International Journal of Mental Health and Addiction
https://doi.org/10.1007/s11469-022-00857-3

ORIGINAL ARTICLE

The Smartphone Addiction Scale: Psychometric Properties, Invariance, Network Perspective, and Latent Profile Analysis Among a Sample of Chinese University Students

Li Li[1] · Zhimin Niu[1] · Mark D. Griffiths[2] · Songli Mei[3]

Accepted: 29 May 2022

Abstract
The Smartphone Addiction Scale (SAS) is one of commonly used measurement tools to assess smartphone addiction. However, studies concerning the psychometric properties, invariance, and network structure of the SAS as well as profiles of smartphone addiction are rare in China. Therefore, the psychometric properties of the SAS, its invariance and network structure, and a latent profile analysis were investigated among Chinese university students in the present study. A sample of 2531 participants from Chinese universities (1003 males [39.6%], mean age = 20.4 years [SD = 1.3 years]) completed the Smartphone Addiction Scale (SAS), the Internet Addiction Diagnostic Questionnaire (IADQ), and the Problematic Cellular Phone Use Questionnaire (PCPU-Q). A total of 17 items were selected from the original SAS using item analysis and exploratory factor analysis. Psychometric properties and measurement invariance showed good validity and reliability for the revised Chinese Smartphone Addiction Scale (SAS-RC). In item-level and facet-level networks, "withdrawal" and "daily-life disturbance" had the stronger edge intensity. There were no significant differences in either network structure or global strength between males and females through the item-level and facet-level network comparison tests (NCTs). Three profiles of smartphone use (normal smartphone use, high-risk smartphone use, and smartphone addiction) were identified among Chinese university students. The SAS-RC demonstrates good psychometric properties and invariance and is suitable to use among Chinese university students. "Withdrawal" (i.e., psychological dependence) and "daily-life disturbance" appear to play contributory roles as core symptom of smartphone addiction. The three profiles also provide new insight into smartphone use and addiction among Chinese university students.

Keywords Smartphone addiction · Psychometric properties · Measurement invariance · Network perspective · Latent profile analysis · Chinese university students

Introduction

Smartphones are capable of multiple functions, not just making calls and sending text messages. Users can surf the web, send emails, update personal microblogs, store and play music, take photographs, make videos, play games, access GPS systems, and make mobile payments. Consequently, smartphones have become an indispensable part of many people's daily lives in today's world. Recent figures released by Statista forecast that the number of smartphone users worldwide will grow from 6.378 billion in 2021 to approximately 7.516 billion in 2026 (Statista, 2021a). According to the report from the China Internet Network Information Centre (CNNIC), the number of people (older than six years) who use smartphones for online service has increased from 90.1% (620 million out of 688 million Chinese online users) in December 2015 to 99.6% (1007 million out of 1011 million Chinese online users) in June 2021 (China Internet Network Information Center, 2016, 2021). Chinese university students use their smartphones for both leisure and educational purposes (e.g., online chatting, playing music, gaming, and coursework learning).

Although smartphones can be used to enable many beneficial behaviors (e.g., leisure, communication, information, education, medical treatment), excessive use may be related to smartphone addiction for a minority of individuals (Chung et al., 2018; Duke & Montag, 2017; Elhai et al., 2020; Rotondi, Stanca, & Tomasuolo, 2017). Smartphone addiction is a form of technological addiction or generalized internet addictions (Chen et al., 2020; Griffiths, 1998). Billieux (2012) has defined smartphone addiction as "an inability to regulate smartphone use which eventually leads to negative outcomes in daily life" (p.299). In addition, some risk factors of smartphone addiction have been examined such as loneliness, individualism, anxiety, depression, low self-esteem, narcissism and high impulsivity traits (Hussain, Griffiths, & Sheffield, 2017; Jiang, Li, & Shypenka, 2018; Kim, Cho, & Kim, 2017; Li, Liu, & Dong, 2019). Additionally, smartphone addiction is associated with poor sleep quality (Chung et al., 2018; Kumar, Chandrasekaran, & Brahadeeswari, 2019), vision problems (Kim et al., 2016), driving risk (Nguyen-Phuoc et al., 2020), and musculoskeletal pain (Alsalameh et al., 2019; Yang et al., 2017).

Many scholars in the behavioral addiction field agree that internet addiction comprises two types: generalized internet addiction and specific internet addiction (Brand, Young, & Laier, 2014; Lopez-Fernandez, 2018; Montag et al., 2015). Generalized internet addiction refers to a general behavioral pattern of internet overuse comprising multiple online activities and that is associated with depression (Sariyska et al., 2015; Vally, 2019), social anxiety (Weinstein et al., 2015), impaired family functioning (Shi, Wang, & Zou, 2017; Wartberg et al., 2015), and poor academic performance (Samaha & Hawi, 2016). Specific internet addiction includes addictions to specific applications on the internet such as social media use, online gaming, online gambling, and online shopping (Chen et al., 2020). However, smartphone addiction (which could be argued to be a generalized internet addiction in that the smartphone is Wi-Fi-enabled and features many different types of applications) is closely associated with social media addiction (SMA) particularly among individuals with SMA who prefer to use their smartphone to engage in social activities (Kuss & Griffiths, 2017; Sha et al., 2019; Throuvala et al., 2019).

Although smartphone addiction may cause psychological and physical problems caused by internet addiction (Porter, 2010), some research has shown that internet addiction is more common among males than females (Demirci et al., 2014; Haug et al., 2015; Lopez-Fernandez, 2017). In contrast, females have a higher risk of developing smartphone addiction than males (Mescollotto et al., 2019; Sfendla et al., 2018). Previous studies have reported that males prefer online gaming, gambling, and cybersex, whereas females prefer chatting, sending messages, and blogging (Baloğlu, Kozan, & Kesici, 2018; Billieux et al., 2007; Morahan-Martin, 1998; Vyjayanthi et al., 2014). Smartphones have unique features, such as high availability, Wi-Fi connectivity, versatility, and is primarily used as a tool for maintaining interpersonal relationships (Van Deursen et al., 2015). Therefore, gender differences in Internet addiction and smartphone addiction need to be determined.

The Smartphone Addiction Scale (SAS) (Kwon et al., 2003b) is one of the most commonly used measurement tools to evaluate smartphone addiction. The 33-item (six-factor) SAS was constructed using a Korean self-diagnostic program originally designed to diagnose internet addiction, and adapted for smartphone users (Kwon et al., 2013b). The six factors of SAS included daily-life disturbance, withdrawal, positive anticipation, overuse, tolerance, and cyberspace-oriented relationships. Subsequently, a 10-item short version of the Smartphone Addiction Scale (SAS-SV) was developed for adolescents (Kwon et al., 2013a). Multiple language versions of the SAS or SAS-SV have also been verified as having good validity (Ching et al., 2015; Demirci et al., 2014; Haug et al., 2015; Lopez-Fernandez, 2017; Mescollotto et al., 2019; Sfendla et al., 2018). Billieux (2012) has argued that translation and evaluation for validated instruments is essential. The short version of the SAS (i.e., SAS-SV) was developed for adolescents (from junior high school, average age = 14.5 years). Therefore, a smartphone addiction scale for university students needs to be developed. In China, some researchers have used mobile phone addiction measurement tools for smartphone addiction, for example, the Mobile Phone Problem Use Scale (MPPUS) (Bianchi & Phillips, 2005), the Mobile Phone Addiction Index (MPAI) (Leung, 2008), the Problematic Mobile Phone Use Questionnaire (PMPUQ) (Billieux, Van der Linden, & Rochat, 2008), the Problematic Cellular Phone Use Questionnaire (PCPU-Q) (Yen et al., 2009). Such instruments ignore specific characteristics of smartphones that are similar to those of computers, overlooking that smartphones are not merely used for calling and sending messages by mobile phone. The Smartphone Application-Based Addiction Scale (SABAS) is a short and unidimensional tool for screening the risk of addiction to smartphone applications (Csibi et al., 2018; Leung et al., 2020; Lin et al., 2019). The six-item SABAS reflects similar content to the Smartphone Addiction Scale (SAS).

Network analysis can help in exploring and verifying the core symptoms of mental disorders, as well as better explaining the interaction of biopsychosocial factors when specific mental disorders occur compared to latent variables analysis. Andrade, Kim et al. (2020a, 2021) reported that the SAS and SAS-SV had both similar network structures when comparing Brazilian university students and adults. Andrade & Scatena et al. (2020) also indicated that symptoms of withdrawal and preoccupation were the key characteristics of smartphone addiction utilizing SAS-SV among Brazilian adolescents. Some researchers have also utilized latent profile analysis to examine the classification of smartphone/internet users. For example, Yue et al. (2021) classified smartphone users into three classes comprising low-risk, moderate-risk and high-risk. Chen et al. (2021) classified university students internet use into four groups comprising pathological users, pathological-tendency users, preferential users, and ordinary internet users. Kim and Nam et al. (2016) identified six classes of problematic internet use patterns using latent profile analysis. These studies highlight that there were different classifications. Therefore, the research purposes were to (i) provide data on the psychometric properties and measurement invariance of the revised Chinese Smartphone Addiction Scale (SAS-RC) for Chinese university students, (ii) conduct network analysis of the SAS-RC, and (iii) identify profiles of smartphone use among Chinese university students.

1. Methods

1.1. Participants and procedure

A cross-sectional and convenient sampling strategy was utilized in the present study. Data were collected from 2705 students in the Liaoning province of China. However, two students who completed the survey were 16 years old, and 172 surveys were incomplete. Therefore, the final sample comprised 2531 participants (1003 males, 1528 females) aged from 17 to 25 years (M = 20.4 years; SD = 1.3).

From May 2015 to April 2016, three universities in the Liaoning province of China were investigated including a comprehensive university (N = 923), a medical university (N = 938), and a technical college (N = 844). Participants were informed that the study investigated smartphone use and then completed the survey in scheduled classes. Students who completed the survey were awarded course credit. First, questions concerning socio-demographic information including gender, age, residential status, their own smartphone status, and amount of time they used their smartphone were asked, as well as a self-evaluation of their smartphone use status where three choices were provided: 'addicted to their smartphone', 'not addicted to their smartphone', and "don't know'. Then, the SAS, the IADQ, and the PCPU-Q were completed in approximately 20 minutes.

The total sample (N = 2531) was divided randomly into two subsamples to assess psychometric properties of the SAS. Item analysis and exploratory factor analysis (EFA) were performed among 1278 participants, whereas confirmatory factor analysis (CFA) was performed on the rest of the sample (n=1253). Utilizing the total sample (n=2531), measurement invariance, reliability analysis, network analysis, and latent profile analysis were conducted. There were no significant differences between gender ($\chi^2 = 2.50$), age (t = 0.79), or the total SAS score (t = 1.50) ($p > 0.05$ for all) between the two samples.

1.2. Measures

1.2.1. SAS Translation

According to guidelines for developing versions of questionnaires in other languages (Beaton, 2000), the English version of SAS was translated into Chinese. First, two Chinese psychology professors who were experts in understanding English translated the initial draft. Then, the draft was retranslated into Chinese by two English professors without a psychology background. Finally, another two psychology professors examined the cultural face validity of the Chinese SAS. The six professors then reached a general consensus of views on the final version. The research into the instrument's cultural face validity raised concerns about two items (i.e., *"Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook" and "Checking SNS (Social Networking Service) sites like Twitter or Facebook right after waking up"*). The two items appeared problematic because, although Twitter and Facebook are two popular social networking sites in America, Europe, as well as Korea, whereas Tencent QQ and WeChat are more widely used in China. According to reports from Statista (2021b, 2021c), QQ, an instant messaging platform, had 595 million monthly active smart device users by the end of 2020; and WeChat, a mobile social platform, had 1.25 billion monthly active users in the second quarter of 2021. Consequently, 33-item Chinese SAS substituted "Tencent QQ or WeChat" for "Twitter or Facebook".

1.2.2. The Smartphone Addiction Scale (SAS)

The Korean SAS contains 33 items assessing six domains: positive anticipation, daily-life disturbance, cyberspace-oriented relationships, overuse, withdrawal, and tolerance. Each item is responded to from 1 (*"strongly disagree"*) to 6 (*"strongly agree"*). Higher scores indicate higher risk of smartphone addiction. The Cronbach's alpha value of the original SAS was 0.97, and for the six factors were 0.86, 0.91, 0.88, 0.90, 0.83, and 0.87, respectively. The Cronbach's alpha of the 33-item Chinese SAS was 0.91 in the present study.

1.2.3. Internet Addiction Diagnostic Questionnaire (IADQ)

The IADQ was utilized to examine the convergent validity of the SAS-RC. The items originate from the DSM-IV criteria for pathological gambling and contains eight items. According to Young (1998), five or more ''yes'' responses indicate a dependency (1: "*Yes*", 0: "*No*"). The 8-item model fitted well (χ^2 = 249.89, *df* = 20, $p < 0.001$; TLI = 0.925; CFI = 0.948; SRMR = 0.049; RMSEA = 0.078). The Cronbach's alpha of the IADQ was 0.86 in the present study.

1.2.4. Problematic Cellular Phone Use Questionnaire (PCPU-Q)

The convergent validity of the SAS-RC was also assessed using the PCPU-Q (Yen et al., 2009). The 12-item PCPU-Q derives from the definitions and classifications of substance use disorders outlined in the DSM-IV. Participants respond to each question by answering 'yes' (=1) or 'no' (=0). The first seven items concern characteristics of problematic cellular phone use (CPU) in the preceding year, whereas the final five items concern subjective functional impairment. In the original validation study, Taiwanese adolescents were recruited to examine positive relationships between problematic CPU and various risky behaviors (e.g., aggressive behavior, smoking cigarettes, drinking alcohol, insomnia, and suicide attempts) and low self-esteem (Yang et al., 2010). The Cronbach's alpha of the PCPU-Q was 0.93 in the present study.

1.3. Data analysis

Descriptive analysis of variables (i.e., SAS-RC scores and socio-demographic characteristics), normal data distribution test (i.e., skewness and kurtosis), item analysis, EFA, CFA, invariance, convergent validity, reliability, and network analysis, as well as latent profile analysis (LPA) were performed. Descriptive analysis, skewness and kurtosis, item analysis, and convergent validity and reliability were conducted utilizing SPSS 20, whereas EFA, CFA, invariance, and LPA were conducted utilizing Mplus 7. Network analysis was conducted utilizing JASP (Jeffrey's Amazing Statistics Program). The R package was used to perform the network comparison test (NCT) on gender (van Borkulo, 2016).

1.3.1. Psychometric properties and invariance

A *t*-test, ANOVA (mean comparison), and a Scheffe's post-hoc test were conducted to analyze the difference on the SAS-RC scores. The skewness and kurtosis levels were used to analyze the data distribution (Finney & DiStefano, 2006; West, Finch, & Curran, 1995).

Means and standard deviations, item-total correlations, and corrected item-total correlations were used to conduct item analysis. The suitability of the respondent data was analyzed utilizing the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (i.e., factorability; KMO, > 0.80) and Bartlett's test of sphericity ($p < 0.05$) (Cerny & Kaiser, 1977). For simplifying interrelated measures, exploratory factor analysis (EFA) was performed (Suhr, 2005), and principal axis factoring and oblique rotation were utilized (Corner, 2009). Every factor should retain at least three items (Maccallum et al., 1999; Velicer & Fava, 1998). Different factor models of the SAS, including four-factor, five-factor, and six-factor models, were assessed using EFA in Sample 1 (N=1278) with Mplus 7. The items that loaded on less than 0.3 or loaded on more than one construct (> 0.3), and items inconsistent with the original SAS dimensions were removed based on the recommendations of Costello and Osborne (2015).

The Tucker-Lewis Index (TLI, > 0.90), comparative fit index (CFI, > 0.90), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), root mean square error of approximation (RMSEA, < 0.06) (90% C.I.) and standardized root mean square residual (SRMR, < 0.08) were calculated to analyze data-model fit of CFA (Byrne, 2013; Hu & Bentler, 1999). Comparison of the first-order and second-order models was performed using a target coefficient (Marsh, Barnes, & Hocever, 1985). Cronbach's alpha greater than 0.7 was considered acceptable (Santos, 1999). Test-retest reliability (i.e., two-week interval) has often been conducted in previous studies (Doty, Newhouse, & Azzalina, 1985; Lewis, McCollum, & Joseph, 1999). Measurement invariance involving configural, metric, scalar, and error variance invariance was assessed to further examine the changes in the model fitting index by gender (Cheung & Rensvold, 2002).

1.3.2. Network analysis

Based on the Extended Bayesian Information Criterion (EBIC; Chen & Chen, 2008), a graphical least absolute shrinkage and selection operator (LASSO; Friedman et al., 2008) regularization was calculated to represent the EBICglasso model. The network system included nodes (i.e., items/factors of SAS-RC) and edges (correlation between two nodes). The centrality of nodes in the network were calculated including betweenness, closeness, and strength (Epskamp et al., 2012). Correlation stability coefficient (*CS*-coefficient) (≥ 0.25) represent the node centrality stability (Epskamp et al., 2018). The tuning parameter was set to 0.5 for a more parsimonious and easier explainable network (i.e., fewer edges, higher specificity and sensitivity). In network analysis, statistical significance can be visualized with a weights matrix and the resulting graph shows different significance in different shades of blue/orange, and omits other non-significant values. Thicker edges and thinner edges represent stronger correlation and weaker correlation, respectively. Edge stability was estimated through bootstrapped 95% confidence intervals (1000 times). The network comparison test (NCT) was conducted to compare the structure network and the global network strength across gender.

1.3.3. Latent profile analysis

For latent profile analysis (LPA), fit indices were as calculated utilizing the Akaike information criteria (AIC), Bayesian information criterion (BIC), the sample size-adjusted BIC (A-BIC), Entropy, Lo-MendellRubin adjusted likelihood ratio test (LMRA-LRT) and Bootstrap Likelihood Ratio Test (BLRT), as well as minimum class membership size. Entropy

($\geq$ 0.8) and decreased AIC, BIC and A-BIC indicate better results (Carragher et al., 2009). The LMRA-LRT and BLRT with a significant *p*-value indicate a better-fitting model (Muthén, & Muthén, 2012). Two to five groups were classified from the sample of 2531 participants. The optimal model was selected based on the best-fit statistics and interpretability (McCutcheon, 2002). Replication analysis was conducted for cross-validation in two random split-samples (n_1 = 1245 and n_2 = 1286). Multinomial logistic regression and multiple comparison (least significant difference [LSD] and Bonferroni) were used for latent profile classes. The cut-off value was calculated through ROC curve analysis.

2.4. Ethics

The research team's University Research Ethics Committee approved the study procedure. The study's purpose and written informed consent were also provided to all participants in the present study.

2. Results

2.1. Descriptive analysis of variables

Among the 2531 participants, the total SAS-RC scores for males and females were 51.94 and 52.03 respectively, which demonstrated there was no statistically significant gender difference ($p > 0.05$) (Table 1). The number of students who lived in urban areas and rural areas were 1284 (50.7%, SAS-RC total score = 52.19) and 1247 (49.3%, SAS-RC total score = 51.80), respectively. There was no significant difference between residential status ($p >$ 0.05). The average time of smartphone usage was 6.21 hours every day (the median was 5.0 hours and Skewness was 0.745). For assessment of smartphone addiction by the participants themselves, 215 students regarded themselves as "addicted" to their smartphones (8.5%), 1293 students regarded themselves as "non-addicted" to their smartphones (54.1%), and the remaining students answered "unsure" (1023, 40.4%). Their SAS-RC scores showed statistically significant differences ($p < 0.001$), with a score of 62.09 for students who considered themselves addicted to their smartphones compared to a score of 52.79 for students who said they were not addicted to their smartphone.

2.2. Psychometric properties

2.2.1. Normal data distribution test (skewness and kurtosis)

The values of skewness and kurtosis ranged from -0.74 to 1.47 and from -1.36 to 2.53, respectively (Appendix S1). Data were regarded as being normally distributed because of the skewness (< 2) and kurtosis (< 7) values. Therefore, the maximum likelihood (ML) was used in the present study.

2.2.2. Item analysis

For checking the consistency of the 33 items of the SAS and smartphone addiction, the item-total correlation test and corrected item-total correlations (i.e., alpha if item deleted) were performed. The good psychometric characteristics (item-total correlation from 0.31 to 0.68 and alpha had little or no change if item deleted) were showed for all 33 items (Appendix S1). Therefore, the 33 items were retained to perform EFA.

2.2.3. Construct validity

2.2.3.1. Exploratory factor analysis (EFA)

The 33-item SAS's KMO was .94 and Bartlett's test of sphericity was 26106.01 ($p < 0.001$). These results indicated that factor analysis was appropriate for the 33-item SAS with a common factor. Considering item loading and factors (Appendix S2), thirteen items (8, 11, 12, 13, 19, 27, 28, 30, 31, 10, 18, 20, 22) were removed in the six-factor model. Moreover, the fifth factor had only two items (24 & 25) in the six-factor model. Therefore, 15 items (8, 11, 12, 13, 18, 19, 20, 22, 24, 25, 27, 28, 30, 31) were removed. Next, EFA was re-run with the remaining 18 items. Item 17 (i.e., "*I will never give up using my smartphone even when my daily life is already greatly affected by it*") was also removed. EFA models with different items and factors also demonstrated that the 17-item model with four factors had better model fit index (Table 2). Ultimately, 17 items were selected for inclusion in the revised Chinese SAS (SAS-RC) based on their theoretical foundation and their loadings in the first sample (N = 1278) (Table 3).

In the original SAS, two factors, overuse and tolerance, had only four items and three items, respectively. In the present study, the items (1, 2, 3, 4, 5, 29, 32, and 33; see Appendix S2) involving three factors (daily-life disturbance, overuse, and tolerance) were integrated into one factor. The mean SAS-RC item score ranged from Item 26 with the lowest score (*"Preferring talking with my smartphone buddies to hanging out with my real-life friends or with the other members of my family"*, M =2.13, SD = 1.13) to Item 6 with the highest score (*"Feeling calm or cozy while using a smartphone"*, M = 3.78, SD = 1.20). The mean scores of the four subscales (daily-life disturbance, positive anticipation, withdrawal, and cyberspace-oriented relationships) were 3.16 (SD = 0.84), 3.62 (SD = 0.96), 3.09 (SD = 1.06), and 2.21 (SD = 0.90), respectively. The average total score of the SAS-RC was 52.00 (SD = 11.33).

2.2.3.2. Confirmatory factor analysis (CFA)

The 17-item and four-factor model fitted well ($\chi^2 = 316.92$, $df = 109$, $p < 0.01$; TLI = 0.924; CFI = 0.939; SRMR = 0.036; RMSEA = 0.039) (Table 2). Subsequently, several observed variables across the constructs were found to be related. Therefore, a second-order model was conducted to verify the definition of smartphone addiction, in which there was a larger factor underlying the four factors ($\chi^2 = 343.01$, $df = 111$, $p < 0.01$; TLI = 0.917; CFI = 0.932; SRMR = 0.041; RMSEA = 0.041) (Table 2). Furthermore, by comparing the first-order and second-order models using the target coefficient (T = 0.92), the factor structure was improved.

2.2.4. Convergent validity

The students' self-assessments of smartphone addiction were closely correlated with their SAS-RC scores. By controlling for gender and residential status, the convergent validity was analyzed using partial correlation to compare the SAS-RC with the original SAS, IADQ, and PCPU-Q. The correlation coefficients of the SAS-RC with the IADQ and the PCPU-Q were 0.57 and 0.51, respectively. The correlation coefficients of the SAS-RC with the SAS were 0.94 for the total scale score and 0.74 for daily-life disturbance, 0.51 for positive anticipation, 0.75 for withdrawal, and 0.61 for cyberspace-oriented relationships ($p < 0.01$ for all). Scores on the SAS-RC were significantly positively associated with scores on both the PCPU-Q and IADQ, which proved good convergent validity for the SAS-RC (Table 4).

2.2.5. Reliability

Cronbach's alpha of the 33-item SAS was 0.91 while Cronbach's alpha decreased to 0.82 for the 17-item SAS-RC. To reduce the order effect, SAS-RC question sequences were rearranged when assessing test-retest reliability for 123 participants randomly sampled from original participants. Two-week test-retest reliability of the SAS-RC was 0.83 in the present study.

2.3. Measurement invariance

As shown in Table 2, invariance was conducted including configural, metric, scalar, and error variance invariance. For gender (1528 females and 1003 males), configural invariance was performed on the SAS-RC. The result showed that TLI and CFI were 0.940 and 0.952 (χ^2 = 577.98, *df* = 218, SRMR = 0.036, RMSEA = 0.036) (N=2531) overall, 0.923 and 0.940 in the male sample (χ^2 = 283.51, *df* = 105, SRMR = 0.040, RMSEA = 0.041) (N=1003), and 0.936 and 0.947 in the female sample (χ^2 = 354.43, *df* = 113, SRMR = 0.035, RMSEA = 0.037) (N=1528), respectively. There was no statistically significant difference in gender ($\triangle\chi^2$ = 20.28, $\triangle df$ = 13, $p > 0.05$). The results of metric, scalar and error variance invariance on the total sample showed that TLI and CFI were 0.936 and 0.949 (χ^2 = 629.64, *df* = 218, SRMR = 0.037, RMSEA = 0.039), 0.937 and 0.949 (χ^2 = 633.19, *df* = 222, SRMR = 0.037, RMSEA = 0.038), 0.934 and 0.942 (χ^2 = 703.60, *df* = 239, SRMR = 0.039, RMSEA = 0.039) , respectively (Table 2). These results indicated that the 17-item and four-factor SAS-RC had good measurement invariance across gender.

2.4. Network analysis

2.4.1. EBICglasso network analysis

The EBICglasso item-level network including 17 items are shown (Figure 1). Node sas15 (*"Feeling that my relationships with my smartphone buddies are more intimate than my relationships with my real-life friends"*) and node sas16 (*"Feeling that my smartphone buddies understand me better than my real-life friends"*) had the strongest edge intensity (r = 0.483) for the total sample (Appendix S3). Node sas14 had the highest strength centrality (betweenness = 2.431, closeness = 1.814, strength = 1.171). Node sas6 had also higher strength centrality (betweenness = 1.304, closeness = 0.948, strength = 1.047) (Appendix S4-S5). The CS-coefficients of the 17 items ranged from from 0.5 to 1.1 (Appendix S7). The facet-level network including daily-life disturbance, positive anticipation, withdrawal, and cyberspace-oriented relationships are shown in Figure 2. Node F1 (daily-life disturbance) and node F3 (withdrawal) had the strongest edge intensity (r = 0.313) (Appendix S8). Node F3 had the highest strength centrality (betweenness =

1.500, closeness = 0.950, strength = 1.388) (Appendix S9-S10). The CS-coefficients of daily-life disturbance, positive anticipation, withdrawal, and cyberspace-oriented relationships were 0.54, 0.4, 0.75, and 0.47, respectively (Appendix S12).

2.4.2. EBICglasso network analysis across gender

In the item-level network, nodes sas15 and sas16 had the strongest edge intensity (for males, r = 0.492; for females, r = 0.442). Node sas6 and node sas14 had the highest strength among males (1.648) and females (1.326), respectively (Appendix S13-S20). In the facet-level network, nodes F1 ("daily-life disturbance") and F3 ("withdrawal") had the strongest edge intensity among males (r = 0.35), while F2 ("positive anticipation") and F3 ("withdrawal") had the strongest edge intensity among females (r = 0.33). Withdrawal had the highest strength among males (1.084) and females (1.478) (Appendix S21-S27).

2.4.3. Comparison of network between gender

The network structure and global strength both had no significant differences between males and females either at the item-level (M=0.104, p= 0.397; 29.8 vs. 28.8, p=0.143) or the facet-level (M= 0.093, p=0.423; 1.00 vs. 1.12, p=0.315) network comparison tests (NCT).

2.5. Latent profile analysis

2.5.1. LPA results

As shown in Appendix S28, models with two to five subgroups were estimated and compared. Decreased AIC, BIC and A-BIC values were demonstrated in the two-profile to five-profile solutions. However, only the three-profile solution's entropy was more than 0.8. The high posterior probabilities of memberships of the three latent classes were 0.93, 0.898, and 0.939, respectively. In addition, the smartphone addiction' theoretical meaningfulness and clinical interpretability were also important for determining the most acceptable profile. Three simple profiles of smartphone addiction were identified for Chinese university students: (i) normal smartphone use group (Class 1, n=1227, 48.5%), (ii) high-risk smartphone use group (Class 2, n=1041, 41.1%), and (iii) smartphone addiction group (Class 3, n=263, 10.4%) (Figure 3). Replication analysis was performed through randomly sampling 1245 participants, which also indicated good discrimination on the three classes of smartphone use (Appendix S28).

2.5.2. Covariate results

The multinomial logistic regression was conducted for covariates with the smartphone addiction class as the reference class compared to other two classes. The results for covariates associated with latent class membership are shown in Appendix S29. Compared to the smartphone addiction class, gender differences were non-significant in normal smartphone use class and high-risk smartphone use class. There were no significant differences in age and residential status in three classes. Demographic results also showed that there were no class differences between males (n = 487) and females (n = 986) (χ^2 =

4.944, p = 0.084, Phi = 0.058) and between those living in urban and rural areas (706 vs. 769, χ^2 = 0.448, p = 0.799, Phi = 0.017). There were no significant differences on total score of SAS-RC and four factors between gender (all p-values > 0.05).

2.5.3. Multiple comparison of four factors and 17 items between three three classes

There were significant differences between classes in relation to daily-life disturbance (including overuse and tolerance) and cyberspace-oriented (i.e., online) relationships. There were no significant differences in positive anticipation and withdrawal between the high-risk smartphone users (Class 2) and addicted smartphone users (Class 30 (p > 0.05). Compared to Class 2, Class 3 had significant differences on Items 8, 13, 15, 16, and 17 (Appendices S30-s32).

2.6. ROC analysis

The ROC plot including sensitivity and 1-specificity for the 17-item SAS-RC is shown in Appendices 33-34. The large area under the curve (AUC) was 0.861 (CI: 0.833-0.888, p < 0.001). The cut-off value was a score of 58, which corresponded to 0.804 sensitivity and 0.742 specificity (1-specificity = 0.258).

3. Discussion

The present study examined the psychometric properties, invariance, and network structure of the SAS-RC, and conducted latent profile analysis for smartphone addiction. All participants used a smartphone and utilized all kinds of applications via their smartphone (e.g., surfing the web, using Tencent QQ and WeChat, making mobile payments). This finding is similar to the CNNIC report that the usage rate of instant messaging apps (e.g., WeChat, QQ) was more than 97.3% of Chinese Netizens in June 2021 (China Internet Network Information Center, 2021). Differences in self-reported smartphone addiction were found, but no gender and residential status differences were found in the total scores of the SAS-RC. These results were similar to the SAS for Korean adults (Kwon et al., 2013b).

The SAS factor structure analysis showed that the 17-item SAS-RC with four factors was confirmed in the present study. In the first EFA, based on the 33-item SAS, four-factor, five-factor, and six-factor models of SAS were tested. The results of the exploratory factor analysis showed that the six-factor model had higher model fit than the other two models. However, in the six-factor model, some items that loaded on less than 0.3 or on more than one factor were not appropriate. In addition, the fifth factor had only two items in both the five-factor model and the six-factor model. Therefore, the four-factor model was more suitable on the fit estimator.

Two factors, 'overuse' and 'tolerance', that had few items in the original SAS were integrated into the 'daily-life disturbance' factor of the SAS-RC by EFA. Because of traditional cultural differences, emotional expression is more implicit in Chinese university students (Gao, 1998). In particular, the expressions of psychological pain and mental symptoms refer to somatization patterns. Therefore, Items 29, 32, and 33 (i.e., *"Using my smartphone longer than I had intended", "Always thinking that I should shorten my* *smartphone use time"* and *"The people around me tell me that I use my smartphone too much"*) were incorporated into the daily-life disturbance factor. In some studies, it has been debated as to whether the 'tolerance' factor is a symptom of addiction (Charlton & Danforth, 2007). Time spent using the internet is not a criterion for addiction (e.g., professional e-sport players legitimately spend many hours a day online) unless such behavior results in serious negative consequences (Charlton & Danforth, 2007).

Next, some items inconsistent with the corresponding factors of the original SAS were removed. In the second EFA, one item was removed for loading more than 0.3 on two factors. Finally, 17 items were retained on the basis of data analysis, and three of the four factors, including positive anticipation, withdrawal and cyberspace-oriented relationships, were consistent with the original SAS.

A series of good fit indices were found in the single-order model of the 17-item SAS-RC, as it had in the aforementioned research. Previous studies on smartphone addiction assessment tools have rarely shown a hierarchical measurement model and measurement invariance. Therefore, a second-order model of CFA was performed to evaluate the four-factor structure of the SAS-RC. Measurement invariance involving configural, metric, scalar, and error variance invariance also indicated the SAS-RC had a high construct validity between gender. In addition, the SAS-RC was positively associated with the original SAS, IADQ, and PCPU-Q in the convergent validity analysis.

In the item-level and facet-level networks, node sas14 ("*Having my smartphone in my mind even when I am not using it*" is part of "withdrawal") and node F3 ("withdrawal" factor) both had the strongest centrality, which was similar to Andrade, Scatena et al. (2020b) who reported that withdrawal and preoccupation were the core symptoms of smartphone addiction using the Brazilian SAS-SV. In addition, node sas6 ("*Using my smartphone longer than I had intended*") had stronger centrality in the total network. Loss of control was the core symptom of problematic smartphone use utilizing the Smartphone Addiction Proneness Scale (SAPS) (Huang et al., 2021). Excessive smartphone use may disturb daily life and be unable to effectively regulate individuals' behaviors. Another study had also found that low self-control was closely connected with problematic smartphone use utilizing network analysis among Italian adolescents (Mancinelli et al., 2021). Moreover, smartphone addiction may result in significant impairment in daily life (e.g., personal, family, social, educational, occupational or other important areas of functioning) and be characterized by impaired control as one of core characteristics of behavioral addiction (e.g., gaming disorder and problematic social media use) (World Health Organization, 2019). Comparison of networks between males and females also demonstrated that network structure and global strength of the SAS-RC were similar across gender, which also indicated the SAS-RC had similar network perspective between genders and is suitable for Chinese university students.

Three profiles of smartphone use (i.e., normal smartphone use class, high-risk smartphone use class, and smartphone addiction class) were identified among Chinese university students. The normal smartphone users (Class 1) spent less than three hours every day on their smartphone, whereas the high-risk smartphone users (Class 2) and the addicted smartphone users (Class 3) spent more than three hours every day on smartphone use. The results indicated one in ten Chinese university students were classed as having smartphone addiction, two-fifths used smartphone excessively, and close to half were normal smartphone users. This was similar to the self-report assessment of smartphone addiction in the present study. A study on smartphone addiction from Korean adolescents reported 13.5% participants had smartphone addiction, whereas the others were healthy smartphone users (Lee, Kim, & Choi, 2017). A systematic review indicated that the prevalence of smartphone addiction among children and young people was between 10% and 30% (Sohn et al., 2019). Three profiles of problematic smartphone use (i.e., mild, moderate, and severe class) were also found among American college students (Elhai et al., 2019).

The results of the covariate analysis also verified that the SAS-RC was appropriate for Chinese university students with different residential status and irrespective of gender, which was consistent with the aforementioned measurement invariance. There were no significant differences in positive anticipation and withdrawal between the high-risk smartphone use class and smartphone addiction class in the present study. This suggests that high-risk smartphone users spend lots of time on their smartphone and believe that smartphone use may enhance their interpersonal communication, help them search rapidly for various types of information rapidly, provide a means for convenient payment, and satisfy their psychological needs, such as coping with stress from academic performance and other stressors, and alleviating negative emotion.

Like addicted smartphone users (Class 3), high-risk smartphone users (Class 2) experience positive anticipation concerning their smartphone use and feel negatively when they are unable to use their smartphone (i.e., withdrawal symptoms), and they yearn for information and fear missing out on important things. However, high-risk smartphone users did not experience (i) psychological distress, or (ii) significant impairment in personal, family, social, educational and/or occupational functioning. Individuals with high-risk smartphone use thought that their smartphone was helpful for their daily life rather than harmful. Therefore, they used smartphone frequently and persistently. Addicted smartphone users may experience impaired social functioning including poor academic performance and compromised interpersonal relationship. Individuals with smartphone addiction showed a preference for online relationships, spent much longer time on their smartphone than those in the other two classes. Once high-risk smartphone users lose control over their smartphone use and give increased priority to smartphone use above other life interests and daily activities, they may become smartphone addicts.

The SAS-RC had high construct validity, convergent validity, reliability, similar to other mobile/smartphone addiction assessment tools (e.g., SAS, SABAS). Therefore, the SAS-RC with good psychometric properties and appropriate profiles and can be used to assess and screen Chinese university students for risk of smartphone addiction. Although smartphones can help individuals build social networks and reduce feelings of isolation, previous work has also shown that smartphone use can impact sleep (Lanaj, Johnson, & Barnes, 2014; Randler et al., 2016) and physical health (İNal et al., 2015; Kim, Kim, & Jee, 2015). Moreover, high-risk smartphone use can cause psychological problems, such as anxiety, depression, and time distortion (Elhai et al., 2017; Lin et al., 2015). As an effective measurement tool, 17-item SAS-RC is able to assess the risk of smartphone addiction for

Chinese university students.

Several study limitations should be noted in relation to the present study. First, all data originated from convenience sampling with universities in one province of China and were self-report, which means there were possible subjective biases regarding the data (e.g., memory recall, social desirability). Related to this is the fact that self-report may differ from actual smartphone usage (e.g., smartphone users may over-estimate how long they actually spent on their smartphones). For instance, Andone et al. (2016) reported among a large sample of over 30,600 smartphone users that they spent an average of 166 minutes a day on their smartphone. Future studies should therefore investigate using representative samples as well as using objective and standardized methods (such as actual account data, i.e., smartphone app monitoring) to provide a more comprehensive understanding to problematic smartphone use. Second, given that participants were asked a question to self-evaluate their smartphone use status (i.e., 'addicted to their smartphone', 'not addicted to their smartphone', and "don't know'), some participants may simply have interpreted 'addiction' as heavy usage rather than a clinical definition of addiction which may have influenced the findings. Third, it should be noted that any self-report instruments cannot be used as a diagnostic tool to assess genuine addiction as this can only be done utilizing clinical interviews by trained practitioners (e.g., psychiatrist, clinical psychologist). Instruments such as that described in the present study assess the risk of addiction at best. Fourth, there were four factors in the SAS-RC. To make sure the factor structure is robust, further confirmatory research is required. In addition, the psychometric properties of the SAS-RC and differences of profile properties of smartphone addiction need to be further evaluated among the general Chinese population as well as among populations in other countries. A replication of the profile solution with other Chinese samples and cross-cultural samples should also be conducted. Given that the SAS was originally developed in Korean, the translation process (i.e., from English to Chinese) may have resulted in some problems involving linguistic validity.

4. Conclusion

The SAS-RC had high construct validity, good reliability, and proven invariance, which indicated robust psychometric properties. Three profiles of smartphone use and addiction were also identified among Chinese university students. Therefore, the SAS-RC has good psychometric properties and is suitable for assessing the risk of smartphone addiction by different profiles among Chinese university students. Positive daily activities and overcoming withdrawal symptoms may decrease smartphone addiction among Chinese university students.

Availability of data and materials

The datasets supporting the conclusions of this article are available from the corresponding author upon reasonable request.

Competing interests

There are no financial or non-financial competing interests. None of the research staff received incentives for recruiting participants or for any other purpose directly associated with the study.

Consent for publication

Not applicable.

References

1. Alsalameh, A. M., Harisi, M. J., Alduayji, M. A., Almutham, A. A., & Mahmood, F. M. (2019). Evaluating the relationship between smartphone addiction/overuse and musculoskeletal pain among medical students at Qassim University. *Journal of Family Medicine and Primary Care, 8*(9), 2953.
2. Andone, I., Błaszkiewicz, K., Eibes, M., Trendafilov, B., Montag, C., & Markowetz, A. (2016, September). *How age and gender affect smartphone usage.* In Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing: adjunct (pp. 9-12). New York: ACM.
3. Andrade, A. L. M., Kim, D. J., Caricati, V. V., Martins, G. D. G., Kirihara, I. K., Barbugli, B. C., ... & De Micheli, D. (2020a). Validity and reliability of the Brazilian version of the Smartphone Addiction Scale-Short Version for university students and adult population. *Estudos de Psicologia (Campinas)*, *37*. e190117.
4. Andrade, A. L. M., Kim, D. J., Scatena, A., Enes, C. C., Enumo, S. R. F., & De Micheli, D. (2021). Validity and Reliability of the Brazilian Version of the Smartphone Addiction Scale-Long Version (SAS-LV). *Trends in Psychology*, *29*(2), 302-319.
5. Andrade, A. L. M., Scatena, A., Martins, G. D. G., de Oliveira Pinheiro, B., da Silva, A. B., Enes, C. C., ... & Kim, D. J. (2020b). Validation of Smartphone Addiction Scale–Short Version (SAS-SV) in Brazilian adolescents. *Addictive Behaviors*, *110*, 106540.
6. Baloğlu, M., Kozan, H. İ. Ö., & Kesici, Ş. (2018). Gender differences in and the relationships between social anxiety and problematic internet use: Canonical analysis. *Journal of Medical Internet Research, 20*(1), e33.
7. Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine, 25*(24), 3186-3191.
8. Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior, 8*(1), 39-51.
9. Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews, 8*(4), 299-307.
10. Billieux, J., Van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 22*(9), 1195-1210.
11. Billieux, J., Van der Linden, M., d'Acremont, M., Ceschi, G., & Zermatten, A. (2007). Does impulsivity relate to perceived dependence on and actual use of the mobile phone? *Applied Cognitive Psychology, 21*(4), 527-537.
12. Brand, M., Young, K. S., & Laier, C. (2014). Prefrontal control and Internet addiction: A

theoretical model and review of neuropsychological and neuroimaging findings. *Frontiers in Human Neuroscience, 8*, 375.

13. Byrne, B. M. (2013). *Structural equation modeling with LISREL, PRELIS, and SIMPLIS: Basic concepts, applications, and programming*. New York: Psychology Press.
14. Carragher, N., Adamson, G., Bunting, B., & McCann, S. (2009). Subtypes of depression in a nationally representative sample. *Journal of Affective Disorders*, *113*(1-2), 88-99.
15. Cerny, B. A., & Kaiser, H. F. (1977). A study of a measure of sampling adequacy for factor-analytic correlation matrices. *Multivariate Behavioral Research, 12*(1), 43-47.
16. Charlton, J. P., & Danforth, I. D. (2007). Distinguishing addiction and high engagement in the context of online game playing. *Computers in Human Behavior, 23*(3), 1531-1548.
17. Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, *95*, 759–771.
18. Chen, J., Liu, J., Zhao, G., & Kong, F. (2021). Internet behavior preferences predict pathological internet use: A latent profile analysis. *Frontiers in Psychology*, *12,* 644623.
19. Chen, I. H., Strong, C., Lin, Y. C., Tsai, M. C., Leung, H., Lin, C. Y., ... & Griffiths, M. D. (2020). Time invariance of three ultra-brief internet-related instruments: Smartphone Application-Based Addiction Scale (SABAS), Bergen Social Media Addiction Scale (BSMAS), and the nine-item Internet Gaming Disorder Scale-Short Form (IGDS-SF9) (Study Part B). *Addictive Behaviors, 101*, 105960.
20. Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*(2), 233-255.
21. China Internet Network Information Center (2016). *The 45th Statistical report on internet development in China*. Retrieved November 22, 2021 from: http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/201601/P020160122469130059846.pdf.
22. China Internet Network Information Center (2021). *The 48th Statistical report on internet development in China*. Retrieved November 22, 2021 from: http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/hlwtjbg/202102/P020210203334633480104.pdf.
23. Ching, S. M., Yee, A., Ramachandran, V., Lim, S. M. S., Sulaiman, W. A. W., Foo, Y. L., & kee Hoo, F. (2015). Validation of a Malay version of the smartphone addiction scale among medical students in Malaysia. *PloS One, 10*(10), e0139337.
24. Chung, J. E., Choi, S. A., Kim, K. T., Yee, J., Kim, J. H., Seong, J. W., ... & Gwak, H. S. (2018). Smartphone addiction risk and daytime sleepiness in Korean adolescents. *Journal of Paediatrics and Child Health, 54*(7), 800-806.
25. Corner, S. (2009). Choosing the right type of rotation in PCA and EFA. *JALT Testing & Evaluation SIG Newsletter, 13*(3), 20-25.
26. Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation, 10*(1), 1-9.
27. Csibi, S., Griffiths, M. D., Cook, B., Demetrovics, Z., & Szabo, A. (2018). The psychometric properties of the smartphone application-based addiction scale (SABAS). *International Journal of Mental Health and Addiction, 16*(2), 393-403.
28. Demirci, K., Orhan, H., Demirdas, A., Akpinar, A., & Sert, H. (2014). Validity and reliability of the Turkish Version of the Smartphone Addiction Scale in a younger population. *Klinik*

Psikofarmakoloji Bülteni-Bulletin of Clinical Psychopharmacology, 24(3), 226-234.
29. Doty, R. L., Newhouse, M. G., & Azzalina, J. D. (1985). Internal consistency and short-term test-retest reliability of the University of Pennsylvania Smell Identification Test. *Chemical Senses, 10*(3), 297-300.
30. Duke, É., & Montag, C. (2017). Smartphone addiction, daily interruptions and self-reported productivity. *Addictive Behaviors Reports, 6*, 90-95.
31. Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders, 207*, 251-259.
32. Elhai, J. D., Rozgonjuk, D., Yildirim, C., Alghraibeh, A. M., & Alafnan, A. A. (2019). Worry and anger are associated with latent classes of problematic smartphone use severity among college students. *Journal of Affective Disorders*, *246*, 209–216.
33. Elhai, J. D., Yang, H., Fang, J., Bai, Y., & Hall, B. J. (2020). Depression and anxiety symptoms are associated with problematic smartphone use severity in Chinese young adults: Fear of missing out as a mediator. *Addictive Behaviors, 101*, 105962.
34. Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212.
35. Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1-18.
36. Finney, S. J., & DiStefano, C. (2006). Non-normal and categorical data in structural equation modeling. *Structural Equation Modeling: A Second Course, 10*(6), 269-314.
37. Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse invariance estimation with the graphical lasso. *Biostatistics*, *9*, 432–441.
38. Gao, G. (1998). ‘‘Don't take my word for it.’’— Understanding Chinese speaking practices. *International Journal of Intercultural Relations, 22*(2), 163-186.
39. Griffiths, M. D. (1998). Internet addiction: Does it really exist? In J. Gackenbach (Ed.). *Psychology and the internet: Intrapersonal, interpersonal and transpersonal applications* (pp. 61-75). New York: Academic Press.
40. Haug, S., Castro, R. P., Kwon, M., Filler, A., Kowatsch, T., & Schaub, M. P. (2015). Smartphone use and smartphone addiction among young people in Switzerland. *Journal of Behavioral Addictions, 4*(4), 299-307.
41. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.
42. Huang, S., Lai, X., Xue, Y., Zhang, C., & Wang, Y. (2021). A network analysis of problematic smartphone use symptoms in a student sample. *Journal of Behavioral Addictions*, *9*(4), 1032-1043.
43. Hussain, Z., Griffiths, M. D., & Sheffield, D. (2017). An investigation into problematic smartphone use: The role of narcissism, anxiety, and personality factors. *Journal of Behavioral Addictions, 6*(3), 378-386.
44. İNal, E. E., Demirci, K., Çetİntürk, A., Akgönül, M., & Savaş, S. (2015). Effects of smartphone overuse on hand function, pinch strength, and the median nerve. *Muscle & Nerve, 52*(2), 183-188.

45. Jiang, Q., Li, Y., & Shypenka, V. (2018). Loneliness, Individualism, and Smartphone Addiction Among International Students in China. *Cyberpsychology, Behavior, and Social Networking, 21*(11), 711-718.
46. Kim, E., Cho, I., & Kim, E. J. (2017). Structural equation model of smartphone addiction based on adult attachment theory: Mediating effects of loneliness and depression. *Asian Nursing Research, 11*(2), 92-97.
47. Kim, J., Hwang, Y., Kang, S., Kim, M., Kim, T. S., Kim, J., ... & Park, S. K. (2016). Association between Exposure to Smartphones and Ocular Health in Adolescents. *Ophthalmic Epidemiology, 23*(4), 269-276.
48. Kim, S. E., Kim, J. W., & Jee, Y. S. (2015). Relationship between smartphone addiction and physical activity in Chinese international students in Korea. *Journal of Behavioral Addictions, 4*(3), 200-205.
49. Kim, D., Nam, J. K., Oh, J., & Kang, M. C. (2016). A latent profile analysis of the interplay between PC and smartphone in problematic internet use. *Computers in Human Behavior*, *56*, 360-368.
50. Kumar, V. A., Chandrasekaran, V., & Brahadeeswari, H. (2019). Prevalence of smartphone addiction and its effects on sleep quality: A cross-sectional study among medical students. *Industrial Psychiatry Journal, 28*(1), 82.
51. Kuss, D. J., & Griffiths, M. D. (2017). Social networking sites and addiction: Ten lessons learned. *International Journal of Environmental Research and Public Health, 14*(3), 311.
52. Kwon, M., Kim, D. J., Cho, H., & Yang, S. (2013a). The smartphone addiction scale: Development and validation of a short version for adolescents. *PloS One, 8*(12), e83558.
53. Kwon, M., Lee, J. Y., Won, W. Y., Park, J. W., Min, J. A., Hahn, C., ... & Kim, D. J. (2013b). Development and validation of a Smartphone Addiction Scale (SAS). *PloS One, 8*(2), e56936.
54. Lanaj, K., Johnson, R. E., & Barnes, C. M. (2014). Beginning the workday yet already depleted? Consequences of late-night smartphone use and sleep. *Organizational Behavior and Human Decision Processes, 124*(1), 11-23.
55. Lee, H., Kim, J. W., & Choi, T. Y. (2017). Risk factors for smartphone addiction in Korean adolescents: Smartphone use patterns. *Journal of Korean Medical Science, 32*(10), 1674–1679.
56. Leung, H., Pakpour, A. H., Strong, C., Lin, Y. C., Tsai, M. C., Griffiths, M. D., ... & Chen, I. H. (2020). Measurement invariance across young adults from Hong Kong and Taiwan among three internet-related addiction scales: Bergen Social Media Addiction Scale (BSMAS), Smartphone Application-Based Addiction Scale (SABAS), and Internet Gaming Disorder Scale-Short Form (IGDS-SF9) (Study Part A). *Addictive Behaviors, 101*, 105969.
57. Leung, L. (2008). Linking psychological attributes to addiction and improper use of the mobile phone among adolescents in Hong Kong. *Journal of Children and Media, 2*(2), 93-113.
58. Lewis, C. A., McCollum, M. A., & Joseph, S. (1999). The Depression-Happiness Scale: Test-retest data over two weeks. *Psychological Reports, 85*(3), 889-892.
59. Li, C., Liu, D., & Dong, Y. (2019). Self-esteem and problematic smartphone use among adolescents: A moderated mediation model of depression and interpersonal trust. *Frontiers in Psychology, 10*, 2872.

60. Lin, C. Y., Imani, V., Broström, A., Nilsen, P., Fung, X. C., Griffiths, M. D., & Pakpour, A. H. (2019). Smartphone application-based addiction among Iranian adolescents: A psychometric study. *International Journal of Mental Health and Addiction, 17*(4), 765-780.
61. Lin, Y. H., Lin, Y. C., Lee, Y. H., Lin, P. H., Lin, S. H., Chang, L. R., ... & Kuo, T. B. (2015). Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App). *Journal of Psychiatric Research, 65*, 139-145.
62. Lopez-Fernandez, O. (2017). Short version of the Smartphone Addiction Scale adapted to Spanish and French: Towards a cross-cultural research in problematic mobile phone use. *Addictive Behaviors, 64*, 275-280.
63. Lopez-Fernandez, O. (2018). Generalised versus specific internet use-related addiction problems: A mixed methods study on internet, gaming, and social networking behaviours. *International Journal of Environmental Research and Public Health*, *15*(12), 2913.
64. MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological Methods, 4*(1), 84-99.
65. Mancinelli, E., Ruocco, E., Napolitano, S., & Salcuni, S. (2021). A network analysis on self-harming and smartphone addiction–The role of self-control, internalizing and externalizing problems in a sample of self-harming adolescents. *Comprehensive Psychiatry*, 152285.
66. Marsh, H. W., Barnes, J., & Hocevar, D. (1985). Self-other agreement on multidimensional self-concept ratings: Factor analysis and multitrait-multimethod analysis. *Journal of Personality and Social Psychology, 49*(5), 1360-1377.
67. McCutcheon, A. L. (2002). *Latent class analysis*. Newbury Park: SAGE Publications.
68. Mescollotto, F. F., de Castro, E. M., Pelai, E. B., Pertille, A., & Bigaton, D. R. (2019). Translation of the short version of the Smartphone Addiction Scale into Brazilian Portuguese: Cross-cultural adaptation and testing of measurement properties. *Brazilian Journal of Physical Therapy, 23*(3), 250-256.
69. Montag, C., Bey, K., Sha, P., Li, M., Chen, Y. F., Liu, W. Y., ... & Reuter, M. (2015). Is it meaningful to distinguish between generalized and specific internet addiction? Evidence from a cross-cultural study from Germany, Sweden, Taiwan and China. *Asia-Pacific Psychiatry, 7*(1), 20-26.
70. Morahan-Martin, J. (1998). The gender gap in Internet use: Why men use the Internet more than women-a literature review. *CyberPsychology & Behavior, 1*(1), 3-10.
71. Muthén, L. K., & Muthén, B. O. (2012). *Mplus user’s guide (7th ed.)*. Los Angeles, CA: Muthén & Muthén.
72. Nguyen-Phuoc, D. Q., Oviedo-Trespalacios, O., Su, D. N., De Gruyter, C., & Nguyen, T. (2020). Mobile phone use among car drivers and motorcycle riders: The effect of problematic mobile phone use, attitudes, beliefs and perceived risk. *Accident; Analysis and Prevention*, *143*, 105592.
73. Porter, G. (2010, June). *Alleviating the “dark side” of smart phone use*. In 2010 IEEE International Symposium on Technology and Society (pp. 435-440). Rutgers, United States: IEEE.
74. Randler, C., Wolfgang, L., Matt, K., Demirhan, E., Horzum, M. B., & Beşoluk, Ş. (2016). Smartphone addiction proneness in relation to sleep and morningness-eveningness in

German adolescents. *Journal of Behavioral Addictions, 5*(3), 465-473.

75. Rotondi, V., Stanca, L., & Tomasuolo, M. (2017). Connecting alone: Smartphone use, quality of social interactions and well-being. *Journal of Economic Psychology, 63*, 17-26.
76. Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior*, *57*, 321-325.
77. Santos, J. R. A. (1999). Cronbach's alpha: A tool for assessing the reliability of scales. *Journal of Extension, 37*(2), 1-5.
78. Sariyska, R., Reuter, M., Lachmann, B., & Montag, C. (2015). Attention deficit/hyperactivity disorder is a better predictor for problematic Internet use than depression: Evidence from Germany. *Journal of Addiction Research & Therapy, 6*(209), 1-6.
79. Sfendla, A., Laita, M., Nejjar, B., Souirti, Z., Touhami, A. A. O., & Senhaji, M. (2018). Reliability of the Arabic Smartphone Addiction Scale and Smartphone Addiction Scale-Short Version in two different Moroccan samples. *Cyberpsychology, Behavior, and Social Networking, 21*(5), 325-332.
80. Sha, P., Sariyska, R., Riedl, R., Lachmann, B., & Montag, C. (2019). Linking internet communication and smartphone use disorder by taking a closer look at the Facebook and WhatsApp applications. *Addictive Behaviors Reports, 9*, 100148.
81. Shi, X., Wang, J., & Zou, H. (2017). Family functioning and Internet addiction among Chinese adolescents: The mediating roles of self-esteem and loneliness. *Computers in Human Behavior*, *76*, 201-210.
82. Sohn, S., Rees, P., Wildridge, B., Kalk, N. J., & Carter, B. (2019). Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: A systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry, 19*(1), 356.
83. Statista (2021a). *Number of smartphone users worldwide from 2016 to 2021*. Retrieved November 10, 2021 from https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/
84. Statista (2021b). *Number of monthly active smart device users of Tencent QQ from 2014 to 2020.* Retrieved November 10, 2021 from https://www.statista.com/statistics/227352/number-of-active-tencent-im-user-accounts-in-china/
85. Statista (2021c). *Number of monthly active WeChat users from 2nd quarter 2011 to 2nd quarter 2021.* Retrieved November 10, 2021 from https://www.statista.com/statistics/255778/number-of-active-wechat-messenger-accounts/
86. Suhr, D. D. (2005). Principal component analysis vs. exploratory factor analysis (paper 203-30). *Proceedings of the Thirtieth Annual SAS® Users Group International Conference (Vol. 203, p. 30).* Cary, NC: University of North Carolina.
87. Throuvala, M. A., Griffiths, M. D., Rennoldson, M., & Kuss, D. J. (2019). A 'controlmodel' of social media engagement in adolescence: A grounded theory analysis. *International Journal of Environmental Research and Public Health, 16*, 4696.
88. Vally, Z. (2019). Generalized problematic Internet use, depression, and explicit self-esteem: Evidence from the United Arab Emirates. *Neurology, Psychiatry and Brain Research*, *33*,

93-100.
89. van Borkulo, C.D. (2016). Network comparison test: Statistical comparison of two networks based on three invariance measures. Retrieved October 5, 2021 from: https://cran.r-project.org/web/packages/NetworkComparisonTest/index.html
90. Van Deursen, A. J., Bolle, C. L., Hegner, S. M., & Kommers, P. A. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior, 45*, 411-420.
91. Velicer, W. F., & Fava, J. L. (1998). Affects of variable and subject sampling on factor pattern recovery. *Psychological Methods, 3*(2), 231-251.
92. Vyjayanthi, S., Makharam, S., Afraz, M., & Gajrekar, S. (2014). Gender differences in the prevalence and features of internet addiction among Indian college students. *MedicaInnovatica, 3*(2), 49-53.
93. Wartberg, L., Kriston, L., Kammerl, R., Petersen, K. U., & Thomasius, R. (2015). Prevalence of pathological internet use in a representative German sample of adolescents: Results of a latent profile analysis. *Psychopathology, 48*(1), 25-30.
94. Weinstein, A., Dorani, D., Elhadif, R., Bukovza, Y., Yarmulnik, A., & Dannon, P. (2015). Internet addiction is associated with social anxiety in young adults. *Annals of Clinical Psychiatry, 27*(1), 4-9.
95. West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56-75). Thousand Oaks, CA: Sage.
96. World Health Organization (2019). ICD-11 for mortality and morbidity statistics. 6C51 Gaming disorder. Retrieved November 10, 2021 from https://icd.who.int/browse11/l-m/en#/http%3a%2f%2fid.who.int%2ficd%2fentity%2f1448597234
97. Yang, S. Y., Chen, M. D., Huang, Y. C., Lin, C. Y., & Chang, J. H. (2017). Association between smartphone use and musculoskeletal discomfort in adolescent students. *Journal of Community Health, 42*(3), 423-430.
98. Yang, Y. S., Yen, J. Y., Ko, C. H., Cheng, C. P., & Yen, C. F. (2010). The association between problematic cellular phone use and risky behaviors and low self-esteem among Taiwanese adolescents. *BMC Public Health, 10*(1), 217.
99. Yen, C. F., Tang, T. C., Yen, J. Y., Lin, H. C., Huang, C. F., Liu, S. C., & Ko, C. H. (2009). Symptoms of problematic cellular phone use, functional impairment and its association with depression among adolescents in Southern Taiwan. *Journal of Adolescence, 32*(4), 863-873.
100. Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. *Cyberpsychology & Behavior, 1*(3), 237-244.
101. Yue, H., Zhang, X., Sun, J., Liu, M., Li, C., & Bao, H. (2021). The relationships between negative emotions and latent classes of smartphone addiction. *Plos One*, *16*(3), e0248555.

Table 1

Sociodemographic characteristics and SAS-RC scores (N = 2531).

Variables		N (%) Mean±SD	SAS-RC Mean±SD	*p*
Own a smartphone	Yes	2531(100%)		
	No	0		
Age		19.4±1.3		
Gender	Male	1003(39.6%)	51.94±11.71	0.84
	Female	1528(60.4%)	52.03±11.07	
Residential status	Urban	1284(50.7%)	52.19±11.25	0.39
	Rural	1247(49.3%)	51.80±11.41	
Amount of time on smartphone (hours)	Everyday	6.21±3.73		
Self-evaluation of smartphone addiction	Non-addiction	1293(54.1%)	52.18±11.22[a]	<0.001
	Addiction	215(8.5%)	62.09±11.47[ab]	
	Don't know	1023(40.4%)	49.65±10.20[b]	

[a, b]: Scheffe test (the means with the same letter were significantly different).

Table 2

Data-model fit of different SAS items in EFA and CFA and gender invariance

Model	X^2	df	TLI	CFI	AIC	BIC	SRMR	RMSEA (90% CI)
33 items four factors EFA (N=1278)	1446.87	402	0.877	0.906	130193.77	131183.16	0.031	0.045(0.043, 0.048)
33 items Five factors EFA (N=1278)	1054.39	373	0.914	0.939	129820.90	130959.72	0.024	0.038(0.035, 0.041)
33 items Six factors EFA (N=1278)	845.50	345	0.931	0.955	129629.47	130912.58	0.021	0.034(0.031, 0.037)
18 items four factors EFA (N=1278)	279.37	87	0.923	0.956	72821.66	73347.27	0.023	0.042(0.036, 0.047)
17 items four factors EFA (N=1278)	217.54	74	0.931	0.962	69253.65	69748.34	0.021	0.039(0.033, 0.045)
17 items four factors CFA (N=1253)	316.92	109	0.924	0.939	67495.86	67808.99	0.036	0.039(0.034,0 .044)
Second-order model 17 items four factors CFA (N=1253)	343.01	111	0.917	0.932	67522.25	67825.11	0.041	0.041(0.036, 0.046)
Male (N=1003)	283.51	105	0.923	0.940	55234.27	55553.47	0.040	0.041(0.035, 0.047)
Female (N=1528)	354.43	113	0.936	0.947	80868.70	81172.61	0.035	0.037(0.033, 0.042)
Configural Invariance Gender (N=2531)	577.98	218	0.940	0.952	136559.38	137271.42	0.036	0.036(0.033, 0.040)
Metric Invariance (N=2531)	629.64	218	0.936	0.949	135827.80	136539.84	0.037	0.039(0.035, 0.042)
Scalar Invariance (N=2531)	633.19	222	0.937	0.949	135823.24	136511.94	0.037	0.038(0.035, 0.042)
Error variance Invariance (N=2531)	703.60	239	0.934	0.942	135871.71	136461.18	0.039	0.039(0.036, 0.043)

Table 3

Factor loading of the 17-item Chinese SAS (SAS-RC) in four factors by CFA

Number	F1	F2	F3	F4
1 Missing planned work due to smartphone use	0.39			
2 Having a hard time concentrating in class, while doing assignments, or while working due to smartphone use	0.54			
3 Experiencing lightheadedness or blurred vision due to excessive smartphone use	0.33			
4 Feeling pain in the wrists or at the back of the neck while using a smartphone	0.63			
5 Feeling tired and lacking adequate sleep due to excessive smartphone use	0.54			
6 Using my smartphone longer than I had intended	0.53			
7 Always thinking that I should shorten my smartphone use time	0.65			
8 The people around me tell me that I use my smartphone too much.	0.69			
9 Feeling calm or cozy while using a smartphone		0.56		
10 Feeling great meeting more people via smartphone use		0.73		
11 Being able to get rid of stress with a smartphone		0.55		
12 Won't be able to stand not having a smartphone			0.59	
13 Feeling impatient and fretful when I am not holding my smartphone			0.69	
14 Having my smartphone in my mind even when I am not using it			0.65	
15 Feeling that my relationships with my smartphone buddies are more intimate than my relationships with my real-life friends				0.68
16 Feeling that my smartphone buddies understand me better than my real-life friends				0.73
17 Preferring talking with my smartphone buddies to hanging out with my real-life friends or with the other members of my family				0.65

Note: F1 = Daily-life disturbance (including overuse and tolerance), F2 = Positive anticipation, F3 = Withdrawal, F4 = Cyberspace-oriented relationships.

Table 4

Correlations between the Chinese Version of the Smartphone Addiction Scale (SAS-RC) subscale scores and other scales (N = 2531)

Factor	SAS-RC	SAS	IADQ	PCPU-Q
Daily-life disturbance	0.86	0.74	0.52	0.51
Positive anticipation	0.52	0.51	0.21	0.13
Withdrawal	0.73	0.75	0.42	0.33
Cyberspace-oriented relationship	0.59	0.61	0.33	0.31
SAS-RC	1.0	0.94	0.57	0.51

Note: IADQ: Internet Addiction Diagnostic Questionnaire. PCPU-Q: Problematic Cellular Phone Use Questionnaire. The correlation coefficients between SAS-C subscales and other (SAS, IADQ, PCPU-Q) scales were all statistically significant at the $p < 0.001$ level

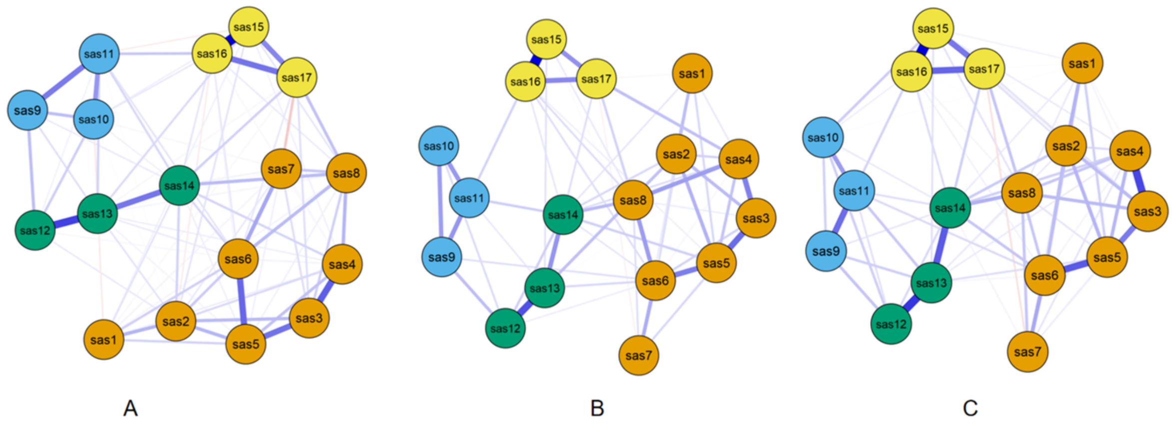

Figure 1. EBICglasso model based on network analysis according to the SAS-RC among total participants (A), males (B) and females (C). Note: sas1-sas17 = SAS, sas1-sas8= Daily-life disturbance, sas9-sas11 = Positive anticipation, sas12-sas14 = Withdrawal, sas15-sas17 = Cyberspace-oriented relationships.

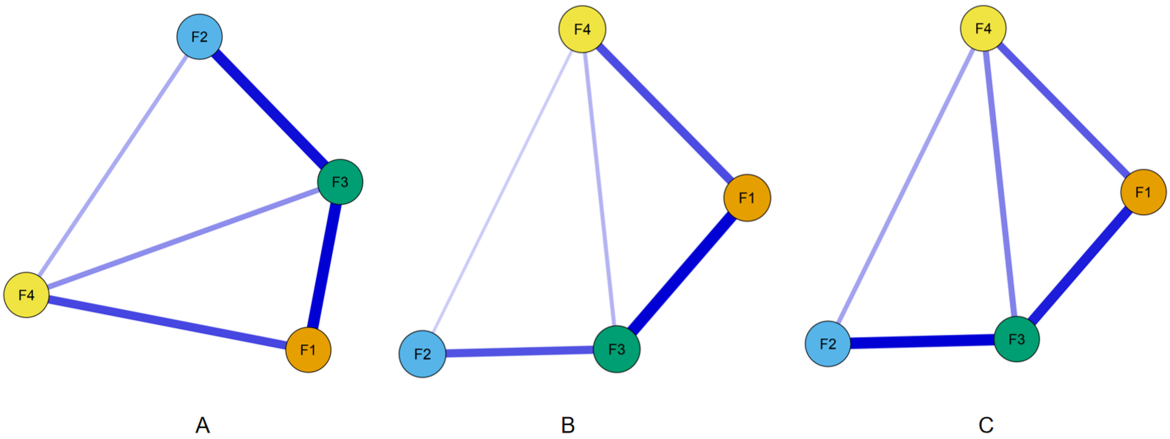

Figure 2. EBICglasso model based on network analysis according to the SAS-RC among total participants (A), males (B) and females (C). Note: F1= Daily-life disturbance, F2 = Positive anticipation, F3 = Withdrawal, F4 = Cyberspace-oriented relationships.

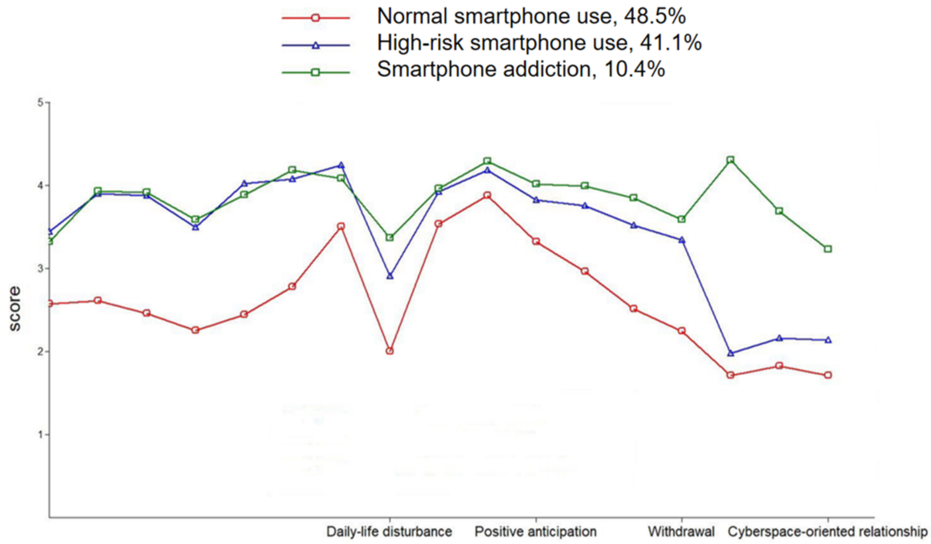

Figure 3. Latent class profile of smartphone addiction