Received: 8 July 2024 | Accepted: 27 September 2024
DOI: 10.1111/add.16699

RESEARCH REPORT

ADDICTION SSA

Psychometric evaluation and measurement invariance of the problematic smartphone use scale among college students: A national survey of 130 145 participants

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Funding information
There is no funding for this research.

Abstract

Background and Aims: Given the insufficient validation of previously imported smartphone addiction scales in China, this study revised and evaluated the Problematic Smartphone Use Scale among Chinese college students (PSUS-C).

Methods: We based our research on a national sample comprising 1324 higher education institutions and 130 145 participants. Using cross-sectional data, comprehensive methods were employed to examine validity, reliability and measurement invariance.

Results: The final scale consists of 20 items across four dimensions: withdrawal and loss of control, negative impact, salience behaviors and excessive use. All Heterotrait-Monotrait (HTMT) values were below 0.85, and the lower 90% and upper 95% confidence intervals were also below 0.85, except for factors 1 and 3. The amount of variance (AVE) values were greater than 0.5, composite reliability (ω) values exceeded 0.89 and all factor loadings were above 0.5. The criterion validity was supported as expected: problematic smartphone usage positively correlated with depression (r = 0.451), loneliness (8 items, r = 0.455), loneliness (6 items, r = 0.504), social media use (r = 0.614) and phone usage duration (r = 0.148); and negatively correlated with life satisfaction (r = −0.218) and self-esteem (r = −0.416). Across sex, type of university and place of residence, the measurement invariance performed well, with most changes in root mean square error of approximation (ΔRMSEA), comparative fit index (ΔCFI) and Tucker–Lewis index (ΔTLI) values being less than 0.005, and no indicator showing a difference greater than 0.010.

Conclusions: The Problematic Smartphone Use Scale for College Students (PSUS-C) demonstrated good factor structure, internal consistency, construct validity, discriminant validity and criterion validity. Strict and structural invariance were demonstrated across sex, type of university and place of residence. The PSUS-C has the potential to assess smartphone addiction among Chinese university students.

KEYWORDS
confirmatory factor analysis, demographic difference, measurement invariance, problematic smartphone use, smartphone addiction, vocational colleges

INTRODUCTION

The rapid development of social media, smartphones and mobile media influences the behavior and well-being of adolescents and youth [1–3]. Despite longitudinal and heterogeneous studies being called for as the next step in research advancement [4], both existing and future studies are based on the assumption that smartphone and social media addiction measurements are accurate. To date, multiple methods have been proposed for measuring social media and smartphone addiction, but many scales have not undergone comprehensive validation checks or shown poor consistency with different groups [5]. Few studies have re-validated these scales [6]. Additionally, the reliability and validity of these scales heavily depend on the representativeness of the data. We believe that, in a strict sense, scales that have not undergone national measurement invariance testing can only be applied locally and cannot be considered universally applicable.

Measurement of smartphone addiction

In current research, the Smartphone Addiction Scale short version (SAS-SV) [7] is among the most widely used instruments. Luk and colleagues [8] developed the Chinese version of SAS-SV. However, the Chinese version of the SAS-SV lacks criterion validity and directly assesses demographic differences without testing for measurement invariance [9]. Because of the differences in cultural environments and socio-economic conditions between the two countries, we believe scales developed through interviews in local context are more suitable than directly validating established scales from other cultural contexts. However, Smartphone Addiction Inventory (SPAI) [10], which was developed based on Chinese context, has not undergone validity or measurement invariance testing as a developing scale.

In contrast, the SAS for college students (SAS-C) [11], the most widely used tool for studying smartphone addiction in Chinese domestic research, was developed within the Chinese context and specifically targeted the college student population. Participants rated each statement using a 4-point scale ranging from strongly disagree to strongly agree. Su pointed out that it is not appropriate to simply apply the criteria for internet addiction [12] to smartphone addiction. Therefore, this study incorporates research on addiction to smartphone applications [13]. The SAS-C used three waves of data, which were respectively used for item analysis and exploratory factor analysis, confirmatory factor analysis and test–retest reliability. The results indicated that SAS-C demonstrates great psychometric properties, consisting of 22 items and six factors: withdrawal behavior, salience behavior, social comfort, negative impact, application (app) use and app update.

However, this scale still faces three main issues. First, despite SAS-C being widely used in China, it has never undergone measurement invariance testing. Second, with a deeper understanding of smartphone addiction, SAS-C has dimensions that are now outdated compared to current theoretical advancements (e.g. items related to smartphone tolerance are categorized under salience behavior). Moreover, debates surrounding the framework of smartphone addiction suggest that substance and behavioral addictions are not directly comparable [14–16]. There is a need for further clarification on the naming and establishing dimensions of the scale. Therefore, we develop a Problematic Smartphone Use Scale for college students (PSUS-C).

MEASUREMENT INVARIANCE AND DEMOGRAPHIC DIFFERENCE

Measurement invariance is rarely considered in media psychology measurements [9, 17]. Without assuming invariance, we cannot interpret statistical results correctly. Group differences cannot be defined as resulting from factors of interest in the study or differences in the scale's measurement constructs [18]. Ignoring measurement non-invariance may lead to biased conclusions in intergroup experiment comparisons [19] and result in abnormal findings in longitudinal studies [20]. Many studies investigated gender differences in smartphone addiction [21–23] and differences based on place of residence [24] without conducting measurement invariance.

Additionally, despite the fact that technical and vocational colleges account for a significant portion of higher education (35.90%), and institutional discrimination and stratification within China's education system [25, 26], research in China has consistently overlooked differences between vocational colleges and universities. The use of smartphones is highly culturally dependent and primarily influenced by occupation and social roles [14]. Therefore, this study examines the measurement differences in smartphone addiction across gender, residency and educational levels.

PRESENT STUDY

Our starting point is to revise the smartphone addiction scale for college student and develop the PSUS-C. We aim to validate the PSUS-C, explore the optimal factor structure and test its psychometric properties. Specifically, we examine (1) the factor structure and internal consistency; (2) construct validity (as indicated by convergent validity) (3) discriminant validity; (4) criterion validity; and (5) measurement invariance of the scale across sex, type of university and residency cities. As part of a large-scale survey, this study responds to the calls for high-quality research with large samples [2] and establishing a localized and contextual understanding of social media use and adolescent well-being [1].

METHOD

Data collection

The data for this research were collected as part of the National Online Survey on College Students' Internet Use and Sexual and Reproductive Health among College Students in China (2020), conducted by China Youth Network, the largest volunteering organization advocating for sexual and reproductive health and rights in China. The survey used a multi-stage sampling method for selecting higher education institutions (Figure 1). At the school level, we used a convenience sampling method.

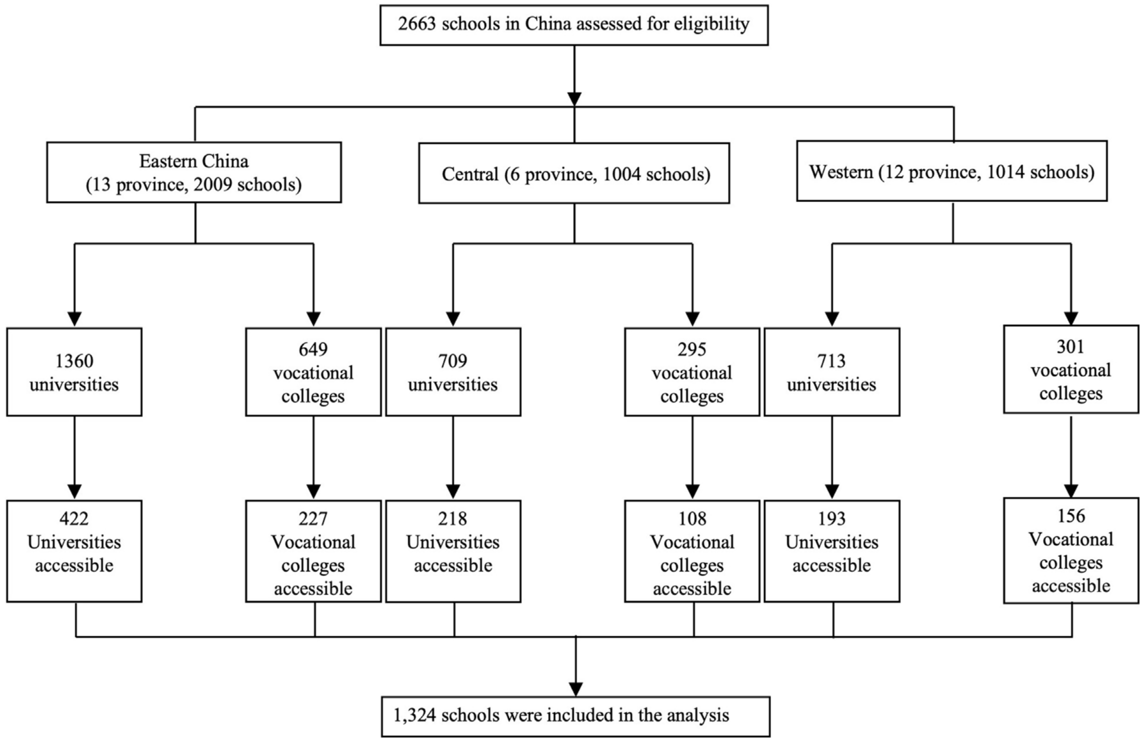

FIGURE 1 Multi-stage sampling framework.

In the first stage, all registered Chinese higher education institutions were categorized into eastern (including northeast), central and western China based on their provincial-level administrative regions. These institutions were further classified into universities and vocational colleges in the second stage [27]. A total of 1324 higher education institutions were selected. The internet-based self-administered questionnaire was distributed to local contacts in each school to recruit participants through convenience sampling from 12 November 2020 to 19 December 2020. Students from all 34 provincial administrative regions in China were eligible to participate.

A total of 164 447 responses were collected (see Table 1). Among these, 34 302 responses (20.86%) were excluded because of failure to provide informed consent, incomplete answers to all questions or not passing consistency checks and logic verification. The remaining dataset comprised a total of 130 145 participants [age mean (M) (SD) = 19.25 (1.38)], with 40 750 male participants [31.31%, age M (SD) = 19.25 (1.46)] and 89 131 female participants [68.49%, age M (SD) = 19.25 (1.35)]. On average, participants used the internet for M = 3.11 (SD = 2.85) hours a day.

Measurement

All English scales used mature Chinese versions or underwent a standardized forward and backward translation process [28]. Before distribution, interviews and pre-tests were conducted and the final questionnaire revealed no ambiguities.

Self-esteem

Self-esteem was assessed using the Rosenberg Self-Esteem Scale (RSES) [29]. This scale consists of 10 items (e.g. 'overall, I am satisfied with myself'). Participants rated each item on a 4-point scale ranging from 1 = strongly disagree to 4 = strongly agree, with higher scores indicating higher levels of self-esteem. The RSES-10 Cronbach's $\alpha = 0.894$.

Satisfaction with life

The scale measuring life satisfaction was adapted from the Satisfaction with Life Scale (SWLS) [30]. It consists of five items with seven response options ranging from 1 = strongly disagree to 7 = strongly agree. Good psychometric properties were reported in Chinese samples [31]. The Cronbach's $\alpha = 0.858$.

Depression

Depression was measured using the Center for Epidemiological Studies Depression scale (CES-D) [32], which comprises 20 items. Respondents indicated how often they experienced symptoms within the last week on a 4-point scale (1 = 'rarely or none of the time' to 4 = 'most or all of the time'). Good psychometric properties were reported among Chinese samples [33]. In the present study, Cronbach's α was 0.861.

TABLE 1 Description of participants.

	Male (n = 40 750)		Female (n = 89 131)		Total (n = 130 145)	
	Mean (n)	SD (%)	Mean (n)	SD (%)	Mean (n)	SD (%)
Age, years	19.25	1.46	19.25	1.35	19.25	1.38
Ethnic minority	5062	12.42	10 530	11.81	15 594	11.98
Vocational colleges	21 313	52.30	50 955	57.17	72 361	0.56
Universities	19 437	47.70	38 176	42.83	57 784	0.44
Full time	39 865	97.83	88 127	98.87		
Religion					128 254	98.55
City	13 975	34.29	25 006	28.06	39 069	0.30
County	13 142	32.25	31 070	34.86	44 304	0.34
Rural	13 633	33.46	33 055	37.09	46 772	0.36
SWL	21.48	5.78	21.14	5.24	21.24	5.42
CES-D	34.77	9.02	34.70	8.47	34.72	8.65
RSES-10	28.96	5.07	28.96	4.76	28.96	4.86
LL-8	15.37	4.70	14.83	4.53	15.00	4.59
LL-6	10.65	4.22	10.55	3.85	10.58	3.97
SMA	54.06	17.72	52.08	15.81	52.69	16.45
Phone usage duration	2.91	3.15	3.20	2.71	3.11	2.85
PSUS	58.05	18.09	57.52	16.12	57.69	16.76

Abbreviations: CES-D, Center for Epidemiological Studies Depression Scale; LL-6, Loneliness Scale with 6 items; LL-8, Loneliness Scale with 8 items; PSUS, Problematic Smartphone Use Scale; RSES-10, Rosenberg Self-Esteem Scale with 10 items; SMA, Social Media Addiction scale; SWL, Satisfaction with Life Scale.

Loneliness

Eight items from the short version of the University of California Los Angeles Loneliness scale (UCLA-8) [34] were used to assess adolescent loneliness. Participants rated each statement using a 4-point scale ranging from 0 = never to 4 = always. Xu and colleagues [35] pointed out that the UCLA Loneliness scale-6 (ULS-6), which excludes two reverse-scored items from the UCLA-8, demonstrated stronger psychometric properties than the UCLA-8. In the present study, we used both UCLA-6 (Cronbach's α = 0.895) and UCLA-8 (Cronbach's α = 0.811).

Social media addiction

We adopted the Internet Addiction Test (IAT) developed by Young [36], a 20-item scale designed to assess the presence and severity of Internet dependency among adults and was verified in China [37]. As part of a large-scale study, we used the rigorously validated IAT and did not opt for newer questionnaires [38]. During pre-testing interviews, participants expressed confusion over the term 'internet,' viewing it as an integral part of contemporary life [39]. Considering that social media usage is one of the most prominent functions of phone, and smartphone addiction often manifests as addiction to social media, we replaced the term 'internet' with 'social media' (Cronbach's α = 0.965).

Control variables

Consistent with prior cultivation research, demographic variables were measured such as age, sex, ethnic minority, type of university (ordinary/vocational), full-time, religion and place of residence (city/county/rural).

Analysis strategy

Considering the discussion on ω and α [40, 41], we simultaneously computed both α and ω (composite reliability) as measures of scale reliability and as references for convergent validity. We conducted exploratory factor analysis (EFA) using SPSS 29 and confirmatory factor analysis (CFA) using Mplus 8.3 to validate the existing scales. It is important to note that the analysis was not pre-registered, and the results should be considered exploratory.

CFA

Based on the kurtosis and skewness of the 22 items (see Table 1), we assessed each item to approximate a normal distribution. To mitigate errors, we used the weighted least square mean and variance adjusted (WLSMV) method, which makes no distributional assumptions about observed variables and instead assumes a normal latent distribution under each observed categorical variable [42]. Although typically underestimating factor loadings on average, factor loadings in WLSMV can be mainly considered unbiased. Maximum likelihood with robust standard errors (MLR) outperforms WLSMV in terms of factor correlations [43, 44] Therefore, we used WLSMV to estimate factor loadings in the CFA model and MLR to compute factor correlations.

Treating items as ordinal data may overestimate model fit, leading to overly optimistic results [45]. Therefore, we reported MLR data to illustrate model fit. Model fit was assessed using the following criteria: comparative fit index (CFI) cut-off of 0.90 [46], Tucker-Lewis index (TLI) cut-off of 0.90, root mean square error of approximation (RMSEA) cut-off of 0.07 [47] and standardized root mean square residual (SRMR) cut-off of 0.08 [48, 49]. Because of inflation in χ^2/d.f. under large sample conditions, this measure has been abandoned. The original purpose of approximate fit indices was to specify data fit, but their current use has erroneously evolved into a form of hypothesis testing [50]. Therefore, as outlined in *Monte Carlo Insights and Extended Examples* [51], assessing model goodness-of-fit based on statistical tests becomes irrelevant when the sample size is enormous. Instead, we focus on identifying an interpretable model that adequately explains the data.

To address dimensional discrepancies theoretically, we used EFA to explore the scale structure and adjusted the scale items accordingly. After determining the scale structure, CFA was reused to confirm the reliability and validity of the new structure.

Discriminant validity used several cross-validation methods to validate the scale's situation post-dimensional reassignment. The heterotrait-monotrait ratio of correlations (HTMT) proposed by Henseler and colleagues [52] demonstrated excellent performance in simulation studies, which suggested that values below 0.8 indicate no issues, and values up to 0.85 are acceptable [53]. Rönkkö and Cho [54] proposed that confidence intervals for latent variable correlations should not include 1 for excellent discriminant validity. They recommended cut-off values for latent variable correlations between 0.8 and 0.9, with the upper limit of the 95% CI below the threshold. Cheung and colleagues [55] suggested a more appropriate strategy of comparing the lower bound of the 90% confidence interval with the threshold. Therefore, based on maximum likelihood (ML) methods with bootstrap = 1000, we reported upper 95% CI for factor correlations and lower 90% CI. Because amount of variance (AVE)/shared variance (SV) exhibits a higher false positive rate [54], we discontinued using this indicator.

Convergent validity standards include AVEs >0.7, standardized factor loadings for all items not significantly <0.5 and composite reliability (ω) >0.7 [55, 56].

We assess the criterion validity of the PSUS-C scale by examining its scores about several dimensions of social-psychological well-being previously associated with smartphone addiction: negative correlations with self-esteem [57] and life satisfaction [58, 59], positive correlations with depression [22, 60, 61] and loneliness [62, 63]. We expect to find weak to moderate correlations between PSUS-C scores and these social-psychological constructs. Last, based on prior research linking PSUS-C use to smartphone usage time and frequency of daily social media use, we anticipate a moderate association between them.

Measurement invariance

Using multiple-group procedures to assess measurement invariance, we used MLR estimation to estimate and report parameters. WLSMV, suitable for ordinal categorical data, tends to inflate Type I error rates and is inappropriate for evaluating Δ approximate fit indexes (ΔAFI) because of its characteristics. MLR, with its scale corrections, minimally impacts ΔAFI and yields results similar to ML estimation [64]. Unlike $\Delta\chi^2$, most ΔAFI are less influenced by sample size, model complexity, number of factors and number of indicators, therefore, offering greater use [65].

We conducted a series of hierarchical nested models [18, 66] to assess the measurement invariance of the scale across sex, type of university and residency cities. Configural invariance was established, confirming that the factor structure remains consistent across groups, implying that the same items measure the same underlying constructs. Metric invariance (weak invariance) was tested to determine if the factor loadings are equivalent across groups. Lack of metric invariance would indicate that some items may have different meanings or response biases across groups. Scalar invariance (strong invariance) assessed whether the intercepts of observed scores on latent variables are uniform across groups, suggesting that groups interpret the scale similarly. Strict invariance examined whether the measurement error (residuals) for each item is comparable across groups. Additionally, we assessed whether factor variances were invariant across groups, ensuring that differences in groups did not affect the variability of latent variables. We also examined factor covariance invariance, indicating that associations among latent variables are consistent across different groups.

Based on the nested nature of each level of the invariance model within the previous one, changes in fit indices are compared to evaluate them [18]. A change in CFI (ΔCFI) ≤ -0.005 or -0.010 and RMSEA (ΔRMSEA) ≤ 0.010 or 0.015 suggests no significant deterioration in model fit, thereby supporting measurement invariance. Sample size has minimal impact on ΔCFI, and whereas ΔRMSEA tends to increase slightly with larger samples, SRMR tests for loadings invariance suggest changes ≤ 0.025 or 0.030. For intercept and residual variances invariance, changes ≤ 0.005 or 0.010 are recommended [46]. According to the review of 126 articles, sample size, number of groups compared and model size do not correlate with the level of achieved invariance [18].

ETHICAL APPROVAL STATEMENT

All study procedures adhered to the Helsinki Declaration and its later amendments. Approval was obtained from Tsinghua University Institutional Review Board [project no: 20190083]. Written informed consents were obtained from schools and students. For students under the age of 18, written consent was provided by their legal guardians.

RESULTS

The following results highlight key findings from the psychometric quality investigation of the PSUS-C (Appendix S1). Results were obtained using the statistical software SPSS 29 and Mplus8.3.

EFA

Based on the consistent structure previously established, the CFA model with six dimensions showed good fit indices: RMSEA = 0.080, CFI = 0.928, TLI = 0.914, SRMR = 0.039. However, there are concerns regarding discriminant validity (see Table 2). Specifically, factor 3 and factor 1 and factor 5 and factor 1 have latent variable correlations above 0.9, corresponding to HTMT values of 0.897 between factor 3 and factor 1, and 0.927 between factor 5 and factor 1. If the issue with discriminant validity arises from cross-loadings, then EFA can be beneficial in understanding this. Alternatively, consolidating into a single construct rather than conducting dimensional analyses could also be considered, depending on the nature of the constructs under study [67]. Using CFA with items grouped into a single dimension did not yield a suitable model fit. Specifically, factor loadings in items 1, 5, 8 and 12 were lower than 0.7. Therefore, considering theoretical advancements, we reconstructed the dimension using EFA.

We conducted principal component factor analysis with Promax rotation. Promax rotation was chosen because it is reasonable to assume that any extracted factors related to smartphone addiction should correlate with each other [68]. Eigenvalues and scree plots were used to determine the number of factors to extract. Bartlett's test of sphericity was significant [$P < 0.001$]. The Kaiser-Meyer-Olkin (KMO) measure was 0.967, and all measures of sampling adequacy (MSA) derived from the anti-image correlation matrix were above 0.5, confirming the presence of common factors in the data and satisfying the prerequisites for exploratory factor analysis.

Principal axis factor analysis yielded two factors with eigenvalues >1. The scree plot and the overall variance indicated that the first factor accounted for the highest variance at 50.357%. The variance explained by additional factors decreased sharply when extracting three, four or five factors, leveling off afterward. The study compared models with three to five factors to determine the optimal number of factors. A four-factor solution was found to align closely with the theoretical framework. Withdrawal and loss of control (7, 13, 8, 14, 22, 15, 11 and 18), negative impact (9, 17, 10 and 3), salience behaviors (16, 20, 12, 19 and 21) and excessive use (2, 1, 5, 6 and 4). The details of items are shown in Table 3.

After identifying and rotating the four factors, the internal reliability was estimated using Cronbach's α, with all factors exceeding 0.8. Each of the five dimensions demonstrated adequate internal consistency.

CFA

The discriminant validity was generally acceptable (see Table 4), with all HTMT values below 0.85 and the lower 90% and upper 95% CI values all below 0.85, except for factor 1 and factor 3, which showed high correlation because of overlapping meanings related to withdrawal and sensitivity to phone updates. Convergent validity was also supported, with AVE values >0.5, composite reliability (ω) values exceeding 0.89 (well above the threshold of 0.7) and all factor loadings above 0.5 (Table 3).

The scale demonstrated good criterion validity (Table 5). As expected, smartphone problematic usage correlates positively with depression ($r = 0.451$), loneliness (8 items, $r = 0.455$), loneliness (6 items, $r = 0.504$), social media use ($r = 0.614$) and phone usage duration ($r = 0.148$); and negatively with life satisfaction ($r = -0.218$) and self-esteem (10 items, $r = -0.416$). All correlations' significance levels (P-values) are <0.001.

Below the diagonal are the correlations controlling for education level, full-time status, age, sex, religious belief, minority status and

TABLE 2 Factor correlations of SAS-C.

	Withdrawal behavior	Salience behavior	Social comfort	Negative impact	App use	App update
Withdrawal behavior	0.920	0.772	0.897	0.726	0.927	0.800
Salience behavior	0.772 (0.767, 0.776)	0.824	0.857	0.776	0.745	0.692
Social comfort	0.901 (0.897, 0.905)	0.859 (0.853, 0.863)	0.750	0.698	0.798	0.871
Negative impact	0.713 (0.708, 0.718)	0.750 (0.744, 0.755)	0.689 (0.682, 0.694)	0.913	0.788	0.575
App use	0.922 (0.918, 0.924)	0.743 (0.736, 0.748)	0.808 (0.802, 0.813)	0.778 (0.771, 0.782)	0.780	0.685
App update	0.800 (0.794, 0.805)	0.692 (0.684, 0.699)	0.879 (0.871, 0.885)	0.573 (0.565, 0.579)	0.710 (0.703, 0.716)	0.707

Note: Below the diagonal are the MLR factor correlations from CFA, with ML bootstrap lower bound of the 90% and upper 95% CI. On the diagonal are Cronbach's α coefficients. Above the diagonal are the HTMT. The same inter-factor correlations were obtained using both ML and MLR.
Abbreviations: App, application; CFA, confirmatory factor analysis; HTMT, heterotrait-monotrait ratio of correlations; MLR, maximum likelihood with robust standard errors; ML, maximum likelihood.

TABLE 3 Description of PSUS-C items and results of EFA and CFA.

	EFA factor loading	Extraction sums	Communalities extraction	CFA factor loading	SMC	ω	AVE	Skewness	Kurtosis
Withdrawal and loss of control		50.357				0.938	0.655		
If my phone is not nearby for a period of time, I often worry about missing something.	0.854		0.652	0.804	0.646			−0.099	−1.030
My phone is an important part of my life, and if I have to use it less, I feel like I'm losing something.	0.815		0.669	0.837	0.701			−0.104	−0.962
I need to open the same mobile app more than three times a day.	0.774		0.486	0.670	0.449			−0.483	−0.655
I feel uneasy if my phone is unresponsive for a period of time, and I subconsciously check if there are any messages.	0.774		0.687	0.854	0.729			−0.066	−1.04
When I have nothing to say to my friends, I open apps on my phone.	0.654		0.537	0.761	0.579			−0.355	−0.936
I feel anxious and irritable when my phone cannot connect to the internet or receive a signal.	0.562		0.604	0.82	0.672			0.117	−0.877
I feel anxious if I cannot use my phone for a period of time.	0.454		0.670	0.884	0.782			0.238	−0.699
I unconsciously open certain mobile apps.	0.373		0.591	0.827	0.684			0.005	−1.042
Negative impact		5.501				0.940	0.798		
I will never give up using my smartphone even when my daily life is already greatly affected by it	0.957		0.848	0.926	0.858			−0.053	−0.739
My academic performance has declined because of using my phone.	0.834		0.773	0.925	0.856			0.128	−0.709
Spending time on my phone lowers my study efficiency.	0.755		0.652	0.816	0.666			−0.214	−0.866
Procrastination caused by using my phone has brought me a lot of trouble.	0.693		0.694	0.902	0.814			0.017	−0.867
Salience behaviors		3.555				0.899	0.642		
I have trouble falling asleep because I check my friends' online status on my phone.	0.784		0.615	0.793	0.629			0.569	−0.182
I always care about updates for the apps on my smartphone and keep them up to date.	0.759		0.557	0.761	0.579			0.549	−0.374
I care about new apps and download them to try them out.	0.720		0.475	0.682	0.465			0.700	0.072
I often have the illusion that my phone has new messages.	0.586		0.614	0.854	0.729			0.41	−0.642
Without my phone, I feel restless.	0.531		0.676	0.899	0.808			0.451	−0.362
Excessive use		2.615				0.893	0.627		
I feel the need to spend more time on my phone to feel satisfied.	0.745		0.693	0.83	0.689			0.536	−0.034
Friends often say I spend too much time on my phone.	0.691		0.592	0.764	0.584			0.254	−0.550
I prefer chatting on my phone and am reluctant to communicate face-to-face.	0.462		0.447	0.74	0.548			0.487	−0.439

(Continues)

TABLE 3 (Continued)

	EFA factor loading	Extraction sums	Communalities extraction	CFA factor loading	SMC	ω	AVE	Skewness	Kurtosis
When I'm feeling sad, the first thing I think of is using my phone.	0.451		0.520	0.796	0.634			0.397	−0.680
Friends and family complain that I use my smartphone too much.	0.437		0.593	0.824	0.679			−0.019	−0.999

Abbreviations: apps, applications; AVE, amount of variance; CFA, confirmatory factor analysis; EFA, exploratory factor analysis; PSUS-C, Problematic Smartphone Use Scale among Chinese college students; SMC, squared multiple correlations.

TABLE 4 Factor correlations of PSUS-C.

	Withdrawal and loss of control	Negative impact	Salience behaviors	Excessive use
Withdrawal and loss of control	0.918	0.760	0.850	0.824
Negative impact	0.739 (0.733, 0.743)	0.913	0.653	0.769
Salience behaviors	0.879 (0.876, 0.881)	0.655 (0.649, 0.660)	0.865	0.806
Excessive use	0.817 (0.813, 0.821)	0.749 (0.743, 0.753)	0.808 (0.803, 0.812)	0.851

Note: Below the diagonal are the MLR factor correlations from CFA, with ML bootstrap lower bound of the 90% and upper 95% CI. On the diagonal are Cronbach's α coefficients. Above the diagonal are the HTMT. The same inter-factor correlations were obtained using both ML and MLR.
Abbreviations: CFA, confirmatory factor analysis; HTMT, heterotrait-monotrait ratio of correlations; MLR, maximum likelihood with robust standard errors; ML, maximum likelihood; PSUS-C, Problematic Smartphone Use Scale among Chinese college students.

TABLE 5 Criterion validity and zero-order correlations between variables.

	SWL	CES-D	RSES-10	LL-8	LL-6	SMA	Phone usage duration	PSUS
SWL	0.858	−0.355***	0.375***	−0.318***	−0.309***	−0.114***	−0.056***	−0.212***
CES-D	−0.357***	0.861	−0.603***	0.638***	0.620***	0.413***	0.100***	0.450***
RSES-10	0.371***	−0.603***	0.849	−0.563***	−0.510***	−0.301***	−0.066***	−0.413***
LL-8	−0.318***	0.638***	−0.563***	0.811	0.929***	0.368***	0.055***	0.454***
LL-6	−0.311***	0.621***	−0.512***	0.930***	0.895	0.398***	0.061***	0.505***
SMA	−0.129***	0.418***	−0.313***	0.370***	0.398***	0.965	0.205***	0.615***
Phone usage duration	−0.060***	0.100***	−0.066***	0.060***	0.064***	0.212***	NA	0.146***
PSUS	−0.218***	0.451***	−0.416***	0.455***	0.504***	0.614***	0.148***	0.955

Abbreviations: CES-D, Epidemiological Studies Depression Scale; LL-6, Loneliness Scale with 6 items; LL-8, Loneliness Scale with 8 items; NA, not applicable; PSUS, Problematic Smartphone Use Scale; RSES-10, Rosenberg Self-Esteem Scale with 10 items; SMA, Social Media Addiction scale; SWL, Satisfaction with Life Scale.
***$P < 0.001$.

place of residence. Above the diagonal are the zero-order correlations. On the diagonal are the Cronbach's α values for each scale. Because smartphone usage time is a single self-reported item, it does not have Cronbach's α.

MEASUREMENT INVARIANCE

Strict invariance and structural invariance were demonstrated across sex (Table 6), type of university (Table 7) and place of residence (Table 8). Most of the ΔRMSEA <0.005, ΔCFI <0.005 and ΔTLI <0.005, with no indicator differing by more than 0.010.

DISCUSSION

This study aims to examine the SAS-C, which is widely used in China. Although the theoretical dimensions of the original scale demonstrated good model fit, discriminant validity showed overlap between different dimensions. This aligns with our expectations, as the original scale expanded the dimensions within the addiction framework by adding app usage and updates to Young's IAT. Because apps are integral to smartphones, withdrawal behaviors and the concept of app usage disorder naturally overlap.

We used EFA to explore feasible structures and CFA to validate the structural validity of this tool. Four dimensions were identified:

TABLE 6 Measurement invariance of PSUS-C across different sexes.

Model	χ^2	d.f.	Scaling correction factor	RMSEA	CFI	TLI	SRMR	ΔRMSEA	ΔCFI	ΔTLI	ΔSRMR
Full model	103 213.618	203	1.530	0.062	0.919	0.908	0.043				
Female	30 524.948	203	1.715	0.061	0.923	0.912	0.042		–		
Male	72 709.31	203	1.447	0.063	0.923	0.906	0.044		–		
Configural invariance	99 653.592	406	1.581	0.061	0.919	0.908	0.043		–		
Metric invariance	101 994.241	424	1.550	0.061	0.917	0.910	0.044	<0.001	−0.002	0.002	0.001
Scalar invariance	105 997.907	442	1.528	0.061	0.914	0.910	0.044	<0.001	−0.003	<0.001	<0.001
Residual invariance	105 819.908	464	1.683	0.059	0.914	0.914	0.045	−0.002	<0.001	0.004	0.001
Latent factor variance invariance	107 128.387	468	1.540	0.059	0.913	0.914	0.059	<0.001	−0.001	<0.001	0.014
Latent factor covariance invariance	107 115.94	474	1.542	0.059	0.913	0.915	0.058	<0.001	<0.001	0.001	−0.001

Abbreviations: CFI, comparative fit index; PSUS-C, Problematic Smartphone Use Scale among Chinese college students; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker–Lewis index.

TABLE 7 Measurement invariance of PSUS-C across different types of university.

Model	χ^2	d.f.	Scaling correction factor	RMSEA	CFI	TLI	SRMR	ΔRMSEA	ΔCFI	ΔTLI	ΔSRMR
Vocational	55 735.772	203	1.578	0.061	0.923	0.912	0.042		–		
College	48 322.645	203	1.471	0.064	0.914	0.902	0.045		–		
Configural invariance	104 317.081	406	1.524	0.063	0.919	0.908	0.044		–		
Metric invariance	106 656.102	424	1.497	0.062	0.917	0.910	0.044	−0.001	−0.002	0.002	<0.001
Scalar invariance	112 966.263	442	1.476	0.063	0.912	0.908	0.045	0.001	−0.005	−0.002	0.001
Residual invariance	116 640.822	464	1.490	0.062	0.909	0.910	0.048	−0.001	−0.003	0.002	0.003
Latent factor variance invariance	117 130.072	468	1.484	0.062	0.909	0.910	0.048	<0.001	<0.001	<0.001	<0.001
Latent factor covariance invariance	117 658.398	474	1.485	0.062	0.909	0.911	0.050	<0.001	<0.001	0.001	0.002

Abbreviations: CFI, comparative fit index; PSUS-C, Problematic Smartphone Use Scale among Chinese college students; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker–Lewis index.

withdrawal and loss of control, negative impact, salience behavior and excessive use. Even now, research often follows the addiction framework to study the effect of the smartphone [69–72]. Therefore, we have adopted some dimensions from the previous addiction/nomophobia framework for consistency with past methods. To avoid the debate over the feasibility of the smartphone addiction framework, we used the term 'problematic use,' which allows for examining the disorder of excessive smartphone use from a more general perspective.

The model demonstrated good performance in terms of factor structure, internal consistency, construct validity and criterion validity. Notably, factor 1 and factor 3 showed high correlations because of the overlapping meanings of withdrawal and loss of control and salience behavior. We believe this overlap is likely unavoidable. Panova and Carbonell [14] cited Sánchez-Carbonell *et al.* [73], stating that 'Loss of control is, besides craving and salience, a component of psychological dependence.'

Panova and Carbonell [14] suggested that using smartphones as the focus of problematic use might lead to confusion between smartphone addiction and other types of addiction. Smartphones are a platform for social network sites and instant messaging [74]. Therefore, we emphasized the smartphone in each item, including the device's status (network, signal and updates) and phone behaviors (turning on the phone, having the phone nearby and phone chatting). These questions help users focus on their smartphone use.

According to the internet gaming disorder proposed criteria in the Diagnostic and Statistical Manual of Mental Disorders fifth edition (DSM-5) [75], there are nine criteria [76]. Our scale covers eight of these criteria, excluding deception. This exclusion might not be an issue because for college students, smartphones have become an

TABLE 8 Measurement invariance of PSUS-C across different residency cities.

Model	χ^2	d.f.	Scaling correction factor	RMSEA	CFI	TLI	SRMR	ΔRMSEA	ΔCFI	ΔTLI	ΔSRMR
City	32 711.076	203	1.559	0.064	0.916	0.904	0.044				
County	36 042.837	203	1.508	0.063	0.917	0.905	0.045		–		
Rural	35 368.141	203	1.514	0.061	0.923	0.913	0.042		–		
Configural invariance	104 057.726	609	1.527	0.063	0.919	0.908	0.044		–		
Metric invariance	106 729.996	645	1.490	0.062	0.917	0.911	0.044	−0.001	−0.002	0.003	<0.001
Scalar invariance	109 597.858	681	1.464	0.061	0.914	0.913	0.044	−0.001	−0.003	0.002	<0.001
Residual invariance	110 609.822	725	1.482	0.059	0.914	0.918	0.046	−0.002	<0.001	0.005	0.002
Latent factor variance invariance	111 483.722	733	1.475	0.059	0.913	0.918	0.052	<0.001	−0.001	<0.001	0.006
Latent factor covariance invariance	111 652.834	745	1.476	0.059	0.913	0.919	0.051	<0.001	0.000	0.001	−0.001

Abbreviations: CFI, comparative fit index; PSUS-C, Problematic Smartphone Use Scale among Chinese college students; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; TLI, Tucker–Lewis index.

integral part of daily life [39], making it nearly impossible to conceal the amount of time spent on phones from family members, therapists or others. It should be noted that the benefits of formally including internet gaming disorder in the DSM-5 are still debated [77, 78].

By conducting a series of measurement invariance tests, we can ensure that the scale is applicable to the university student population, demonstrating that the constructs have the same meaning and that the relationships between dimensions are consistent across sex, type of university and place of residence. This means that using this scale to measure differences in problematic smartphone use among groups reduces measurement bias. There are 3013 higher education institutions in China, and this survey included more than one-third of them. China has 46.55 million higher education students [79], accounting for 22.26% of the world's total [80]. Our revisions have effectively addressed the measurement issues associated with such a large population.

Finally, considering the artificial intelligence [AI] and human-computer interaction theories [81–83] the problematic use of smartphones is shifting from a human-machine relationship issue to an interpersonal issue. As smartphones become integral to daily life [39], failing to manage our relationship with them correctly may lead to antisocial behaviors [72]. We believe that emphasizing the problematic use of smartphones is crucial.

LIMITATIONS

This study has several limitations that need to be acknowledged. First, although the scale demonstrated good invariance within China, cross-national issues have not been addressed [84]. Second, although the sample comes from a nationwide survey, the sampling at each site is still convenience sampling. Finally, as this research is based on a nationwide survey, we did not conduct a retest to examine the test–retest reliability and assess temporal stability.

CONCLUSION

This study is the first to examine the SAS-C for Chinese college students in the context of China and adapt it into the PSUS-C. We used comprehensive methods to test the validity and reliability using cross-sectional data and conducted measurement invariance tests based on a national sample. Our results provide robust evidence for the validity of the PSUS-C. The PSUS-C has the potential to assess problematic smartphone use among Chinese university students. Through this work, we aim to provide a conceptualization based on a Chinese contextual sample to contribute to the trend of de-pathologizing smartphone addiction. We hope to provide a useful tool for practitioners across various disciplines to study problematic smartphone use among Chinese university students.

AUTHOR CONTRIBUTION

Kun Tang is responsible for conceptualization, data curation, project administration, resources, supervision, validation and writing—review and editing. Haocan Sun is responsible for conceptualization, data curation, formal analysis, methodology, visualization and writing—original draft and review and editing.

ACKNOWLEDGEMENTS

We thank the management team and the volunteers from CYN and all participants for their invaluable contributions to this study.

DECLARATION OF INTERESTS

None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Sun H, Tang K. Psychometric evaluation and measurement invariance of the problematic smartphone use scale among college students: A national survey of 130 145 participants. Addiction. 2024. https://doi.org/10.1111/add.16699