psychological distress was significant for female teachers (indirect effect = 0.21,  $SE = 0.08$ ,  $p = 0.008$ , 95% bootstrap CI [0.06, 0.41];  $\beta = 0.13$ ) but not for male teachers. The indirect effect of phone obsession through psychological distress was not significant for either gender. Despite these descriptive differential patterns, chi-square difference tests indicated that none of the structural path coefficients differed significantly between genders (see Table 6 for a summary of the multi-group path comparisons). Accordingly, H3 was not supported: although the indirect effect of communication disturbance on insomnia through psychological distress was significant among female teachers but not among male teachers at the descriptive level, the formal moderation tests did not confirm statistically significant gender differences in any of the structural paths.

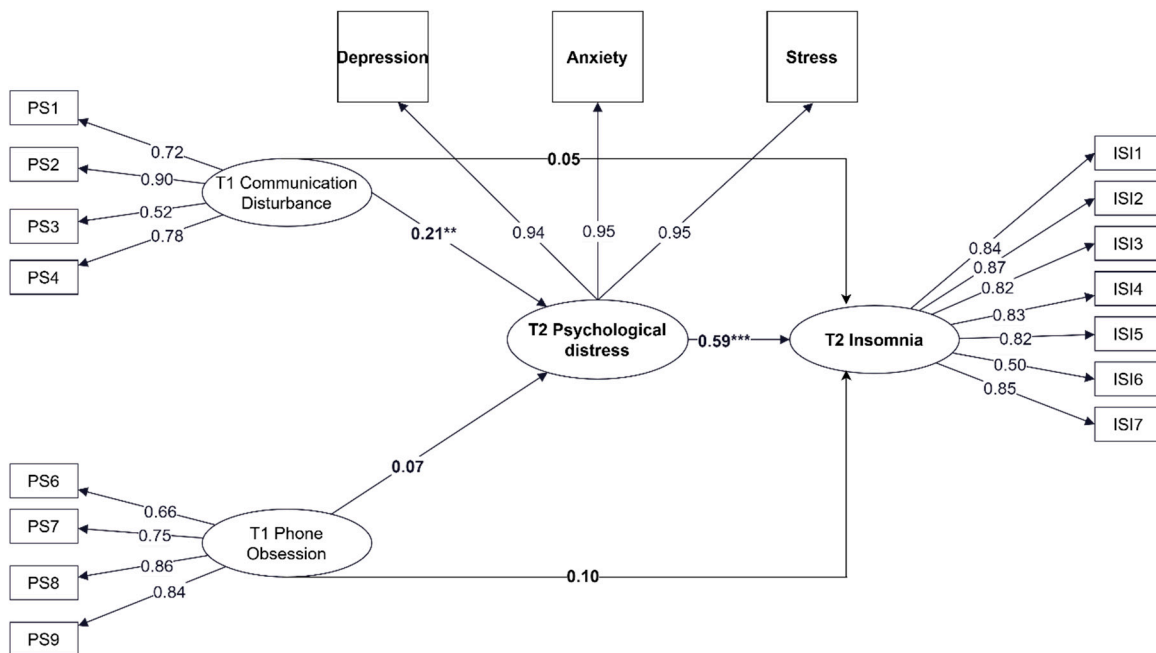
**Table 6:** Summary of Multi-Group Path Comparisons across Gender.

Structural Path	Male ( $\beta$ )	Female ( $\beta$ )	$\Delta\chi^2(1)$	$p$
<b>Direct Effects</b>				
CD → Psychological Distress	0.09	0.21**	0.63	0.429
PO → Psychological Distress	0.13	0.07	0.13	0.722
CD → Insomnia	0.15	0.05	0.34	0.563
PO → Insomnia	0.14	0.10	0.02	0.893
Distress → Insomnia	0.59***	0.59***	2.13	0.145
<b>Indirect Effects</b>				
CD → Distress → Insomnia	0.05	0.13**	1.03	0.309
PO → Distress → Insomnia	0.08	0.04	0.07	0.789

Note: CD = Communication Disturbance; PO = Phone Obsession; Distress = Psychological Distress. Standardized path coefficients ( $\beta$ ) are presented.  $\Delta\chi^2(1)$  tests were conducted by constraining each path to equality across groups; none reached statistical significance. \*\* $p < 0.01$ . \*\*\* $p < 0.001$ .



**Figure 2:** SEM results for male teachers. Note: Standardized coefficients are presented. Teacher age and school type (with primary school as the reference category) were included as covariates of both psychological distress and insomnia; their standardized coefficients ranged from  $-0.09$  to  $0.20$  (see Table S7 for full details) while not shown in the figure for clarity. \*\*\* $p < 0.001$ . PS: Phubbing Scale; ISI: Insomnia Severity Index; T1: Time 1; T2: Time 2.



**Figure 3:** SEM results for female teachers. Note: Standardized coefficients are presented. Teacher age and school type (with primary school as the reference category) were included as covariates of both psychological distress and insomnia; their standardized coefficients ranged from  $-0.15$  to  $0.07$  (see Table S8 for full details) while not shown in the figure for clarity. \*\* $p < 0.01$ . \*\*\* $p < 0.001$ . PS: Phubbing Scale; ISI: Insomnia Severity Index; T1: Time 1; T2: Time 2.

## 4 Discussion

Although insomnia has been recognized as a significant occupational health concern among teachers, prior research has predominantly focused on traditional workplace stressors such as workload and job satisfaction [54,55], with limited attention to technology-related behaviors. Moreover, the extant literature has relied primarily on cross-sectional designs, precluding inferences about temporal relationships. The present study addressed these gaps by employing a two-wave longitudinal design to examine whether phubbing behavior prospectively predicts insomnia among a sample of Chinese teachers, controlling for teacher age and school type, while investigating psychological distress as a mediating mechanism and gender as a potential moderator. The findings revealed divergent pathways for the two phubbing dimensions: phone obsession directly predicted subsequent insomnia, whereas communication disturbance indirectly contributed to sleep disturbances by elevating psychological distress. Although descriptive gender-specific patterns were observed in the group-level analyses, formal moderation tests did not confirm statistically significant gender differences. These results extend current understanding of modifiable risk factors for teacher insomnia and highlight the importance of addressing both phubbing behavior and psychological distress in intervention development.

Consistent with prior research [2], insomnia was prevalent among teachers in this study, with 55% of participants reporting varying degrees of insomnia (36.8% subthreshold, 13.7% moderate, and 4.5% severe). Importantly, the present study identified phubbing behavior as a potential contributor to this problem, with T1 phubbing dimensions significantly predicting T2 insomnia through distinct pathways. This longitudinal evidence establishes phubbing as a prospective risk factor for teacher insomnia. In contemporary educational environments, smartphones have become central tools for parent-teacher communication, policy updates, and administrative management [56,57], rendering teachers particularly susceptible to compulsive device use habits. In this context, phubbing reflects the erosion of boundaries between work and personal life: teachers who frequently check work messages after hours not only carry occupational stress into their sleep environment but also disrupt sleep preparation through sustained cognitive arousal and blue light exposure, both of which have been identified as detrimental to sleep health [7,58,59]. Consequently, identifying phubbing as a modifiable risk factor holds considerable practical value for intervention development.

Crucially, the present study revealed that the two dimensions of phubbing contributed to insomnia through distinct mechanisms. Phone obsession directly predicted subsequent insomnia ( $\beta = 0.12$ ), whereas communication disturbance did not exert a significant direct effect. This finding suggests that the intrapsychic, compulsive dimension of phubbing, characterized by habitual preoccupation with the device itself, is the primary driver of the direct phubbing-insomnia link among teachers. The direct association between phone obsession and insomnia is broadly consistent with prior longitudinal evidence on related constructs; for instance, Refs. [22,60,61] found that problematic mobile phone use unidirectionally predicted subsequent sleep quality among college students, and Refs. [24,62,63] demonstrated that internet addiction longitudinally predicted insomnia. However, the present study extends these findings by demonstrating that not all facets of problematic smartphone behavior affect sleep through the same mechanism. Whereas prior research has treated phubbing as a unitary construct in relation to sleep outcomes, the current results reveal that the interpersonal dimension (communication disturbance) influences insomnia exclusively through psychological distress, a pattern consistent with meta-analytic evidence linking phubbing to anxiety and depression [26,64]. This distinction has not been previously documented in the phubbing-sleep literature and underscores the importance of examining phubbing at the subscale level.

Beyond the direct effect of phone obsession, psychological distress emerged as a significant mediator linking communication disturbance to insomnia [65,66]. Communication disturbance may engender

psychological distress through multiple pathways: notifications and unread messages create sustained cognitive load and anxiety [67]; distraction during face-to-face interactions may lead to interpersonal friction and guilt [68,69]; and nighttime work-related screen activity impedes necessary psychological detachment, allowing occupational stress to persist [70,71]. The resulting depression, anxiety, and stress further exacerbate pre-sleep cognitive rumination and physiological arousal, culminating in distress-induced insomnia. This suggests that communication disturbance functions not merely as a behavioral distraction but also as a source of emotional strain [72–74]. The present study confirms that a substantial portion of communication disturbance's disruptive effect on sleep operates through the deterioration of emotional wellbeing, indicating that interventions targeting teacher insomnia should incorporate the cultivation of emotion regulation skills.

These divergent pathways can be further understood through the occupational characteristics specific to teaching. Communication disturbance, which reflects interpersonal disruption caused by phone use during social interactions, may be particularly distress-inducing for teachers because the teaching profession is inherently relational and demands sustained emotional labor [13,75,76]. Teachers who frequently disrupt face-to-face interactions with students, colleagues, or parents through phone use may experience heightened guilt, role conflict, and interpersonal friction, all of which contribute to psychological distress. In contrast, phone obsession, reflecting an intrapsychic preoccupation with the device, may affect insomnia more directly through bedtime-specific mechanisms [26]. The erosion of work-home boundaries in contemporary education, where teachers are implicitly expected to remain available via digital platforms outside working hours [11,77,78], means that phone-obsessed teachers are particularly likely to engage in pre-sleep device use, disrupting sleep through blue light exposure and sustained cognitive arousal [12,79]. Thus, the two phubbing dimensions map onto distinct occupational vulnerability pathways: communication disturbance operates through the emotional demands of teaching, whereas phone obsession operates through the boundary-blurring digital ecology of the profession.

The study also examined gender as a moderator of the structural paths. However, formal tests of moderation (chi-square difference tests) did not reach statistical significance for any structural path (see Table 6), and thus H3 was not supported. Several factors may account for the absence of significant gender moderation. First, the unbalanced gender composition of the sample (approximately 69% female) may have resulted in insufficient statistical power to detect moderation effects, particularly given the relatively small male subsample. Second, the non-significant moderation may reflect the possibility that the mechanisms linking phubbing to insomnia through psychological distress operate similarly across genders within the teaching profession, as both male and female teachers share the same digitalized work environment and occupational demands [80]. Third, the four-month interval may have been insufficient to capture gender-differentiated trajectories that might unfold over longer periods. Moreover, gender moderation of the phubbing-mental health relationship has rarely been tested directly, and the limited available evidence has generally found non-significant effects (e.g., Ivanova et al. [29]), suggesting that gender may not be a robust moderator in this domain. Future research with larger and more balanced gender subsamples, longer follow-up periods, and more fine-grained measures of gender-related constructs (e.g., emotional labor, role conflict) rather than biological sex alone is needed to more adequately test whether and how gender shapes the phubbing-insomnia relationship.

The divergent pathways identified in this study carry specific implications for intervention design. For communication disturbance, which operates through psychological distress, interventions should target the emotional consequences of interpersonal phone use. Cognitive behavioral strategies focusing on reducing guilt associated with phubbing during social interactions, combined with emotion regulation training to

manage the resulting distress, may help break the communication disturbance-distress-insomnia chain. School-level policies promoting phone-free zones during staff meetings and parent conferences could also reduce opportunities for communication disturbance. For phone obsession, which directly affects insomnia, sleep hygiene interventions should specifically address bedtime device use habits, including establishing device-free periods before sleep and using screen-dimming applications to reduce blue light exposure. These dimension-specific recommendations suggest that a one-size-fits-all approach to addressing phubbing may be insufficient; rather, interventions should be tailored to the specific phubbing dimension involved. Given that the formal moderation tests did not confirm statistically significant gender differences, the present findings support universal rather than gender-differentiated interventions. Nonetheless, future research that confirms or disconfirms gender-specific vulnerability profiles could further refine these recommendations to incorporate targeted components for different teacher subgroups.

Several limitations warrant consideration. First, the sample was drawn primarily from specific provinces in China using convenience sampling, and the particular educational culture and digitalized work environment may constrain the generalizability of findings to broader populations or different cultural contexts. Accordingly, the present findings should be interpreted within the context of this specific sample and two-wave study design. Second, data collection relied exclusively on self-report measures, which may be subject to response biases such as social desirability and recall bias. Third, although this study employed a longitudinal design, it comprised only two time points; the four-month interval may be insufficient to fully capture the dynamic relationships among variables or establish definitive causal inferences. In particular, the present design cannot rule out reverse causality (e.g., insomnia at T1 leading to increased phubbing) or bidirectional relationships among the study variables. Future research employing three or more waves of data collection would allow for cross-lagged panel models or random-intercept cross-lagged panel models that can more rigorously disentangle the temporal ordering and reciprocal effects among phubbing, psychological distress, and insomnia. Fourth, the structural model did not control for baseline (T1) levels of psychological distress or insomnia. As a result, the observed longitudinal associations between T1 phubbing dimensions and T2 outcomes may partly reflect stable individual differences in distress and insomnia that were already present at baseline, rather than genuine change attributable to phubbing behavior over time. Additionally, because both the mediator (psychological distress) and the outcome (insomnia) were assessed concurrently at T2, the distress-insomnia path represents a cross-sectional association, and causal inference regarding this specific mediating link is not warranted. The three-or-more-wave designs recommended above would also enable the inclusion of autoregressive controls and temporally separated measurement of the mediator and outcome, providing a more rigorous test of the proposed mediation mechanism. Fifth, while descriptive gender-specific patterns emerged in the structural paths, chi-square difference tests did not reach statistical significance, indicating that these gender differences should be interpreted with caution as suggestive rather than conclusive. Sixth, the Phubbing Scale used in this study measures general communication disturbance and phone obsession but does not differentiate between work-related phubbing (e.g., checking parent messages or administrative notifications) and personal or entertainment-related phubbing (e.g., social media browsing or gaming). Given that teachers' smartphone use often blurs these boundaries, future research should develop or adapt measures that can distinguish between these qualitatively different types of phubbing, as they may have differential effects on psychological distress and sleep outcomes. To address the above limitations, future research should include samples from diverse regions and cultural backgrounds, incorporate objective measurements such as device usage logs and actigraphy-based sleep monitoring, employ multi-wave designs with longer follow-up periods that enable autoregressive controls and temporally separated measurement of mediators and outcomes,

utilize larger samples with more balanced gender subsamples to adequately test gender moderation effects, and develop or adapt phubbing measures capable of distinguishing between work-related and personal smartphone use.

## 5 Conclusions

In conclusion, the present study demonstrates, within a sample of Chinese teachers assessed across two waves spanning one academic semester, that the two dimensions of phubbing contribute to insomnia through distinct pathways. Phone obsession directly predicted subsequent insomnia, whereas communication disturbance indirectly contributed to insomnia by elevating psychological distress. These findings identify phubbing as a modifiable behavioral risk factor for teacher insomnia and suggest that intervention strategies should be tailored to the specific phubbing dimension involved: distress-focused interventions for communication disturbance and sleep hygiene interventions for phone obsession. Although descriptive gender-specific patterns were observed in the group-level analyses, formal moderation tests did not confirm statistically significant gender differences; future research with larger and more balanced gender subsamples is needed to clarify whether these tentative patterns are replicable.

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**Availability of Data and Materials:** The data that support the findings of this study are available from the corresponding authors upon reasonable request.

**Ethics Approval:** The study protocol was approved by the Institutional Review Board of the Jiangxi Psychological Consultant Association (IRB Reference: JXSXL-2024-JA08). Electronic informed consent was obtained from all participants, where the purpose of the study, researcher’s affiliation, and privacy guarantee were explained.

**Conflicts of Interest:** The authors declare no conflicts of interest.

**Supplementary Materials:** The supplementary material is available online at <https://www.techscience.com/doi/10.32604/ijmh.2026.079774/s1>.

## References

1. American Psychiatric Association. Diagnostic and statistical manual of mental disorders. Washington, DC, USA: American Psychiatric Association; 2013.
2. Gierc M, Jackowich RA, Halliday S, Davidson JR. A scoping study of insomnia symptoms in school teachers. *Behav Sleep Med*. 2023;21(3):304–21. [CrossRef].
3. Domagalska J, Rusin M, Razzaghi M, Nowak P. Personality type D, level of perceived stress, insomnia, and depression among high school teachers in Poland. *Front Psychol*. 2021;12:626945. [CrossRef].
4. Bannai A, Ukawa S, Tamakoshi A. Long working hours and sleep problems among public junior high school teachers in Japan. *J Occup Health*. 2015;57(5):457–64. [CrossRef].

5. Hori D, Sasahara S, Oi Y, Doki S, Andrea CS, Takahashi T, et al. Relationships between insomnia, long working hours, and long commuting time among public school teachers in Japan: A nationwide cross-sectional diary study. *Sleep Med.* 2020;75:62–72. [[CrossRef](#)].
6. Pereira C, Almeida C, Veiga N, Amaral O. Prevalence and determinants of insomnia symptoms among schoolteachers. *Aten Primaria.* 2014;46(Suppl 5):118–22. [[CrossRef](#)].
7. Cropley M, Dijk DJ, Stanley N. Job strain, work rumination, and sleep in school teachers. In: *Work and rest: A topic for work and organizational psychology.* Hove, UK: Psychology Press; 2006. p. 181–96.
8. Kalam BM, Omkaram S, Murthy PS, Chaudhury S. Assessment of depression, anxiety, stress, and insomnia among government school teachers in the rural catchment areas of Nandyal district: A cross-sectional study. *Ind Psychiatry J.* 2024;33(Suppl 1):S77–83. [[CrossRef](#)].
9. Chotpitayasunondh V, Douglas KM. How “phubbing” becomes the norm: The antecedents and consequences of snubbing via smartphone. *Comput Hum Behav.* 2016;63:9–18. [[CrossRef](#)].
10. Karadağ E, Tosuntaş ŞB, Erzen E, Duru P, Bostan N, Şahin BM, et al. Determinants of phubbing, which is the sum of many virtual addictions: A structural equation model. *J Behav Addict.* 2015;4(2):60–74. [[CrossRef](#)].
11. Durnali M. Tiny but functional? Unpacking the role of smartphones in driving digital transformation in school administration and teaching practices. *Educ Inf Technol.* 2025;30(16):23111–40. [[CrossRef](#)].
12. Daraj LR, AlGhareeb M, Almutawa YM, Trabelsi K, Jahrami H. Systematic review and meta-analysis of the correlation coefficients between nomophobia and anxiety, smartphone addiction, and insomnia symptoms. *Healthcare.* 2023;11(14):2066. [[CrossRef](#)].
13. Liu J, Wang W, Hu Q, Wang P, Lei L, Jiang S. The relationship between phubbing and the depression of primary and secondary school teachers: A moderated mediation model of rumination and job burnout. *J Affect Disord.* 2021;295:498–504. [[CrossRef](#)].
14. Suh S, Cho N, Zhang J. Sex differences in insomnia: From epidemiology and etiology to intervention. *Curr Psychiatry Rep.* 2018;20(9):69. [[CrossRef](#)].
15. Riemann D, Krone LB, Wulff K, Nissen C. Sleep, insomnia, and depression. *Neuropsychopharmacology.* 2020;45(1):74–89. [[CrossRef](#)].
16. Benjafeld AV, Sert Kuniyoshi FH, Malhotra A, Martin JL, Morin CM, Maurer LF, et al. Estimation of the global prevalence and burden of insomnia: A systematic literature review-based analysis. *Sleep Med Rev.* 2025;82:102121. [[CrossRef](#)].
17. Deschamps A, Fortier MÈ, Gómez NM, Auger AM, Fitzpatrick C, Brodeur M. Understanding phubbing behavior: A scoping review of qualitative and mixed-methods studies. *Comput Hum Behav Rep.* 2025;18:100684. [[CrossRef](#)].
18. Zeng W. An empirical research on China’s policy for ICT integration in basic education from 1988 to 2021. *Educ Technol Res Dev.* 2022;70(3):1059–82. [[CrossRef](#)].
19. Pohl M, Feher G, Kapus K, Feher A, Nagy GD, Kiss J, et al. The association of Internet addiction with burnout, depression, insomnia, and quality of life among Hungarian high school teachers. *Int J Environ Res Public Health.* 2022;19(1):438. [[CrossRef](#)].
20. Tsumura H, Kanda H, Sugaya N, Tsuboi S, Fukuda M, Takahashi K. Problematic Internet use and its relationship with psychological distress, insomnia, and alcoholism among schoolteachers in Japan. *Cyberpsychol Behav Soc Netw.* 2018;21(12):788–96. [[CrossRef](#)].
21. Arayici ME, Arayici SG, Geyiktepe OE, Simsek H. Assessment of the relationship between Internet addiction, psychological well-being, and sleep quality: A cross-sectional study involving adult population. *Behav Sci.* 2025;15(3):344. [[CrossRef](#)].
22. Cui G, Yin Y, Li S, Chen L, Liu X, Tang K, et al. Longitudinal relationships among problematic mobile phone use, bedtime procrastination, sleep quality and depressive symptoms in Chinese college students: A cross-lagged panel analysis. *BMC Psychiatry.* 2021;21(1):449. [[CrossRef](#)].
23. Oh WO, Heo YJ. Reciprocal relationship among perceived sleep quality, smartphone overdependence, and depression in Korean adolescents: A cross-lagged analysis using national big data. *Sci Rep.* 2026;16:3402. [[CrossRef](#)].
24. Yao L, Liang K, Huang L, Xiao J, Zhou K, Chen S, et al. Longitudinal associations between healthy eating habits, resilience, insomnia, and Internet addiction in Chinese college students: A cross-lagged panel analysis. *Nutrients.* 2024;16(15):2470. [[CrossRef](#)].

25. Bitar Z, Akel M, Salameh P, Obeid S, Hallit S. Phubbing among Lebanese young adults: Scale validation and association with mental health (depression, anxiety, and stress). *Curr Psychol*. 2023;42(23):19709–20. [[CrossRef](#)].
26. Nuñez TR, Radtke T. Is socially disruptive smartphone use detrimental to well-being? A systematic meta-analytic review on being phubbed. *Behav Inf Technol*. 2024;43(7):1283–311. [[CrossRef](#)].
27. Mengelkoch S, Slavich GM. Sex differences in stress susceptibility as a key mechanism underlying depression risk. *Curr Psychiatry Rep*. 2024;26(4):157–65. [[CrossRef](#)].
28. Zhang H, Xia Y, Fu P, Li C, Shi K, Yang Y. Gender differences in psychosocial pathways to depression and anxiety: Cross-sectional and Bayesian causal network study. *J Med Internet Res*. 2025;27:e76913. [[CrossRef](#)].
29. Ivanova A, Gorbaniuk O, Błachnio A, Przepiórka A, Mraka N, Polishchuk V, et al. Mobile phone addiction, phubbing, and depression among men and women: A moderated mediation analysis. *Psychiatr Q*. 2020;91(3):655–68. [[CrossRef](#)].
30. Febrianto PT, Mas'udah S, Megasari LA. Female teachers' double burden during the pandemic: Overcoming challenges and dilemma between career and family. *Sociol Probl Práticas*. 2022:87–105. [[CrossRef](#)].
31. Eagly AH, Wood W. Social role theory. *Handb Theor Soc Psychol*. 2012;2(9):458–76.
32. Glavin P, Schieman S, Reid S. Boundary-spanning work demands and their consequences for guilt and psychological distress. *J Health Soc Behav*. 2011;52(1):43–57. [[CrossRef](#)].
33. Chen C, Zhang KZK, Gong X, Zhao SJ, Lee MKO, Liang L. Examining the effects of motives and gender differences on smartphone addiction. *Comput Hum Behav*. 2017;75:891–902. [[CrossRef](#)].
34. Nolen-Hoeksema S. Emotion regulation and psychopathology: The role of gender. *Annu Rev Clin Psychol*. 2012;8:161–87. [[CrossRef](#)].
35. Roberts JA, Yaya LHP, Manolis C. The invisible addiction: Cell-phone activities and addiction among male and female college students. *J Behav Addict*. 2014;3(4):254–65. [[CrossRef](#)].
36. Lapierre MA, Zhao P, Custer BE. Short-term longitudinal relationships between smartphone use/dependency and psychological well-being among late adolescents. *J Adolesc Health*. 2019;65(5):607–12. [[CrossRef](#)].
37. Bastien CH, Vallières A, Morin CM. Validation of the insomnia severity index as an outcome measure for insomnia research. *Sleep Med*. 2001;2(4):297–307. [[CrossRef](#)].
38. Badiie Aval Baghyahi S, Torabi S, Gao Y, Cao KG, Badiie Aval Baghyahi HR. Reliability and validity of the Chinese translation of insomnia severity index (C-ISI) in Chinese patients with insomnia. *Eur Psychiatr*. 2011;26(S2):1556. [[CrossRef](#)].
39. Lovibond PF, Lovibond SH. The structure of negative emotional states: Comparison of the depression anxiety stress scales (DASS) with the beck depression and anxiety inventories. *Behav Res Ther*. 1995;33(3):335–43. [[CrossRef](#)].
40. Cao CH, Liao XL, Jiang XY, Li XD, Chen IH, Lin CY. Psychometric evaluation of the depression, anxiety, and stress scale-21 (DASS-21) among Chinese primary and middle school teachers. *BMC Psychol*. 2023;11(1):209. [[CrossRef](#)].
41. Zhou XH, Shen ZZ, Cao CH, Liao XL, Jiang XY, Griffiths MD, et al. Psychometric evaluation of DASS versions among Spanish and Chinese teachers using exploratory structural equation modeling (ESEM). *Acta Psychol*. 2024;251:104626. [[CrossRef](#)].
42. Wang X, Cao CH, Liao XL, Jiang XY, Griffiths MD, Chen IH, et al. Comparing the psychometric evidence of the depression, anxiety, and stress scale-21 (DASS-21) between Spanish and Chinese primary schoolteachers: Insights from classical test theory and Rasch analysis. *BMC Psychol*. 2025;13(1):450. [[CrossRef](#)].
43. Błachnio A, Przepiórka A, Gorbaniuk O, Bendayan R, McNeill M, Angeluci A, et al. Measurement invariance of the phubbing scale across 20 countries. *Int J Psychol*. 2021;56(6):885–94. [[CrossRef](#)].
44. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J Appl Psychol*. 2003;88(5):879–903. [[CrossRef](#)].
45. Ding JL, Chen XM, Liao XL, Wang XL, Chen IH, Malas O. Examining problematic Internet use, mattering, and distress in interpersonally vulnerable senior high school students: A longitudinal study during summer holidays and academic terms. *Acta Psychol*. 2024;251:104594. [[CrossRef](#)].
46. Gamble JH, Li HM, Liao XL, Cao CH, Chen XM, Chen IH. Effects of psychological need thwarting during COVID-19 remote instruction on Chinese, math, and EFL teachers' well-being and online teaching intentions. *Sci Rep*. 2024;14(1):27787. [[CrossRef](#)].

47. Horwood S, Anglim J, Mallawaarachchi SR. Problematic smartphone use in a large nationally representative sample: Age, reporting biases, and technology concerns. *Comput Hum Behav.* 2021;122:106848. [[CrossRef](#)].
48. Brewster GS, Riegel B, Gehrman PR. Insomnia in the older adult. *Sleep Med Clin.* 2018;13(1):13–9. [[CrossRef](#)].
49. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct Equ Model A Multidiscip J.* 1999;6(1):1–55. [[CrossRef](#)].
50. Kline R. Principles and practice of structural equation modeling. New York, NY, USA: Guilford Publications; 2023.
51. Chen FF. Sensitivity of goodness of fit indexes to lack of measurement invariance. *Struct Equ Model A Multidiscip J.* 2007;14(3):464–504. [[CrossRef](#)].
52. Cheung GW, Rensvold RB. Evaluating goodness-of-fit indexes for testing measurement invariance. *Struct Equ Model A Multidiscip J.* 2002;9(2):233–55. [[CrossRef](#)].
53. Beaufort IN, De Weert-Van Oene GH, Buwalda VAJ, de Leeuw JRJ, Goudriaan AE. The depression, anxiety and stress scale (DASS-21) as a screener for depression in substance use disorder inpatients. *Eur Addict Res.* 2017;23(5):260–8.
54. Huyghebaert T, Gillet N, Beltou N, Tellier F, Fouquereau E. Effects of workload on teachers’ functioning: A moderated mediation model including sleeping problems and overcommitment. *Stress Health.* 2018;34(5):601–11. [[CrossRef](#)].
55. Yang Z, Wang D, Fan Y, Ma Z, Chen X, Zhang Y, et al. Relationship between sleep disturbance and burnout among Chinese urban teachers: Moderating roles of resilience. *Sleep Med.* 2023;108:29–37. [[CrossRef](#)].
56. Çakır R, Aktay S. Primary school principals’ experiences with smartphone apps. *J Educ Train Stud.* 2016;4(12):14–20. [[CrossRef](#)].
57. Lin LC. Fostering teacher–parent communication: Line plays a significant role in Taiwan. *Sage Open.* 2019;9(3):2158244019862667. [[CrossRef](#)].
58. Bauwens R, Muylaert J, Clarysse E, Audenaert M, Decramer A. Teachers’ acceptance and use of digital learning environments after hours: Implications for work-life balance and the role of integration preference. *Comput Hum Behav.* 2020;112:106479. [[CrossRef](#)].
59. Silvani MI, Werder R, Perret C. The influence of blue light on sleep, performance and wellbeing in young adults: A systematic review. *Front Physiol.* 2022;13:943108. [[CrossRef](#)].
60. Zhang J, Yuan G, Guo H, Zhang X, Zhang K, Lu X, et al. Longitudinal association between problematic smartphone use and sleep disorder among Chinese college students during the COVID-19 pandemic. *Addict Behav.* 2023;144:107715. [[CrossRef](#)].
61. Li C, Sriram S, Holý O, Rehman S. A longitudinal investigation on the reciprocal relationship of problematic smartphone use with bedtime procrastination, sleep quality, and mental health among university students. *Psychol Res Behav Manag.* 2024;17:3355–67. [[CrossRef](#)].
62. Ren H, Dang J, Liu J, Zou H. Insomnia and Internet addiction: A longitudinal examination using random intercept cross-lagged panel modeling. *BMC Psychol.* 2025;14(1):70. [[CrossRef](#)].
63. Wang D, Xu B, Scherffius A, Wei H, Li Y, Chen H, et al. A longitudinal study of bidirectional associations between sleep disturbance and Internet addiction among Chinese adolescents. *Early Interv Psychiatry.* 2025;19(6):e70069. [[CrossRef](#)].
64. Buckner JD, Bernert RA, Cromer KR, Joiner TE, Schmidt NB. Social anxiety and insomnia: The mediating role of depressive symptoms. *Depress Anxiety.* 2008;25(2):124–30. [[CrossRef](#)].
65. Brissette I, Cohen S. The contribution of individual differences in hostility to the associations between daily interpersonal conflict, affect, and sleep. *Pers Soc Psychol Bull.* 2002;28(9):1265–74. [[CrossRef](#)].
66. Zhang J, Xiang S, Li X, Tang Y, Hu Q. The impact of stress on sleep quality: A mediation analysis based on longitudinal data. *Front Psychol.* 2024;15:1431234. [[CrossRef](#)].
67. Ohly S, Latour A. Work-related smartphone use and well-being in the evening. *J Pers Psychol.* 2014. [[CrossRef](#)].
68. Chotpitayasunondh V, Douglas KM. The effects of “phubbing” on social interaction. *J Appl Soc Psychol.* 2018;48(6):304–16. [[CrossRef](#)].
69. Knausenberger J, Giesen-Leuchter A, Echterhoff G. Feeling ostracized by others’ smartphone use: The effect of phubbing on fundamental needs, mood, and trust. *Front Psychol.* 2022;13:883901. [[CrossRef](#)].

70. Park Y, Liu Y, Headrick L. When work is wanted after hours: Testing weekly stress of information communication technology demands using boundary theory. *J Organ Behav.* 2020;41(6):518–34. [[CrossRef](#)].
71. Santos A, Roberto MS, Camilo C, Chambel MJ. Information and communication technologies-assisted after-hours work: A systematic literature review and meta-analysis of the relationships with work-family/life management variables. *Front Psychol.* 2023;14:1101191. [[CrossRef](#)].
72. Nuñez TR, Radtke T, Eimler SC. A third-person perspective on phubbing: Observing smartphone-induced social exclusion generates negative affect, stress, and derogatory attitudes. *Cyberpsychology.* 2020;14(3):1–22. [[CrossRef](#)].
73. Basta M, Chrousos GP, Vela-Bueno A, Vgontzas AN. Chronic insomnia and stress system. *Sleep Med Clin.* 2007;2(2):279–91. [[CrossRef](#)].
74. Aslanturk A, Arslan C. How does being phubbed affect commitment? Exploring the roles of emotional loneliness and relationship satisfaction. *J Marital Fam Ther.* 2025;51(3):e70027. [[CrossRef](#)].
75. Sui M, Zhou M, Yang Y. The impact of emotional labor on the mental health of vocational college teachers in China: The mediating role of occupational identity and the moderating role of teacher-student relationships. *BMC Psychol.* 2025;14(1):76. [[CrossRef](#)].
76. Thomas TT, Carnelley KB, Hart CM. Phubbing in romantic relationships and retaliation: A daily diary study. *Comput Hum Behav.* 2022;137:107398. [[CrossRef](#)].
77. Chen IH, Chen CY, Zhao KY, Gamble JH, Lin CY, Griffiths MD, et al. Psychometric evaluation of fear of COVID-19 scale (FCV-19S) among Chinese primary and middle schoolteachers, and their students. *Curr Psychol.* 2023;42(15):12557–73. [[CrossRef](#)].
78. Kazancı Yabanova E. The effect of after-hours mobile connectivity on work-family conflict and psychological detachment: A meta-analysis study. *Educ Process Int J.* 2025;19(1):e2025555. [[CrossRef](#)].
79. Tähkämö L, Partonen T, Pesonen AK. Systematic review of light exposure impact on human circadian rhythm. *Chronobiol Int.* 2019;36(2):151–70. [[CrossRef](#)].
80. İllıç U, Tanyerî T. Is phubbing a matter for educators: A case for pre-service and in-service teachers. *Malays Online J Educ Technol.* 2020;9(1):70–9. [[CrossRef](#)].