



Heterogeneity of smartphone dependence among university students and its network relationship with perceived stress and fear of missing out

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Abstract: The present study examined the heterogeneity of smartphone dependence and its network relationships with perceived stress and fear of missing out. A total of 1014 university students completed the Fear of Missing Out Scale, Mobile Phone Addiction Index, and Perceived Stress Scale (females = 67.8%; juniors or above = 28.8%; mean age = 19.4 years, SD = 1.4). A latent profile analysis identified three smartphone dependence risk profiles: low-risk, moderate-risk, and high-risk. Moreover, a Gaussian graphical model showed that the ‘tension’ dimension of perceived stress was the most central and bridging node within the network. In the moderated network model, significant pairwise interaction edges were observed among the dimensions, although no significant moderation effect was observed. The study findings support the Interaction of Person-Affect-Cognition-Execution (I-PACE) model by demonstrating heterogeneous risk profiles and by identifying tension as a central and bridging node. The heterogeneity and network patterns underlying smartphone dependence suggest a need for targeted interventions that consider both individual risk profiles and the role of tension in the symptom network.

Keywords: Fear of missing out; smartphone dependence; perceived stress; latent profile analysis; network analysis

Introduction

Smartphone dependence is a norm among university students for various reasons other than convenience. Some may become dependent due to the fear of missing out on topical issues. Smartphone dependence refers to an obsessive state of behavioral dyscontrol resulting from excessive smartphone use, in which such loss of control leads to significant impairment in physical condition, psychological state, and social functioning (Kim et al., 2018). Fear of missing out (FoMO) is defined as a pervasive apprehension that others might be having rewarding experiences from which the individual is absent, and is characterized by the desire to stay continually connected with what others are doing (Przybylski et al., 2013). Conceivably, FoMO is associated with psychological distress (Gupta & Sharma, 2021). Perceived stress refers to an individual’s subjective assessment of the intensity of stress arising when environmental demands are perceived as threatening (Yilmaz Koğar & Koğar, 2024). The university student population is notably heterogeneous in terms of the patterns, severity, and manifestations of smartphone dependence (Dong et al., 2025). However, few studies have investigated patterns in smartphone dependence, perceived stress, and fear of missing out in this population.

Smartphone dependence and fear of missing out

The prevalence of smartphone dependence among college students has been widely documented (Peng et al., 2022a). Among the array of psychological factors contributing to this phenomenon, FoMO has emerged as a particularly robust predictor. Previous research has demonstrated a significant and positive association between FoMO and smartphone dependence among university students. This relationship holds even after controlling for demographics,

underscoring the unique role that social anxiety about missed experiences plays in shaping students’ digital habits (Elhai et al., 2025). FoMO drives individuals to frequently use smartphones to stay connected and reduce inner insecurity, thereby increasing the propensity for smartphone dependence (Gong et al., 2022).

The present study examined the heterogeneity of smartphone dependence among university students. It aimed to identify distinct subgroups and underlying patterns in smartphone dependence and to systematically examine the interrelationships among smartphone dependence, perceived stress, and FoMO, using the Interaction of Person-Affect-Cognition-Execution (I-PACE) model as a conceptual organizing framework rather than a confirmatory model to be tested.

Heterogeneity of smartphone dependence

Past research on smartphone dependence has predominantly employed variable-centered approaches, which are limited in systematically showing the inherent heterogeneity among study populations (Tang & Li, 2025). Latent profile analysis (LPA), an advanced person-centered method, offers distinct advantages for identifying subgroups and detecting differential intervention effects (Yang et al., 2022). Existing research employing LPA has demonstrated the heterogeneous structure of smartphone dependence among university students. One study identified three latent subgroups: high addiction, low addiction, and non-addiction to smartphones, confirming significant differences in positive and negative affect among these groups (Zeng et al., 2023). Another study with first-year university students also categorized individuals into low-, medium-, and high-risk groups, with significant differences observed in their levels of psychological resilience



(Dong et al., 2024). While these findings collectively confirm the group heterogeneity of university smartphone dependence among students, the specific characteristics of the latent subgroups identified across studies remain inconsistent. This inconsistency suggests that the understanding of the complex mechanisms underlying this heterogeneity is still incomplete.

Network relationships among perceived stress, fear of missing out, and smartphone dependence

Prior network research indicates that the tension dimension of perceived stress may function as such a central and bridging node (Peng & Liao, 2023; Wang et al., 2023). Network analysis, a graph-theoretic approach that visualizes and describes complex interrelationships among psychological variables (Borsboom, 2022; Cai et al., 2020) has been increasingly applied in psychopathology and behavioral addiction research (Li et al., 2024a), most commonly through the partial correlation network (Gaussian graphical model [GGM]) to uncover symptom structures and identify core symptoms (Chen et al., 2021).

The moderating effect of perceived stress

Prior research has consistently found positive associations and predictive relationships among perceived stress, FoMO, and smartphone dependence (Jeong & Bae, 2024; Peng et al., 2022b). Moreover, the interaction between stress and FoMO significantly influences smartphone dependence, with FoMO exerting a stronger predictive effect among individuals with high stress levels (Yang et al., 2021), suggesting a potential moderating role of perceived stress. The I-PACE model similarly posits that perceived stress, as a cognitive process, may moderate the FoMO-smartphone dependence relationship (Brand et al., 2019).

To further explore the complex interactive mechanisms among the aforementioned variables, the present study applied a moderated network model (MNM). This method integrates network analysis with moderation effect analysis, enabling not only the examination of interactive relationships among multiple variables but also the identification of potential moderating effects within the network (Haslbeck et al., 2021). In recent years, MNM has been widely applied in psychological research and has demonstrated methodological robustness (Li et al., 2025).

Theoretical foundations

The I-PACE model posits that the development and maintenance of smartphone dependence results from the interaction among an individual's predisposing traits (person), affective responses (affect), cognitive processes (cognition), and executive functions (execution) (Brand et al., 2019). The I-PACE model posits that affective responses (e.g., FoMO) and cognitive processes (e.g., perceived stress) may interact synergistically, moderated by person and execution factors, and that these factors contribute to addictive behaviors (e.g., smartphone dependence). Given the heightened social pressures and ubiquitous digital connectivity among university students, this synergistic interaction may be especially pronounced.

Unlike latent variable approaches that overlook symptom-level interactions (Chen et al., 2021), the present study focused on the affect-cognition and execution-cognition interfaces of the model. The person components were not assessed, and therefore, the study uses this interface as a conceptual starting point rather than providing a complete test of the model. According to the network theory of mental disorders, disorders constitute dynamic networks of mutually reinforcing symptoms rather than being caused by latent variables (Borsboom, 2017). Accordingly, smartphone dependence is conceptualized as part of an interconnected system with FoMO and perceived stress, within which one or more central nodes can act as bridges.

The Chinese context

With the rapid advancement of mobile communication technology, smartphones have become indispensable in Chinese life. According to a report released by the China Internet Network Information Center (2025), the number of mobile internet users in China reached 1.116 billion, with 99.4% of internet users accessing the internet via smartphones. Consequently, smartphone dependence has become increasingly prevalent, particularly among university students, emerging as a social issue of growing concern (Peng et al., 2022a). Statistics show an increasing prevalence of smartphone dependence within this demographic, with daily smartphone use averaging 5.2 hours (Hong et al., 2024). These results should be understood within the broader cultural context of Chinese higher education, where academic competition, family expectations, and regional disparities in educational resources may jointly shape students' stress experiences and smartphone use habits.

The present study

The present study examined the heterogeneity of smartphone dependence and its network relationships with perceived stress and fear of missing out. Based on the aforementioned literature, it was hypothesized that among university students: (i) there would be distinct latent classes of smartphone dependence (H_1), (ii) a connected network would exist among smartphone dependence, perceived stress, and FoMO in university students, with tension as a central node (H_2), and (iii) perceived stress would moderate the relationship between FoMO and smartphone dependence.

Method

Participants and setting

The present sample comprised 1014 undergraduate students from two universities in Jiangxi and Heilongjiang Provinces in China (female = 67.8%) (see Table 1 for participant demographics). By college placement, 556 were freshmen (54.8%), 166 were sophomores (16.4%), and 292 were juniors or above (28.8%). Regarding family structure, 349 were only children (34.4%), while 665 had at least one sibling (65.6%). As for residence, 397 were from urban areas (39.2%), and 617 were from rural areas (60.8%).

Table 1. Descriptive statistics and demographic group differences for all study variables

Variable	<i>M</i> (<i>SD</i>)	Gender (<i>t</i>)	Family structure (<i>t</i>)	Residence (<i>t</i>)	Academic year (<i>F</i>)
FoMO	2.17 (0.72)	1.33	−1.83	−2.35*	2.568
FMI	1.87 (0.79)	−0.19	−2.33*	−3.67**	3.380*
FMS	2.47 (0.90)	2.31*	−0.85	−0.53	0.897
Smartphone dependence	2.49 (0.71)	2.33*	−5.05**	−3.45**	4.957**
Loss of control	2.23 (0.80)	4.01**	−5.63**	−4.36**	2.440
Withdrawal	2.33 (1.03)	0.52	−2.56*	−0.74	2.474
Escape	3.06 (0.52)	1.47	−0.53	−0.22	6.764**
Inefficiency	2.73 (1.07)	0.42	−5.65**	−4.34**	6.159**
Perceived stress	2.92 (0.56)	−0.72	−3.75**	−4.05**	14.764**
Sense of loss of control	3.19 (0.70)	−2.11*	−1.88	−3.58**	7.489**
Tension	2.65 (0.77)	0.86	−3.75**	−2.65**	10.781**

Note. * $p < 0.05$, ** $p < 0.01$. *M* and *SD* represent the mean and standard deviation of the variables, respectively. The *t*-statistic denotes results from independent-samples *t*-tests for two-group comparisons (gender, family structure, and residence). The *F*-statistic denotes results from one-way ANOVAs for multi-group comparisons across academic years. FoMO: fear of missing out; FMI: fear of missing information; FMS: fear of missing situations.

Measures

The participants self-reported their sociodemographics of gender, academic year of study, family structure, and residence. They completed the following measures.

Fear of missing out scale (FoMOS)

The FoMOS (Przybylski et al., 2013; Chinese version: Li et al., 2019) consists of eight items across two dimensions: fear of missing information (FMI) and fear of missing situations (FMS). Items are rated on a five-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Higher total scores indicate a greater level of FoMO. In the present study, the scale demonstrated good internal consistency (Cronbach's α for the total scale = 0.82, Cronbach's α for FMI = 0.81, Cronbach's α for FMS = 0.77). Confirmatory factor analysis (CFA) of the two-factor model yielded acceptable fit ($\chi^2/df = 3.84$, Comparative Fit Index (CFI) = 0.93, Root Mean Square Error of Approximation (RMSEA) = 0.05).

Mobile phone addiction index (MPAI)

The MPAI (Leung, 2008; Chinese version: Huang et al., 2014) consists of 17 items across four dimensions: loss of control, withdrawal, escape, and inefficiency, with no reverse-scored items. Items are rated on a five-point Likert scale from 1 (*almost never*) to 5 (*always*). Higher total scores indicate a greater risk of smartphone dependence. In the present study, the scale demonstrated good internal consistency (Cronbach's α for the total scale = 0.87; for loss of control = 0.81; for withdrawal = 0.81; for escape = 0.76; for inefficiency = 0.80). CFA of the four-factor model yielded an acceptable fit ($\chi^2/df = 4.17$, CFI = 0.91, RMSEA = 0.06).

Perceived stress scale (PSS)

The PSS (Cohen et al., 1983; Chinese version: Yang & Huang, 2003) consists of 14 items across two dimensions: sense of loss of control and tension, and includes some reverse-scored items. Items are rated on a five-point Likert

scale from 1 (*never*) to 5 (*always*). Higher total scores indicate greater perceived stress. In the present study, the scale demonstrated good internal consistency (Cronbach's α for the total scale = 0.75; for sense of loss of control = 0.72; for tension = 0.79). CFA of the two-factor model yielded acceptable fit ($\chi^2/df = 3.63$, CFI = 0.90, RMSEA = 0.05).

Procedure

This study was approved by the Gannan Medical University Research Ethics Committee (2025562) on 27 January 2026. All surveys were completed anonymously, and written informed consent was obtained from all participants. Data were obtained via both online administration (Wenjuanxing) and on-site surveys.

Data analysis

The present study utilized SPSS 23.0, Mplus 8.3, and RStudio for data processing and analysis. First, descriptive statistics and correlation analyses were conducted using SPSS 23.0. Subsequently, LPA was performed using Mplus 8.3. After model estimation, the most appropriate model was selected based on model fit indices and theoretical considerations to confirm the distribution proportions of each profile (Peugh & Fan, 2013).

Secondly, network analysis was conducted using RStudio to construct a GGM and MNM. In the present study, the GGM was estimated with the *bootnet* package (Epskamp et al., 2018). Edges represent regularized partial correlations among eight subscale mean scores (nodes). Graphical LASSO was applied with the Extended Bayesian Information Criterion (EBICglasso) using the default tuning parameter $\gamma = 0.5$; small edge weights were further thresholded to zero to retain only robust connections. Network layout followed the Fruchterman–Reingold (spring) algorithm, and the plot was generated with *qgraph*.

Node centrality was assessed by strength, expected influence, closeness, and betweenness. Strength was chosen as the primary index because it reflects the sum of absolute edge weights and demonstrated the highest

stability (CS-coefficient > 0.7). Bridge strength was computed with the *networktools* package. Nodes were assigned to three communities based on theoretical constructs: (i) smartphone dependence (loss of control, withdrawal, escape, inefficiency), (ii) fear of missing out (fear of missing information, fear of missing situations), and (iii) perceived stress (sense of loss of control, tension). Higher bridge strength indicates a stronger bridging role for the node between different symptom clusters (Jones et al., 2021). Edge-weight accuracy and centrality stability were evaluated via a non-parametric case-dropping bootstrap (500 iterations) using *bootnet*. The correlation stability (CS) coefficient was computed for each centrality index; values above 0.5 were considered sufficiently stable. Bootstrapped difference tests were performed to identify statistically significant differences in edge weights and node centrality.

To examine the robustness of the GGM across demographic subgroups, network invariance tests were conducted using the *NetworkComparisonTest* (NCT) package. Networks were separately estimated for each subgroup using the same EBICglasso procedure. Permutation tests (1000 iterations) compared global strength and edge weights between subgroup pairs. The community assignment used for bridge centrality was also applied in the NCT analyses to test the stability of bridge edges. All comparisons used the same set of node variables and the same estimation settings as the full-sample GGM.

The MNM was fitted with the *mgm* package using L1-regularized nodewise regression. The Extended Bayesian Information Criterion (EBIC; $\gamma = 0.5$) was used for model selection, and the “OR” rule aggregated pairwise relationships. All predictor variables were treated as continuous Gaussian variables and standardized prior to estimation to avoid parameter penalty. Given the exploratory nature of the MNM, all variables were included as potential moderators to exhaustively detect the interaction effects and moderation effects (three-way interactions). Regularization and model selection procedures followed Haslbeck et al. (2021).

Results

Common method bias effect test

Following Wen et al. (2018), an unmeasured latent method construct (ULMC) approach was used to evaluate the potential impact of common method variance. A baseline multi-trait model with three conceptually distinct factors (FoMO, perceived stress, smartphone dependence) was first estimated. Subsequently, an orthogonal method factor was introduced, with method loadings constrained to be equal within each construct. Compared with the trait-only model, the addition of the method factor resulted in only marginal improvements in fit. The increments in CFI and Tucker-Lewis Index (TLI) were both below 0.10, and the reductions in RMSEA and Standardized Root Mean Square Residuals (SRMR) were both below 0.05. These negligible changes indicated that common method bias did not substantially inflate the observed inter-item relationships. Moreover, the subsequent network analyses were conducted using partial correlations, which further controlled for shared variance among nodes. Accordingly,

common method variance was not considered a serious threat to the validity of the findings.

Descriptive statistics

The descriptive statistics for the three main variables and their respective dimensions in the present study are presented in Table 1. Independent-sample *t*-tests and one-way ANOVAs were conducted to examine whether smartphone dependence, perceived stress, FoMO, and their respective sub-dimensions differed by gender, family structure, residence, and academic year. Significant differences emerged across several demographic groupings. The detailed statistics are presented in Table 1. Because these demographic characteristics were associated with the key study variables, their potential influence was taken into account in the subsequent latent profile analysis and network analysis.

Pearson correlation analysis was conducted to examine the relationships among FoMO, perceived stress, and smartphone dependence, as well as among their dimensions, within the university student sample. The results are summarized in Figure 1. The correlation analysis results indicated that, there were significant positive correlations among the major variables—smartphone dependence (including sub-dimensions: loss of control, withdrawal, escape, inefficiency), FoMO (including sub-dimensions: FMI, FMS), and perceived stress (including sub-dimension: tension) (all *p*-values < 0.01). Additionally, another dimension of perceived stress (i.e., ‘sense of loss of control’), exhibited distinct associative patterns. It had significant positive correlations with perceived stress, tension, and inefficiency (all *p*-values < 0.05), and significant negative correlations with FoMO and FMS (both *p*-values < 0.05). However, it had no significant correlations with smartphone dependence, loss of control, withdrawal, or FMI (all *p*-values > 0.05).

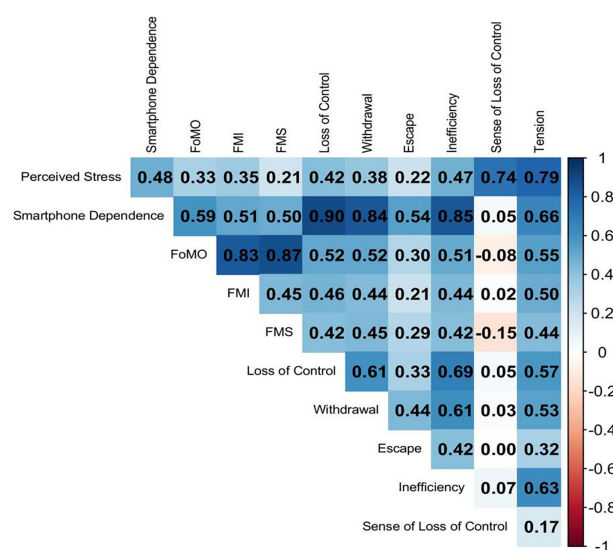
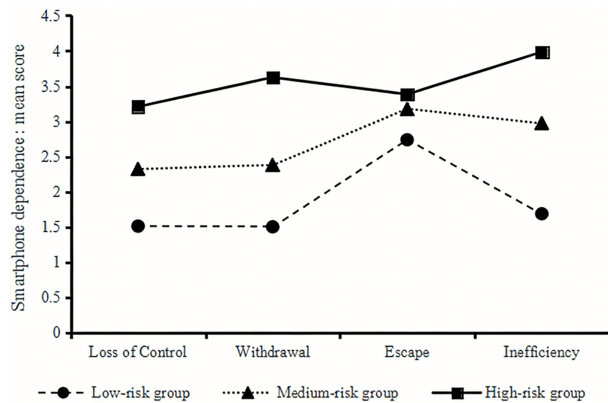


Figure 1. Correlation matrix heatmap (*r*). *Note.* Correlation matrix heatmap of Pearson's correlation coefficients (*r*). Colors represent the strength and direction of correlations.

Table 2. Results of various fitting metrics for the latent profile analysis

Model	AIC	BIC	aBIC	Entropy	LMR (<i>p</i>)	BLRT (<i>p</i>)	Number of samples (proportion)
1	9955.01	9994.38	9968.97	—	—	—	1
2	8781.51	8845.49	8804.20	0.79	$p < 0.001$	$p < 0.001$	549 (54.1%)/465 (45.9%)
3	8471.06	8559.65	8502.48	0.77	$p < 0.001$	$p < 0.001$	364 (35.9%)/440 (43.4%)/210 (20.7%)
4	8419.22	8532.41	8459.36	0.73	0.14	$p < 0.001$	293 (28.9%)/364 (35.9%)/284 (28.0%)/73 (7.2%)

Note. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; aBIC: adjusted Bayesian Information Criteria; LMR: Lo-Mendell-Rubin-Adjusted Likelihood Ratio Test; BLRT: Bootstrap-based Likelihood Ratio Test.

**Figure 2.** University students' smartphone dependence profiles

Latent classes of smartphone dependence among university students

As shown in Table 2, as the number of latent profiles increased, the information criterion values (i.e., Akaike Information Criterion [AIC]; Bayesian Information Criterion [BIC]; aBIC: adjusted Bayesian Information Criteria [aBIC]) decreased, indicating better model fit. The entropy values for all four models were above 0.7, and the proportion of the smallest profile in each model exceeded 5%. However, the likelihood ratio tests (i.e., Lo-Mendell-Rubin-Adjusted Likelihood Ratio Test [LMR]) for Model 4 were non-significant, suggesting that Model 4 was not significantly better than Model 3 in comparison. Considering all model fit indices, parsimony, and theoretical interpretability, Model 3 was the optimal fitting model.

As presented in Table S1, in this three-class model, the posterior classification probabilities were 91% for the first class, 88% for the second class, and 91% for the third class. These results indicated that the LPA in the present study produced highly reliable classification results. As shown in Figure 2, Class 1 demonstrated the lowest scores across all four dimensions of smartphone dependence compared to the other two classes, with its scores on all dimensions falling below the mean. Therefore, this was labeled the 'low-risk' smartphone dependence group ($n = 364$, 35.9%). Class 2 scored near the mean on these four dimensions, placing it in the middle among the three groups, and was therefore labeled the 'moderate-risk' smartphone dependence group ($n = 440$, 43.4%). Class 3 exhibited the highest scores across these four dimensions among the three classes, well above the mean, and was therefore labeled the 'high-risk' smartphone dependence group ($n = 210$, 20.7%). The result supported H_1 .

To further evaluate the interpretability of the three-profile solution and to provide statistical justification for the adopted labels, one-way ANOVAs with Games-Howell post-hoc comparisons were conducted, and standardized means (z-scores) were computed for each profile. All four smartphone dependence dimensions differed significantly across the three profiles (all p -values < 0.01), with the high-risk group scoring highest, followed by the moderate-risk and low-risk groups. The standardized means showed that the low-risk profile consistently scored below the overall mean (z range: -0.98 to -0.64), the moderate-risk profile scored near the mean (z range: 0.07 to 0.24), and the high-risk profile scored substantially above the mean (z range: 0.61 to 1.30). These patterns supported the descriptive labels assigned to each profile. Detailed statistics are reported in Table S2.

To examine whether demographic characteristics predicted latent profile membership, a multinomial logistic regression was performed with smartphone dependence profiles as the outcome and gender, family structure, residential background, and academic year as predictors. The low-risk profile served as the reference category. Following Xin et al. (2024), odds ratios (ORs) were used to evaluate the predictive utility of each demographic factor. The full results are presented in Table 3. Regarding gender, females were more likely than males to belong to the low-risk profile. For family structure, students with at least one sibling were more likely to be classified in the moderate-risk and high-risk profiles. In terms of academic year, sophomores were more likely to be in the high-risk profile than freshmen, whereas juniors or above showed elevated odds of membership in both the moderate-risk and high-risk profiles.

Connected networks among smartphone dependence, perceived stress, and FoMO

The dimensional network comprising the dimensions of smartphone dependence, FoMO, and perceived stress among university students is shown in Figure 3. A regularized network with eight nodes and 28 potential edges was estimated, which contained 17 non-zero edges. The average edge weight was 0.1. The network structure showed widespread positive correlations among the nodes, with the 'tension' dimension of perceived stress emerging as a central node within the network. The result supported H_2 .

The strength centrality for the dimensional network of smartphone dependence, FoMO, and perceived stress is shown in Figures S1 and S2. Ranked by strength centrality, the 'tension' dimension exhibited the highest strength centrality ($M = 1.09$), indicating the strongest associations

Table 3. Multinomial logistic regression predicting latent profile membership

Demography variable	Moderate-risk		High-risk	
	OR	CI	OR	CI
Gender (with male as reference)	0.719	[0.50, 1.05]	0.605**	[0.40, 0.91]
Family structure (with only child as reference)	1.531*	[1.05, 2.24]	3.053**	[1.85, 5.03]
Residence (with urban areas as reference)	1.294	[0.89, 1.89]	1.420	[0.91, 2.22]
Sophomores (with freshmen as reference)	1.652	[1.00, 2.73]	1.964*	[1.14, 3.38]
Juniors or above (with freshmen as reference)	1.600*	[1.07, 2.40]	1.964*	[1.26, 3.07]

Note. * $p < 0.05$, ** $p < 0.01$. Significance was determined by whether the confidence interval included 1. An odds ratio (OR) less than 1 indicates a lower probability of belonging to the given latent profile compared to the reference group, whereas an OR greater than 1 indicates a higher probability. CI = 95% confidence interval.

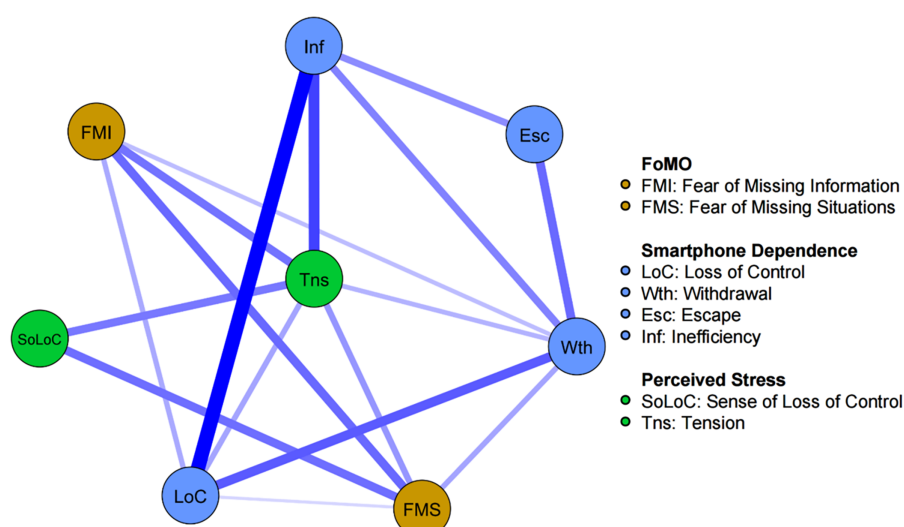


Figure 3. Gaussian graphical model. Note. nodes represent variables, edges denote partial correlations, with thickness reflecting coefficient magnitude (thicker = stronger). Blue edges indicate positive correlations, and red edges negative correlations. Network layout follows the SPRING layout.

with other variables. In contrast, the ‘escape’ dimension showed the lowest strength centrality ($M = 0.39$), indicating the weakest associations. Further analysis of the bridge strength of network nodes (see Figures S3 and S4 for details) showed that the ‘tension’ dimension exhibited the highest bridge strength among all nodes ($M = 0.89$). This indicates that tension plays the most critical mediating and transmitting role in connecting the three relatively distinct psychological variables (i.e., smartphone dependence, FoMO, and perceived stress).

This dimension acted as the core bridge that integrated the entire cross-domain symptom network. The ‘tension’ dimension in the present study demonstrated both the highest strength centrality and the highest bridge strength, positioning it at the core of the network. This indicated that tension functions as a central and bridging hub within the network. Otherwise, the strongest edge was observed between ‘loss of control’ and ‘inefficiency’ ($r = 0.38$), followed by ‘loss of control’ and ‘withdrawal’ ($r = 0.28$).

The bootstrap confidence intervals for edge weights were generally narrow (see Figure S5), indicating that the dimensional network of smartphone dependence, FoMO, and perceived stress among university students demonstrated adequate accuracy. The correlation stability

estimation of network node centrality indices (see Figure S6) indicated adequate stability of the network, with a correlation stability coefficient of 0.75, exceeding the recommended threshold of 0.50.

To examine whether the network structure varied by demographic characteristics, network invariance tests were conducted across gender, family structure, residential background, and academic year. The NCT showed no significant differences in global strength or edge weights for any of the subgroup comparisons (all p -values > 0.05). These results indicated that the network topology was invariant across the examined demographic variables, supporting the robustness of the overall network findings.

The moderating effect of perceived stress

The results of the MNM are presented in Figure 4. The moderation effects (i.e., three-way interactions) were not significant. However, pairwise interaction edges between variables were observed. Among these, the edge between ‘loss of control’ and ‘inefficiency’ was the strongest (edge weight = 0.37), followed by the edge between ‘tension’ and ‘inefficiency’ (edge weight = 0.27). A negative edge emerged between FMS and sense of loss of control (edge weight = -0.14). The result did not support H_3 .

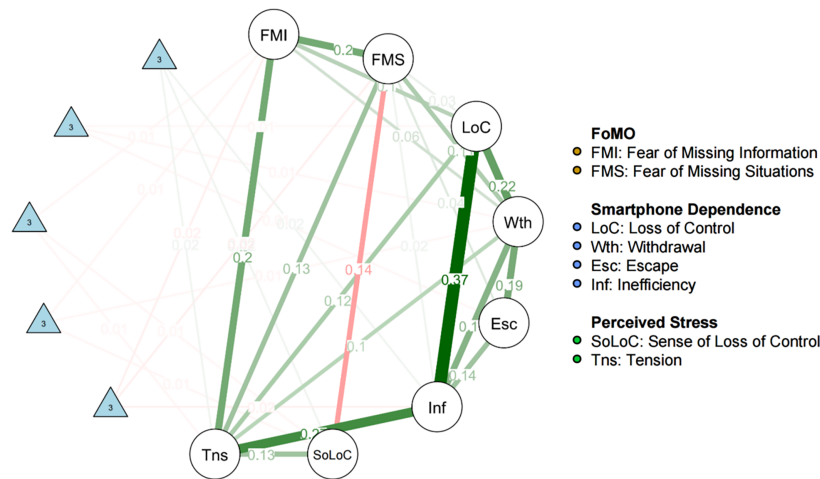


Figure 4. Moderated network model. *Note.* Blue triangles represent moderation effects. Green edges indicate positive interactions, red edges indicate negative interactions, and gray edges denote moderating effects. Edge thickness corresponds to effect strength (thicker = stronger). Network layout follows the CIRCLE layout.

Discussion

The results of the present study indicated that smartphone dependence among university students was heterogeneous. LPA showed that the three-class model demonstrated the best fit. Based on their dependence characteristics, these three latent classes in relation to smartphone dependence were labeled as ‘low-risk’, ‘moderate-risk’ and ‘high-risk’. This classification aligns with findings from previous research (Chen et al., 2024; Li et al., 2024b).

The three profiles suggest a tiered intervention approach. Those in the ‘high-risk’ profile (20.7%) scored highest on all four dependence dimensions. Previous research exhibited poorer psychosocial well-being (Wu et al., 2024). This represents a priority group for comprehensive programs such as personalized cognitive-behavioral therapy (Lan et al., 2018). Those in the ‘moderate-risk’ profile (43.4%), the largest group, scored near the sample average, indicating a noticeable but not severe problem that requires proactive measures such as digital literacy programs to prevent escalation (Kent et al., 2021). Those in the ‘low-risk’ profile (35.9%) scored below the mean on all dimensions, reflecting a baseline risk level. Preventive interventions such as themed lectures and workshops are recommended to reinforce positive digital habits and prevent progression to higher-risk stages (Malinauskas & Malinauskiene, 2019).

Additionally, demographic characteristics significantly predicted latent profile membership. Females were more likely than males to belong to the low-risk profile. This finding aligns with some previous research but contradicts other studies that reported no gender effect or found males at greater risk (Dong et al., 2025; Li et al., 2024b). Notably, the present sample comprised 67.8% females, and because LPA solutions are influenced by sample composition, this gender imbalance may have amplified the predictive effect of gender. Prior research has also shown that male adolescents tend to exhibit higher levels of internet accessibility and use frequency, which could explain why male university students may demonstrate a higher risk of smartphone dependence (Kunwar et al., 2024).

Regarding family structure, students with at least one sibling were more likely to belong to the moderate-risk and high-risk profiles, which may be related to lower life satisfaction among non-only-children (Zhao et al., 2022). With respect to academic year, both sophomores and juniors or above showed similarly elevated odds of belonging to the high-risk profile compared to freshmen, likely reflecting heightened academic and employment pressures (Mussi et al., 2019) and elevated perceived stress among senior students (Jeong & Bae, 2024).

The Gaussian graphical model showed that smartphone dependence, FoMO, and perceived stress among university students formed a densely interconnected network. This indicates that smartphone dependence and its socio-psychological factors are interrelated at the dimensional level, supporting the network theory of mental health disorders (Borsboom, 2017). Within this network, the ‘tension’ dimension of perceived stress emerged as a central and bridging node, signifying its role as a core component. This finding is consistent with previous research (Peng & Liao, 2023; Wang et al., 2023). Tension reflects various forms of physical and mental strain (Cohen et al., 1983). Research has shown that difficulty relaxing (i.e., high tension) is positively associated with emotion dysregulation, relapse, interpersonal conflict, and withdrawal symptoms (Peng & Liao, 2023). This suggests that, for university students, tension may serve as a hub for multiple negative psychological experiences, thereby influencing both the onset and maintenance of smartphone dependence.

From an emotion regulation model standpoint, the centrality of tension may reflect emotional dysregulation processes. Individuals experiencing high tension often have difficulty relieving inner distress through adaptive strategies, and may turn to smartphones for immediate relief (Squires et al., 2020). This maladaptive coping may create a negative reinforcement loop (i.e., smartphone use temporarily reduces tension, which increases the likelihood of future use while the underlying regulatory deficit remains unaddressed). Tension’s bridging role, which connects FoMO as an affective trigger with dependence symptoms such as withdrawal and inefficiency, is

consistent with this account. These patterns align with broader emotion regulation frameworks that highlight the role of emotional dysregulation in maintaining smartphone dependence (Squires et al., 2020).

In summary, tension emerged as a central and bridging node that was strongly interconnected with other symptoms of smartphone dependence, perceived stress, and FoMO. Given its prominence in the network, tension may represent a promising candidate for future intervention research. If subsequent studies confirm a causal role, programs such as mindfulness-based stress reduction training or cognitive-behavioral therapy that target tension could potentially contribute to reductions in smartphone dependence.

The moderated network model showed several notable pairwise interaction edges. The strongest edge was between inefficiency and loss of control, followed by that between inefficiency and tension. Tension, already identified as a central node in the GGM, also showed strong pairwise interaction with multiple nodes. This pattern suggests close interconnectedness among these nodes. However, no statistically significant moderation effects were found in the present study.

Several explanations may account for this non-significant moderation. From a theoretical perspective, perceived stress and FoMO may influence smartphone dependence through independent, additive pathways rather than through a synergistic interaction. That is, each factor may uniquely increase risk without amplifying the other's effect. Alternatively, the relationship may be mediated rather than moderated (Yang et al., 2021). FoMO could heighten perceived stress, which in turn promotes smartphone dependence, but this is only a possibility because it was not directly assessed in the present study. From a methodological standpoint, moderated network models require large samples to reliably detect three-way interactions, and the relatively modest sample size ($N = 1014$) and the sparsity imposed by L1-regularization may have limited power to identify small moderation effects (Haslbeck et al., 2021).

Implications for research and practice

The results primarily indicated that inefficiency and loss of control, as dimensions within smartphone dependence, demonstrated the strongest interaction. Moreover, the findings further confirm tension's pivotal bridging role within the network. This finding aligns with previous research indicating that the strongest connections within a network often occur within rather than across theoretical dimensions (Gong et al., 2023; Yuan et al., 2022).

Consistent with the I-PACE model (Brand et al., 2019), inefficiency (a cognitive component) and loss of control (an execution component) were strongly associated in the network, reflecting a possible reciprocal relationship in which perceived declines in productivity and goal disruption co-occur with an inability to regulate the amount and frequency of smartphone use (Leung, 2008). Similarly, tension and inefficiency showed a close coupling. These patterns are consistent with prior evidence associating tension with withdrawal symptoms (Zhao et al., 2025) and suggest that cognitive and affective processes

may jointly contribute to the maintenance of smartphone dependence.

A negative interaction effect was observed between FMS and the sense of loss of control. This finding appears inconsistent with previous reports of a positive association between FoMO and perceived stress (Andersen et al., 2023). This discrepancy may be attributed to the possibility that intense FMS prompts individuals to engage in persistent social connection behaviors to seek a sense of belonging and well-being (Reed & Arin, 2025). Some research indicates that FoMO may provide individuals with a sense of short-term relief, and their coping strategies can also include positive methods (Matijašević et al., 2025). This behavioral pattern, to some extent, may buffer the sense of loss of control experienced under stress.

The I-PACE model posits that cognitive and affective variables may exhibit compensatory or inhibitory relationships (Brand et al., 2019). More specifically, when experiencing intense FMS, individuals may increase smartphone use to maintain social connections. The sense of control derived from this behavior, in the short-term, may mitigate the sense of loss of control associated with perceived stress. Conversely, when the sense of loss of control is extremely high, emotional exhaustion or avoidance may be associated with a temporary reduction in attention to social information, which may lessen the FMS. However, this relief may be transient. From a long-term perspective, such patterns could paradoxically exacerbate behavioral dependence and psychological conflict. The underlying patterns warrant further investigation.

In summary, to address the negative impacts arising from the interplay of perceived stress, FoMO, and smartphone dependence among university students, psychological intervention programs could consider integrating cognitive-behavioral therapy and emotion regulation training paradigms, based on the learning emotion regulation framework proposed by Wright et al. (2025). Such interventions may help individuals correct irrational cognitions about smartphone use and develop emotion regulation skills, which could in turn alleviate smartphone dependence and safeguarding their physical and mental health.

Limitations of the study and future research directions

The present study has several limitations. First, the participant sample was limited in scope (i.e., a convenience sample with a higher proportion of females), potentially limiting the representativeness and external validity. Future studies should employ more balanced gender ratios and stratified sampling across multiple provinces to enhance representativeness and generalizability. Second, the study comprised self-report data via paper-based surveys, which may introduce biases such as social desirability bias and careless responding. Future studies could incorporate multiple data collection methods to mitigate these issues. Third, the study employed a cross-sectional design, which makes it impossible to determine definitive causal relationships among the three study variables. Future research could employ longitudinal designs to systematically delineate the temporal sequence and causal

pathways among the three variables. Relatedly, the non-significant moderation effect should be re-examined with larger, preregistered samples and alternative models such as mediation in the future. Moreover, high centrality in a cross-sectional network reflects strong statistical associations rather than causal importance. Whether targeting a central node leads to clinical improvement requires experimental or longitudinal confirmation. Fourth, the person components of the I-PACE model were not assessed. Future research should incorporate measures of personality functioning to provide a more complete evaluation based on the I-PACE framework.

Conclusion

This study's findings indicate that smartphone dependence among university students is heterogeneous and can be categorized into three risk profiles: low-risk, moderate-risk, and high-risk. The 'tension' dimension of perceived stress emerged as the central node connecting smartphone dependence, perceived stress, and FoMO within the symptom network. Moreover, significant interactions were observed among the three variables, although no moderating effects were detected. The findings support both the heterogeneous nature and the networked maintenance pattern of smartphone dependence among university students. The study lays a foundation for future tiered intervention research that considers key central nodes, and may inform the development of strategies aimed at reducing smartphone dependence.

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