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FULL-LENGTH REPORT

From everyday life to measurable problematic smartphone use: The development and validation of the Smartphone Use Problems Identification Questionnaire (SUPIQ)

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ABSTRACT

Background and aims: Problematic smartphone use (PSU) has gained attention, but its definition remains debated. This study aimed to develop and validate a new scale measuring PSU-the Smartphone Use Problems Identification Questionnaire (SUPIQ). *Methods:* Using two separate samples, a university community sample ($N = 292$) and a general population sample ($N = 397$), we investigated: (1) the construct validity of the SUPIQ through exploratory and confirmatory factor analyses; (2) the convergent validity of the SUPIQ with correlation analyses and the visualized partial correlation network analyses; (3) the psychometric equivalence of the SUPIQ across two samples through multi-group confirmatory factor analyses; (4) the explanatory power of the SUPIQ over the Short Version of Smartphone Addiction Scale (SAS-SV) with hierarchical multiple regressions. *Results:* The results showed that the SUPIQ included 26 items and 7 factors (i.e., Craving, Coping, Habitual Use, Social Conflicts, Risky Use, Withdrawal, and Tolerance), with good construct and convergent validity. The configural measurement invariance across samples was established. The SUPIQ also explained more variances in mental health problems than the SAS-SV. *Discussion and conclusions:* The findings suggest that the SUPIQ shows promise as a tool for assessing PSU. Further research is needed to enhance and refine the SUPIQ as well as to investigate its clinical utility.

KEYWORDS

problematic smartphone use, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), partial correlation network analysis, SUPIQ

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INTRODUCTION

The global smartphone user population has nearly doubled in 7 years, reaching an estimated 6,841 million in 2023 (O'Dea, 2023), raising concerns about the potential health, social, and economic impacts of excessive smartphone use (Elhai, Levine, Dvorak, & Hall, 2017; Jannusch, Shannon, Völler, Murphy, & Mullins, 2021; Olson et al., 2022). "Problematic smartphone use (PSU)" describes the persistent and excessive smartphone use patterns related to daily-life malfunctioning (e.g., Elhai & Contractor, 2018; Kardefelt-Winther et al., 2017).

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PSU shares features with addictive disorders (Haug et al., 2015; Lin et al., 2014), but the concept of "smartphone addiction" remains debated (e.g., Horvath et al., 2020; Larsen, Wiers, Su, & Cousijn, 2023). This study aimed to develop and validate a new PSU questionnaire.

PSU is typically assessed with various scales, including the Mobile Phone Problem Use Scale (MPPUS; Bianchi & Phillips, 2005), the Problematic Mobile Phone Use Questionnaire (PMPUQ; Billieux, der Linden, & Rochat, 2008), the Smartphone Addiction Scale (SAS; Kwon, Lee, et al., 2013), the Short Version of Smartphone Addiction Scale (SAS-SV; Kwon, Kim, Cho, & Yang, 2013), the Smartphone Addiction Inventory (SPAI; Lin et al., 2014) and the Short-Form of Smartphone Addiction Inventory (SPAI-SF; Lin, Pan, Lin, & Chen, 2017), which measure factors like tolerance, withdrawal, overuse, loss of control and dangerous/prohibited use. While cross-cultural validation studies have shown satisfactory psychometric properties for these scales (e.g., Agus, Mascia, Bonfiglio, & Penna, 2022; Andrade et al., 2022; Khoury et al., 2017; Lopez-Fernandez, Honrubia-Serrano, Freixa-Blanxart, & Gibson, 2014, 2018; Sfendla et al., 2018; Wang, Long, Liu, Liu, & Billieux, 2020; Zhao, Rafik-Galea, Fitriana, & Song, 2022), we would argue that there is room for improvement.

While previous scales were developed based on existing "addiction" criteria (see Supplementary Table S1), they may not fully capture the current problems people face in relation to PSU (see a review, Nawaz, 2023), particularly issues specific to smartphone use like distracted driving and impaired productivity (e.g., D. Ding & Li, 2017; Fitch, Hanowski, & Guo, 2015; Jannusch et al., 2021; Oviedo-Trespalacios, Haque, King, & Washington, 2016). They also may not address general addiction-like features like compromised relationships and cognitive impairments (e.g., D. Ding & Li, 2017; Gutiérrez, de Fonseca, & Rubio, 2016; Wilmer, Sherman, & Chein, 2017). Therefore, PSU measurement should consider the everyday smartphone use experiences to avoid over-pathologizing normal behaviors.

To optimize PSU assessment, person-centered and process-based qualitative research can provide valuable insights into individuals experiencing functional impairment and emotional distress due to smartphone use (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015; Billieux, Philippot, et al., 2015; Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015; Flayelle, Schimmenti, Starcevic, & Billieux, 2022; Kardefelt-Winther et al., 2017). However, few in-depth qualitative studies (see Supplementary Table S1) have been conducted to identify PSU assessment themes (e.g., Yildirim & Correia, 2015). Instead, several studies used relatively informal interviews to generate scale items, without formal coding and analyses (e.g., Cho & Lee, 2015; J. E. Ding et al., 2019; Lee et al., 2017; Merlo, Stone, & Bibbey, 2013). A thorough qualitative approach with deductive and inductive thematic analyses can offer a richer understanding of PSU-related experiences in everyday life, leading to more accurate and valid measurements.

In this study, we have developed the Smartphone Use Problems Identification Questionnaire (SUPIQ) based on an in-depth semi-structured interview protocol (Su et al., 2023) that incorporated DSM-5 (American Psychiatric Association, 2013a) and ICD-11 (World Health Organization, 2019) "addiction" criteria, existing PSU scales (e.g., SAS, Kwon, Lee, et al., 2013; SPAI, Lin et al., 2014) and the recent research (e.g., D. Ding & Li, 2017; Fitch et al., 2015; Gutiérrez et al., 2016; Jannusch et al., 2021; Oviedo-Trespalacios et al., 2016; Wilmer et al., 2017). Our primary aim is to assess the SUPIQ's reliability and validity in measuring PSU, beginning with examining its construct validity. We will also evaluate its convergent validity by exploring the associations between SUPIQ scores and mental health problems. High levels of PSU have been related to higher levels of mental health and cognitive problems like depression and anxiety (e.g., Elhai et al., 2017, 2020; Jin et al., 2021; Kim et al., 2019), personality disorders (e.g., Pearson & Hussain, 2016), sleep problems (e.g., Cheung et al., 2019; S. Y. Sohn, Krasnoff, Rees, Kalk, & Carter, 2021), somatic symptoms (e.g., Winkler, Jeromin, Doering, & Barke, 2020), suicidal ideation (e.g., Arrivillaga, Rey, & Extremera, 2020), memory problems (e.g., Madore et al., 2020), and repetitive thoughts and behaviors (e.g., Brailovskaia, Stirnberg, Rozgonjuk, Margraf, & Elhai, 2021). To assess convergent validity, we also include the Short Version of Smartphone Addiction Scale (SAS-SV; Kwon, Kim, et al., 2013), frequently used to assess PSU (e.g., Khalily, Saleem, Bhatti, Ahmad, & Hussain, 2019; Kwon, Kim, et al., 2013; Kwon, Lee, et al., 2013; Luk et al., 2018; Zhao et al., 2022).

Besides mental health problems, we will explore how smartphone use frequency and duration relate to PSU (Harris, Regan, Schueler, & Fields, 2020; James, Dixon, Dragomir, Thirlwell, & Hitcham, 2023; Parry et al., 2021), akin to other addictive behaviors like alcohol use (AUDIT; Mattiko, Olmsted, Brown, & Bray, 2011; Saunders, Aasland, Babor, De La Fuente, & Grant, 1993) and problematic social media use (Social Media Disorder Scale; Van Den Eijnden, Lemmens, & Valkenburg, 2016). To assess the relationships, we will differentiate between screen time and unlock frequency (Ryding & Kuss, 2020), social versus nonsocial screen time (Elhai et al., 2017, 2020), active (i.e., actively interacting with others via social media on smartphone) versus passive (i.e., passively scrolling and checking via social media on smartphone) social media use (Su, Larsen, Cousijn, Wiers, & Van DenEijnden, 2022). Partial correlations between the SUPIQ factors, smartphone use statistics, and mental health problems will be tested and visualized with network analysis to further show the convergent validity. Additionally, we will compare the SUPIQ with the SAS-SV to assess its explanatory power in hierarchical multiple regression models (Kwon, Kim, et al., 2013; Olson et al., 2022). While prior PSU scale studies have primarily focused on student and adolescent populations (e.g., Andrade et al., 2022; Cheung et al., 2019; Khoury et al., 2017; Leung, 2008; Lin et al., 2014; Lopez-Fernandez et al., 2014; Pavia, Cavani, Di Blasi, & Giordano, 2016; Walsh, White, & McDYoung, 2010; Wang et al., 2020; see Supplementary Table S1), leaving the applicability of these scales to the general population largely unexplored

(Busch, Hausvik, Ropstad, & Pettersen, 2021; Rosales & Fernández-Ardèvol, 2019). We will extend its applicability using two separate samples: one from the university community and a general population sample.

In summary, we aimed to develop a comprehensive and widely applicable PSU assessment tool, conducting an exploratory factor analysis (EFA), a confirmatory factor analysis (CFA), correlation analyses, and partial correlation network analyses, examining measurement invariance, and assessing explanatory power with hierarchical multiple regression models in two diverse samples.

METHODS

Participants and procedures

The study involved two samples: Sample 1 (university community sample) was comprised of 323 participants (Mean age = 20.81, SD = 4.34, the range = 18–66 years; 72.76% females), recruited through the university's internal study platform, primarily composed of university students. However, note that other volunteers could also sign up through the University's recruitment platform, therefore it is not exclusively a student sample. Sample 2 (the general population sample) included 618 participants (Mean age = 28.47, SD = 7.39, the range is 18–75 years, 43.85% females), recruited on social media including LinkedIn, X (Twitter), and Facebook as well as through posters. The survey was administered online using Qualtrics XM software (Qualtrics, 2021). The general population sample had a 1 in 20 chance of winning a 20-euro gift card by providing their email, while the university community sample could earn 0.50 psychology research credits in addition to the lottery. Data collection took place from March 20 to April 12 spanned 3.5 weeks period in 2021. The survey, mainly conducted in the Netherlands, used English as the primary language. Participants confirmed their English proficiency in the consent form. Table 1 displays participants' country of residence and nationality distribution.

Measures

The quality control questions. To ensure the quality of online responses, three quality control measures were implemented (DeSimone, Harms, & DeSimone, 2015): (1) participants were instructed to select "always" from the response options "never" to "always" for the indication question; (2) they were supposed to select "false" for the statement of "I have never used a smartphone" in the bogus question; (3) participants rated their survey effort and attention on a scale of 0–100 at the survey's end.

The Smartphone Use Problems Identification Questionnaire (SUPIQ). The initial items of the first version of the Smartphone Use Problems Identification Questionnaire (SUPIQ) were developed from a separated qualitative study among 28 university students with smartphone use problems (Su et al., 2023). The inclusion criteria for participant recruitment were university students between 18 and 25 years old, possessed at least one European nationality, and scored above 31 (males) or 33 (females) on the Short Version of the Smartphone Addiction Scale (SAS-SV; Kwon, Kim, et al., 2013). These cut-off scores were determined based on the established thresholds for identifying PSU. The ultimate qualitative sample, consisting of 28 participants (24 males, 26 Bachelor students, 2 Master students), demonstrated an average SAS-SV score of 46.82 (SD = 3.22). The participants, with an average of 7.39 years of smartphone usage (SD = 1.47), originated from 17 distinct European countries, with six individuals holding dual nationality. The first author conducted interviews, recording, transcriptions, and coding, with the results discussed among the research team. Based on the qualitative results, the first author drafted a preliminary questionnaire comprising 126 items. This draft was then thoroughly deliberated upon with the entire research team. Based on the discussions, the initial version of SUPIQ contained 57 items (see Supplementary Table S2), including 2 negatively worded items. The SUPIQ aimed to capture 8 theory-derived factors related to PSU according to DSM-5 (American Psychiatric Association, 2013a) and ICD-11 (World Health Organization, 2019): (1) Impaired Control, (2) Preoccupation, (3) Craving, (4) Escapism/Relief/Coping, (5) Negative effects/Consequences/Risks, (6) Ignorance of Negative Effects/Consequences/Risks, (7) Tolerance, and (8) Withdrawal. Participants rated their smartphone use during the past 12 months, using a 5-point Likert scale (1 = never to 5 = always).

Mental health problems: DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure-adult. The DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure was used to assess participants' mental health problems over the past 12 months instead of the original 2-week version (American Psychiatric Association, 2013b). It consists of 20 questions on a 5-point Likert scale (0 = Never to 4 = Always) measuring depression, anxiety, personality functioning, sleep, somatic symptoms, suicidal ideation, memory, repetitive thoughts and behaviors, mania, psychosis, and dissociation. The total score ranges from 0 to 80, with higher scores indicating more mental health problems. See Table 4 for means, standard deviations, and internal consistencies including Cronbach's α and McDonald's ω values of the DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure.

Smartphone use statistics

The amount of smartphone use. Participants reported total screen time, social screen time, and unlock frequency in the past 7 days using the Digital Wellbeing (Android) or Screen Time (iPhone) application on their smartphones. If participants were unable to access the data directly on their phones, they were asked to estimate these indicators to the best of their ability.

Active and passive social media use frequency on smartphone. Participants were asked to estimate the frequency of their past 7-day social media use with 6 questions. Active social media use involved active interactions with others by sending, posting, liking, and commenting on the social media apps (e.g., Estimate how many times in 7 days you send a text, message, photo or video via the social media apps (e.g., Instagram, Facebook, iMessage, TikTok, WhatsApp, LinkedIn, etc.) on your smartphone?). Passive social media use included passive scrolling behaviors like reading and browsing on these social media apps (e.g., Estimate how many times in 7 days you read messages, photos or videos from others via the social media apps (e.g., Instagram, Facebook, TikTok, WhatsApp, LinkedIn, etc.) on your smartphone?).

App usage. Participants reported the three most frequently used social media apps and three most frequently used apps after they pick up their smartphones.

The short version of smartphone addiction scale (SAS-SV). The short version of smartphone addiction scale (SAS-SV) was developed by Kwon, Kim, and colleagues (2013), which includes 10 items and measures problematic smartphone use (Khalily et al., 2019; Kwon, Kim, et al., 2013; Kwon, Lee, et al., 2013; Luk et al., 2018; Zhao et al., 2022). Participants were asked to rate their smartphone use in the past 12 months from 1 (strongly disagree) to 6 (strongly agree), on questions like: "I use my smartphone longer than I have intended". The means, standard deviations, and internal consistencies including Cronbach's α and McDonald's ω values of the SAS-SV were presented in Table 4.

Statistical analysis

The case-selection procedure with the Quality Control Questions and the descriptive analyses on demographic information of the two samples were performed with R (version 4.2.2; R Core Team, 2022) and RStudio (Allaire, 2022), using "janitor" (Mansley, 2021), "dplyr" (Wickham, François, & Henry, 2020), "plyr" (Wickham & Wickham, 2020), "sjmisc" (Lüdecke, 2021a), and "sjPlot" (Lüdecke, 2021b) packages. The factor analyses were conducted using Mplus 8.3 (Muthén & Muthén, 2017) and the package "MplusAutomation" (Hallquist & Wiley, 2018).

To ensure data quality in both samples, participants were excluded if they spent less than 2 s per item, reported less than 50% effort/attention, or answered quality control questions incorrectly (DeSimone et al., 2015, see more detailed explanations in Measures) were excluded from analysis. To ensure the comparability of our previous study, participants from the university community were selected based on criteria (i.e., aged 18–24 years and had completed upper secondary or bachelor's level education) in the qualitative study (Su et al., 2023).

Construct validity of the SUPIQ: exploratory factor analysis (EFA). To examine the SUPIQ's factor structure, we conducted an EFA. Since the SUPIQ questionnaire uses 5-point Likert scales and the data deviated from the normal distribution, we employed weighted least squares estimation, accounting for the categorical and nonnormal data nature (DiStefano & Morgan, 2014; Holgado-Tello et al., 2010; Rhemtulla, Brosseau-Liard, & Savalei, 2012; Wu & Leung, 2017). To determine the number of factors underlying the data, we fitted a series of models that varied in the number of factors (starting with a one-factor model) model-based approach in which we fit a series of models that increase in their number of factors, but in which all items are allowed to load on all factors. This model-based approach is the default method in Mplus 8.3 (Muthén & Muthén, 2017). Such an approach is grounded in the benefits of a model-based strategy, which relies on an explicit statistical model instead of principal axis factoring (Brown, 2015). This approach enables a more comprehensive and objective selection of the best fitting model with diverse model fit indices: the root-mean-square-error of approximation (RMSEA), the standardized root mean square residual (SRMR), the comparative fit index (CFI), and the Tucker–Lewis index (TLI). Generally, good model fit is indicated by RMSEA <0.05, SRMR <0.08, and CFI/TLI >0.95, while acceptable fit is indicated by RMSEA <0.08, and CFI/TLI >0.90 (see Brown, 2015; Goulter et al., 2022; Little, 2013). Within the best fitting model, we retained items based on criteria: 1) no cross-factor loadings (i.e., with two factors' loadings >0.30; 2) factor loading >0.50 and <1 (William Jr, 2013); 3) alignment with the SUPIQ's intended factors according to our theoretical framework.

Construct validity of the SUPIQ and the SAS-SV: confirmatory Factor Analysis (CFA). To investigate whether the SUPIQ factor structure found using EFA replicated in the general population sample, we used CFA with weighted least squares estimation. For the factor structure (as established in the university sample) to be replicable, the fit of the CFA model should at least be acceptable in the general population sample. In addition, we have also used CFA to test the construct validity of the SAS-SV, with residual covariances added among items 1 to 3 and items 4 to 7 since they belonged to one factor in the original version of SAS-SV (Kwon, Kim, et al., 2013; Kwon, Lee, et al., 2013; Luk et al., 2018). To assess the fit of the confirmatory model, we relied on the same model fit statistics discussed above.

Psychometric equivalence analyses of the SUPIQ: measurement invariance test. To examine whether the SUPIQ factor structure remained invariant across the university community and the general population samples, we conducted multigroup confirmatory factor analyses (MG-CFA): Three models were employed: 1) a configural model (Model 1), fitting the same factor model to the two samples with all factor model parameters freely estimated; 2) a metric measurement invariance model (Model 2), restricting item loadings to be equal across the samples while allowing differences in the factor variances; 3) a scalar measurement invariance model (Model 3), with equal factor loadings and equal item threshold parameters while allowing differences in the factor means and variances. A decrease in CFI by more than 0.01 or an increase in RMSEA by more than 0.015 indicates that measurement invariance is not established (Chen, 2007).

The analyses on descriptive statistics, reliability, and convergent validity. The descriptive statistics were done after the final version of SUPIQ was determined. For the reliability test of the SUPIQ, both Cronbach's α and McDonald's ω values were reported since they represent mean test level and general factor saturation separately (Revelle & Condon, 2019). For the convergent validity analyses, the linear correlations and partial correlation network analyses were used. The linear correlations between the SUPIQ, the SAS-SV, mental health problems, and smartphone use statistics were calculated. The SUPIQ total score was included in the analyses to provide a comprehensive assessment of the construct, enhancing understanding of participants' responses across all measured factors. Unreasonable smartphone use statistics, such as minutes exceeding 59 (as participants reported hours and minutes separately), reported screen time of 0, or nonsocial screen time less than 0, were treated as missing values and the missing values were dealt with pairwise deletion method. Partial correlation network analyses among the sum scores of different factors of the SUPIQ, mental health problems, and smartphone use statistics were performed using the packages "bootnet" (Epskamp & Fried, 2015, 2020), "qgraph" (Epskamp, Epskamp, & Rcpp, 2020) packages. We mainly focused on visualizing network results, where nodes represented the variables including mental health problems, the smartphone use statistics, and the SUPIQ factors. Edges depicted the connections between variables, with edge thickness and color saturation indicating association strength (Monteleone et al., 2022). With dealing with the missing values of the smartphone use statistics with pairwise deletion method, partial correlation networks were separately computed for the two samples (Borsboom et al., 2021; Epskamp & Fried, 2018). The stability of the edges in two networks was tested with bootstrapping (nboots = 2000). We used the "EBICglasso" algorithm, which implements the least absolute shrinkage and selection operator (LASSO) regularization method to shrink estimates and remove false positive edges. A hyperparameter of 0.5 was used to remove nonsignificant edges from the network.

The explanatory power of the SUPIQ: hierarchical multiple regression. The multivariate stepwise regression analyses used the sum score of mental health problems as the outcome variable. The first step included the SAS-SV as a predicting variable. In the second step, the SUPIQ was added to assess its additional explanatory power compared to the SAS-SV. The hierarchical multiple regression analyses were done separately in the two samples. The standardized coefficients were estimated with package "lm. beta" (Behrendt, 2022). In addition, the relative importance of the SAS-SV and the SUPIQ were compared with package "relaimpo" (Groemping, 2021).

Ethics

Participants received an information letter before starting the questionnaire and the study protocol was approved by the Ethical Review Board (ERB ID # 2021-DP-13072).

RESULTS

Demographic information for the final samples

The data screening process is shown in Supplementary Fig. S3: the final university community sample consisted of 292 participants, and the final general population sample consisted of 397 participants. Demographic information for the two samples is shown in Table 1.

The construct validity results: exploratory factor analysis (EFA) for the SUPIQ

Based on the results of the EFA with the university community sample, we reached 24 items in a 7-factor version of the SUPIQ (see Supplementary Table S4). We restored 3 items since there were only two items for 3 of the 7 factors (i.e., craving, coping, and tolerance, see Supplementary Table S5). Item 26 was removed since the removal increased the Cronbach's α values of the corresponding subscale by 0.10 (see Supplementary Tables S6 and S7; Cronbach's alpha of the full questionnaire increased by 0.01). The final version of the SUPIQ includes 26 items with 7 factors (see Table 2). The 7 factors can be described as follows: Craving, Coping, Habitual Use, Social Conflicts, Risky Use, Withdrawal, Tolerance. The model fit indices showed a good fit: CFI = 0.993, TLI = 0.986, RMSEA = 0.030, SRMR = 0.031. The network analysis also showed the 7-factor structure well fitted the data (see Supplementary Fig. S10), the centrality indices (e.g., closeness, strength, betweenness) of the network were shown in Supplementary Figs S11 and S12.

The construct validity results: confirmatory factor analysis (CFA) for the SUPIQ and the SAS-SV

Results of the CFA (CFI = 0.970, TLI = 0.965, RMSEA = 0.072, SRMR = 0.047) for the SUPIQ indicated that there is a residual covariance between item 1 (i.e., I think about my smartphone when I am not using it.) and item 15 (i.e., I continue using my smartphone after others ask me not to.) of the SUPIQ. After adding this covariance, the model fit indices of the CFA in the general population sample indicated an acceptable to good model fit (CFI = 0.971, TLI = 0.966, RMSEA = 0.070, SRMR = 0.047). The standardized factors loadings and correlations between factors of the SUPIQ based on the CFA were presented in Supplementary Tables S13 and S14.

Results of the CFA of the SAS-SV in the two samples were as follows: CFI = 0.959, TLI = 0.932, RMSEA = 0.064, SRMR = 0.043 in the university community sample; CFI = 0.949, TLI = 0.915, RMSEA = 0.097, SRMR = 0.040 in the general population sample.

Psychometric equivalence of SUPIQ: measurement invariance test results

See Table 3 for the results concerning the measurement invariance analyses. The SUPIQ demonstrated configural

Table 1. The demographic information of the university community sample ($N = 292$) and the general population sample ($N = 397$), including the Number (n), Range, Means (M) and Standard Deviations (SD)

	University community sample				General population sample		
	n (%)	Range	*M* (*SD*)		*n* (%)	Range	*M* (*SD*)
Age		18–24	20 (1.48)			18–75	28.02 (7.66)
The onset age when starting to use smartphone		6–18	12.37 (1.73)			4–71	17.50 (7.44)
The years for smartphone use		3–13	7.64 (1.70)			3–33	10.49 (3.98)
Gender*							
Male	70 (23.97)				193 (48.61)		
Female	217 (74.32)				203 (51.13)		
Other	5 (1.71)				1 (0.25)		
Highest level of education							
Primary education	–				2 (0.50)		
Lower secondary education	–				3 (0.76)		
Upper secondary education	249 (85.28)				77 (19.40)		
Post-secondary non-tertiary education	12 (4.11)				19 (4.79)		
Short-cycle tertiary education	6 (2.05)				65 (16.37)		
Bachelor’s or equivalent level	25 (8.56)				156 (39.29)		
Master’s or equivalent level	–				64 (16.12)		
Doctoral or equivalent level	–				11 (2.77)		
The marital status							
Married	2 (0.68)				109 (27.46)		
Engaged	1 (0.34)				18 (4.53)		
Living together	14 (4.79)				45 (11.349)		
In a relationship/having a boyfriend/girlfriend	90 (30.82)				96 (24.18)		
Registered partnership	–				3 (0.76)		
Divorced	–				6 (1.51)		
Separated	–				5 (1.26)		
Single	185 (63.36)				115 (28.97)		
Country currently live in							
Netherlands	214 (73.29)			United States of America	289 (72.80)		
Germany	27 (9.25)			Netherlands	43 (10.83)		
Poland	4 (1.37)			Canada	20 (5.04)		
Other countries	47 (16.09)			Germany	12 (3.02)		
				Other countries	33 (8.31)		
Nationality							
Dutch	100 (34.25)			American	302 (76.07)		
German	73 (25.00)			English	32 (8.06)		
English	15 (5.14)			German	19 (4.79)		
American	12 (4.11)			Dutch	16 (4.03)		
Italian	11 (3.77)			Canadian	14 (3.53)		
Other nationalities	81 (27.74)			Italian	7 (1.76)		
				Other nationalities	39 (9.82)		
Whether live in home country or abroad							
At home	155 (53.08)				357 (89.92)		
Abroad	137 (46.92)				40 (10.08)		
The years of living abroad	137	0–18	2.21 (4.00)		40	0–21	4.85 (4.21)

Note. Here is one missing value with the general population sample in terms of “The onset age when starting to use smartphone” and “The years for smartphone use” because one participant’s years for smartphone use is “−1”.* Gender here implies the participants’ self-identified gender.

invariance with acceptable model fit of Model 1. This indicated that the general structure of SUPIQ was consistent across the two samples. However, according to the criteria of changed CFI (decrease of ≥0.015) and RMSEA (increase of ≥0.015), both metric and scalar invariance were not tenable, as the model fit indices deteriorate, suggesting that some items’ factor loadings and thresholds in the SUPIQ differed in the two samples (Chen, 2007). We consulted modification indices to see if there were some specific items responsible for the misfit. However, there was no clear source of misfit identifiable.

Table 2. Factor Loadings of the final 26 items (adding three extra items, item) based on EFA with the university community sample (N = 292)

Final order	Initial order	Item	Factor 1-Craving	Factor 2-Tolerance	Factor 3-Social Conflicts	Factor 4- Withdrawal	Factor 5- Risky Use	Factor 6-Habitual Use	Factor 7-Coping
2	2	I feel a strong urge to check my smartphone.	0.631						
1	1	I think about my smartphone when I am not using it.	0.624						
19	**35**	**I feel a strong need to be available via my smartphone.**	**0.275**			**0.302**		**0.287**	
3	3	I feel empty even when I spend a lot of time on my smartphone.		0.867					
15	27	I feel unsatisfied even when I spend a lot of time on my smartphone.		0.532					
7	**14**	**I need to spend more and more time on my smartphone to satisfy myself.**		**0.346**	**0.298**				
9	16	I tell lies about my smartphone use.			0.864				
12	21	I hide my smartphone use from others (e.g., family, partner, friend, etc.).			0.812				
10	19	I have conflicts with others (e.g., family, partner, friend, etc.) due to my smartphone use.			0.780				
14	25	I jeopardize important relationships (e.g., family, partner, friend, etc.) due to my smartphone use.			0.745				
25	55	People around me tell me that I use my smartphone too much.			0.674				
8	15	I continue using my smartphone after others ask me not to.			0.541				
6	10	I feel anxious/nervous when there are internet connection problems (e.g., unstable connection, no connection, etc.) on my smartphone.				0.851			
22	46	I feel anxious/nervous when I do not have access to my smartphone (e.g., exams, out of battery, etc.).				0.801			
20	42	I feel angry when there are internet connection problems (e.g., unstable connection, no connection, etc.) on my smartphone.				0.759			

(continued)

Table 2. Continued

Final order	Initial order	Item	Factor 1-Craving	Factor 2-Tolerance	Factor 3-Social Conflicts	Factor 4- Withdrawal	Factor 5- Risky Use	Factor 6-Habitual Use	Factor 7-Coping
13	22	I feel angry when I do not have access to my smartphone (e.g., exams, out of battery, etc.).				0.654			
24	53	I still use my smartphone in traffic (e.g., driving a car, cycling, walking, etc.) even though I (almost) get into traffic accidents due to my smartphone use.					0.906		
4	5	I (almost) get into traffic accidents (e.g., when driving a car, when cycling, when walking, etc.) due to my smartphone use.					0.858		
16	29	I use my smartphone in situations that could be physically dangerous (e.g., driving a car, cycling, crossing the road, operating heavy machinery, etc.).					0.798		
17	30	I automatically open apps on my smartphone.						0.910	
23	48	I automatically unlock my smartphone.						0.860	
18	31	I automatically check my smartphone, even when I just checked it.						0.686	
26	57	I check my smartphone when I am entertaining myself in other ways (e.g., watching movies, TV series, reading, etc.).						0.576	
5	7	Using my smartphone makes me feel better when I feel bad (e.g., sad, anxious, insecure, lonely, etc.).							0.721
21	43	I distract myself from negative feelings (e.g., sad, anxious, insecure, lonely, etc.) by using my smartphone.							0.645
11	**20**	**My smartphone is the solution to my boredom.**						**0.316**	**0.369**

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire. This version contains 26 items, 7 factors. Applied rotation method is oblimin in EFA. Only factor loadings ≥ 0.250 were listed in the table. The model fits were good: CFI = 0.991, TLI = 0.983, RMSEA = 0.032, SRMR = 0.031. The three restored items were marked in bold. The 7-factor structure was also supported by parallel analyses and the scree plot (see supplementary Fig. S8). The Cronbach's α values of the three factors when excluding the restored three items are shown in supplementary Table S9.

Table 3. Measurement invariance analysis of the SUPIQ: Multi-group CFA

Model test	Overall model fit constrained model							Changes in model fit			
	χ^2	*df*	BIC	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	ΔCFI	ΔRMSEA
Group equivalence	1,036.20	278	44,478.73	0.923	0.911	0.063	0.061	–	–	–	–
Configural (Model 1)	1,153.52	556	43,708.69	0.932	0.920	0.056	0.053	–	–	–	–
Metric (Model 2)	1,348.63	575	43,779.63	0.912	0.900	0.062	0.076	195.112***	19	−0.020	0.006
Scalar (Model 3)	1,723.33	594	44,030.16	0.871	0.859	0.074	0.082	374.699***	19	−0.041	0.012

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire; BIC = Bayesian information criterion; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; Difference tests are displayed for configural versus metric and metric versus scalar, respectively. ***χ^2 test was statistically significant at $p < 0.001$ level.

The descriptive statistics, reliability, and convergent validity results

The descriptive statistics including Means (*M*), Standard Deviations (*SD*), Range, and Reliability Coefficients including Cronbach's α and McDonald's ω values for mental health problems, the SAS-SV, the sum scores of SUPIQ, and its Seven Factors are shown in Table 4. The reliability coefficients indicated that SUPIQ has good reliability.

The descriptive statistics of the smartphone use statistics across two samples are presented in Table 5.

Regarding convergent validity results, the Correlation Coefficients for mental health problems, the smartphone use statistics, the SAS-SV, the SUPIQ, and its Seven Factors are displayed in Table 6. Based on the results, all the factors and scales were highly positively correlated with each other in the general population sample ($p < 0.001$). However, in the university community sample, Risky Use was not correlated with Craving and Coping, and the correlation coefficients between Risky Use and Habitual Use, Social Conflicts, Withdrawal, and Tolerance were relatively lower than those between other factors of the SUPIQ. The total scores of the SUPIQ were positively correlated with mental health problems, SAS-SV, active and passive social media use on smartphone in both samples. Mental health problems were positively correlated with all the SUPIQ factors in both samples. In the university community sample, the SUPIQ factors including Craving, Habitual Use, Social Conflicts, Withdrawal, and Tolerance were positively correlated with active social media use on smartphone, while Craving, Coping, Habitual Use, and Withdrawal were positively correlated with passive social media use on smartphone. In the general population sample, the SUPIQ factors including Social Conflicts, Risky Use, and Tolerance were positively correlated with active social media use on smartphone, while Coping, Social Conflicts, Risky Use, Withdrawal, and Tolerance were positively correlated with passive social media use on smartphone. In the university community sample, the total score of the SUPIQ, Craving, Coping and Social Conflicts were positively correlated with non-social screen time per day. The results indicated that the SUPIQ has good convergent validity generally.

The partial correlation network with the university community sample demonstrated that Tolerance and Withdrawal were positively correlated with mental health problems (Fig. 1). In addition, passive social media use was negatively associated with Social Conflicts while positively associated with Habitual Use. The correlation stability coefficient was 0.671, indicating sufficient stability (see Supplementary Fig. S15 for bootstrapping results). The centrality indices of the network were shown in Supplementary Figs S16 and S17. The estimation of significant differences between edge weights and bootstrapped results were shown in Supplementary Fig. S18.

The partial correlation network with the general population sample showed Craving, Social Conflicts, Risky Use, Tolerance, and Withdrawal were positively correlated with mental health problems (Fig. 2). Active social media use was negatively associated with Habitual Use and positively associated with Social Conflicts. Moreover, passive social media use was positively associated with Habitual Use. The correlation stability coefficient was 0.751, indicating sufficient stability (see Supplementary Fig. S19 for bootstrapping results). The centrality indices of the network were shown in Supplementary Figs S20 and S21. The estimation of significant differences between edge weights and bootstrapped results were shown in Supplementary Fig. S22.

The explanatory power of the SUPIQ: hierarchical multiple regression results

Hierarchical multiple regression analyses showed that the SUPIQ generally outperformed the SAS-SV in the regression models of step 2 when the SUPIQ and the SAS-SV were added to the regression model as predictors for mental health problems at the same time (Table 7). Based on the results of relative importance analyses (Table 8), the SUPIQ played a more important role than the SAS-SV when explaining the variance of mental health problems with step 2 models.

DISCUSSION

Derived from a qualitative study involving problematic smartphone users from diverse European countries, we have gained contemporary and comprehensive perspectives on PSU in everyday life, which moves beyond existing "addiction" criteria. Based on such perspectives, we developed and tested the comprehensive Smartphone Use Problems

Table 4. Summary of Means (M), Standard Deviations (SD), Range, and Reliability Coefficients for mental health problems, the SAS-SV, the SUPIQ and its Seven Factors in the university community sample (N = 292) and general population sample (N = 397)

	University community sample (N = 292)					General population sample (N = 397)				
	M (*SD*) Sum score	*M* (*SD*) Item average	Range Sum score	Cronbach's α	McDonald's ω	*M* (*SD*) Sum score	*M* (*SD*) Item average	Range Sum score	Cronbach's α	McDonald's ω
Mental health problems	18.70 (10.14)	0.94 (0.51)	0–55	0.89	0.90	25.83 (17.22)	1.29 (0.86)	0–63	0.97	0.97
SAS-SV	27.54 (8.06)	2.75 (0.81)	10–50	0.83	0.86	33.16 (10.32)	3.32 (1.03)	10–57	0.91	0.93
SUPIQ-Total	56.65 (13.21)	2.18 (0.51)	34–103	0.90	0.92	66.85 (18.30)	2.57 (0.70)	26–104	0.94	0.96
SUPIQ-Craving	8.09 (2.44)	2.70 (0.81)	3–14	0.73	0.77	8.93 (2.48)	2.98 (0.83)	3–15	0.67	0.68
SUPIQ-Coping	7.76 (2.31)	2.59 (0.77)	3–14	0.68	0.71	8.31 (2.54)	2.77 (0.85)	3–15	0.69	0.70
SUPIQ-Habitual Use	12.60 (3.68)	3.15 (0.92)	5–20	0.85	0.88	11.52 (3.22)	2.88 (0.80)	4–20	0.75	0.78
SUPIQ-Social Conflicts	7.98 (2.99)	1.33 (0.50)	6–25	0.85	0.90	13.47 (5.52)	2.25 (0.92)	6–26	0.91	0.94
SUPIQ-Risky Use	4.34 (1.70)	1.45 (0.57)	3–12	0.76	0.79	6.44 (2.94)	2.15 (0.98)	3–14	0.83	0.84
SUPIQ-Withdrawal	8.28 (3.41)	2.07 (0.85)	4–20	0.83	0.87	10.27 (3.41)	2.57 (0.85)	4–20	0.81	0.84
SUPIQ-Tolerance	7.59 (2.70)	2.53 (0.90)	3–15	0.69	0.70	7.91 (2.55)	2.64 (0.85)	3–14	0.68	0.68

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire, SAS-SV = the short version of smartphone addiction scale. For t values, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5. Summary of Means (M), Standard Deviations (SD) and Range for the smartphone use statistics in the university community sample ($N = 292$) and the general population sample ($N = 397$)

	University community sample ($N = 275/292$)		General population sample ($N = 315/397$)		
	M (*SD*)	Range	*M* (*SD*)	Range	*t*
Total screen time per day (hours)	4.72 (2.30)	0.43–11.88	7.19 (3.89)	0.08–19.36	−11.37***
Non-social screen time per day (hours)	2.24 (1.74)	0.06–10.55	3.14 (2.19)	0–12.62	−6.45***
Active social media use frequency per day	64.38 (49.50)	0–268.14	94.53 (72.49)	0–314.71	−7.03***
Passive social media use frequency per day	92.93 (71.13)	0–357.14	94.79 (70.62)	0–361.71	−0.36
Pickup frequency per day	71.34 (40.94)	0.43–142.86	52.82 (28.44)	4.14–142.86	6.99***
Top 3 social media apps (frequency)	WhatsApp (51), Instagram (47), YouTube (16), SnapChat (13), Reddit (9), TikTok (6), Twitter (6)		Facebook (211), Instagram (206), TikTok (171), WhatsApp (125), LinkedIn (62), Twitter (30), YouTube (14), SnapChat (13), Messages (11), Spotify (8)		
Top 3 pickup apps (frequency)	WhatsApp (57), Instagram (34), YouTube (19), Chrome (17), SnapChat (12), Spotify (10)		Instagram (191), WhatsApp (150), Facebook (120), TikTok (92), Safari (75), Messages (25), LinkedIn (24), Spotify (16), Twitter (16), Chrome (14)		

Note. For the numeric data, the missing values have been considered. For the top 3 apps, we have used the whole samples to do the data analyses. For *t* values, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Identification Questionnaire (SUPIQ) to assess PSU. The SUPIQ exhibited good construct and convergent validity, reliability, and explanatory power in both samples. The initial version of the questionnaire comprised 8 factors and 57 items based on DSM-5 (American Psychiatric Association, 2013a) and ICD-11 (World Health Organization, 2019) criteria, after exploratory and confirmatory factor analyses, the final SUPIQ consists of 7 correlated factors: Craving, Coping, Habitual Use, Social Conflicts, Risky Use, Withdrawal, Tolerance. The final SUPIQ showed good construct validity and reliability, while the structure is different from the initial version.

The final inclusion of Craving and Coping factors aligns with the established scales like MPPUS (Bianchi & Phillips, 2005) and SPAI (Lin et al., 2014), with adaptions based on the descriptions from the qualitative study on problematic smartphone users. Impaired Control items were included in the Habitual Use factor. This aligns with previous studies (e.g., Van Deursen, Bolle, Hegner, & Kommers, 2015), indicating that Habitual Use may be a more critical factor than control-related problems in measuring PSU. This factor is distinctive compared to existing questionnaires like MPPUS (Bianchi & Phillips, 2005), PMPUQ (Billieux et al., 2008), SAS (Kwon, Lee, et al., 2013), and SPAI (Lin et al., 2014), which emphasize control issues. In the SUPIQ, the Social Conflicts and Risky Use factors retained as the main negative consequences. Risky Use measurement has been expanded to include items on frequency of real-life accidents and reluctance to change after, accidents deviating from the Dangerous Use factor of PMPUQ (Billieux et al., 2008). The retainment of social and physical risks is different from other questionnaires that encompass broader negative consequences, including MPPUS (Bianchi & Phillips, 2005), PMPUQ (Billieux et al., 2008), SAS (Kwon, Lee, et al., 2013), and SPAI. This difference may imply the significance of the two aspects to differentiate PSU from normal smartphone use. However, it is worth noting that Risky Use showed weaker correlations with other factors in the university community sample, similar to the findings in problematic cannabis use (see a review, Casajuana et al., 2016). This suggests that the Risky Use items may need optimization for different contexts, aligning with the findings related to problem drinking, where the specific scale has been designed for adolescents (White & Labouvie, 1989; White, Labouvie, & Papadaratsakis, 2005). While the inclusion of Tolerance and Withdrawal in defining behavioral addictions remains debated (e.g., Starcevic, 2016), both factors were incorporated in the final SUPIQ based on participants' everyday experiences. The inclusion of the two factors are consistent with the existing questionnaires (Bianchi & Phillips, 2005; Kwon, Lee, et al., 2013; Lin et al., 2014), expands their measurement. Tolerance of the SUPIQ involves feeling "empty" after spending much time on smartphones, while Withdrawal covers both issues with the internet connection and smartphone access. In terms of the covariances between item 1 and item 15, the correlation can be explained by the notion that individuals who genuinely contemplate and crave for their smartphones are more likely to overlook or disregard requests from others to stop using their smartphones.

While the configural invariance of the SUPIQ was established across the university community and general population samples, other forms of measurement invariances were not. As noted, it is not uncommon for addictive behaviors to show different indicators of problems

Table 6. Correlation Coefficients between Mental health problems, the SAS-SV, the SUPIQ and its Seven Factors, and smartphone use statistics in the university community sample (N = 292) and the general population sample (N = 397, in bold)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Mental health problems	1	**0.71*****	**0.78*****	**0.51*****	**0.59*****	**0.47*****	**0.73*****	**0.72*****	**0.62*****	**0.65*****	**−0.04**	**0.04**	**0.22****	**0.21****	**−0.10**
2. SAS-SV	0.46***	1	**0.77*****	**0.58*****	**0.62*****	**0.53*****	**0.69*****	**0.55*****	**0.69*****	**0.64*****	**−0.03**	**0.04**	**0.19****	**0.17***	**−0.10**
3. SUPIQ-Total	0.52***	0.77***	1	**0.74*****	**0.77*****	**0.72*****	**0.87*****	**0.78*****	**0.86*****	**0.83*****	**−0.10**	**0.02**	**0.22****	**0.22****	**−0.14**
4. SUPIQ-Craving	0.33***	0.67***	0.78***	1	**0.60*****	**0.64*****	**0.49*****	**0.38*****	**0.63*****	**0.58*****	**−0.13**	**−0.06**	**0.12**	**0.14**	**−0.08**
5. SUPIQ-Coping	0.39***	0.48***	0.67***	0.49***	1	**0.66*****	**0.55*****	**0.44*****	**0.61*****	**0.64*****	**−0.11**	**0.02**	**0.15**	**0.18***	**−0.04**
6. SUPIQ-Habitual Use	0.30***	0.60***	0.78***	0.64***	0.49***	1	**0.41*****	**0.37*****	**0.57*****	**0.57*****	**−0.05**	**0.02**	**−0.01**	**0.09**	**−0.12**
7. SUPIQ-Social Conflicts	0.31***	0.53***	0.66***	0.39***	0.25***	0.31***	1	**0.82*****	**0.71*****	**0.68*****	**−0.09**	**0.04**	**0.28*****	**0.22*****	**−0.16**
8. SUPIQ-Risky Use	0.20**	0.19**	0.34***	0.11	0.05	0.18**	0.28***	1	**0.59*****	**0.60*****	**−0.06**	**0.001**	**0.24*****	**0.20****	**−0.19**
9. SUPIQ-Withdrawal	0.46***	0.60***	0.75***	0.54***	0.50***	0.43***	0.41***	0.15*	1	**0.68*****	**−0.07**	**0.02**	**0.14**	**0.17***	**−0.08**
10. SUPIQ-Tolerance	0.45***	0.49***	0.67***	0.44***	0.37***	0.43***	0.41***	0.14*	0.36***	1	**−0.07**	**0.02**	**0.20****	**0.19****	**−0.07**
11. Total screen time per day (hours)	0.03	0.07	0.11	0.11	0.09	0.06	0.07	0.04	0.08	0.07	1	**0.58*****	**0.002**	**−0.002**	**0.20****
12. Non-social screen time per day (hours)	0.08	0.14*	0.16**	0.12*	0.16**	0.10	0.12*	0.04	0.11	0.11	0.66***	1	**0.08**	**0.05**	**0.04**
13. Active social media use frequency per day	0.12*	0.28***	0.25***	0.27***	0.10	0.19**	0.15*	−0.06	0.27***	0.14*	0.04	0.03	1	**0.84*****	**0.01**
14. Passive social media use frequency per day	0.03	0.27***	0.21***	0.29***	0.15*	0.29***	−0.05	−0.08	0.19**	0.10	0.09	0.07	0.63***	1	**0.004**
15. Pickup frequency per day	−0.04	0.05	0.07	0.04	0.01	0.03	0.15**	0.08	0.004	0.01	0.37***	0.20**	0.09	0.03	1

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire, SAS-SV = the short version of smartphone addiction scale. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Numbers of missing values in smartphone use statistics are separately 17 in the university community sample and 82 in the general population sample, the method to deal with the missing values is pairwise deletion.

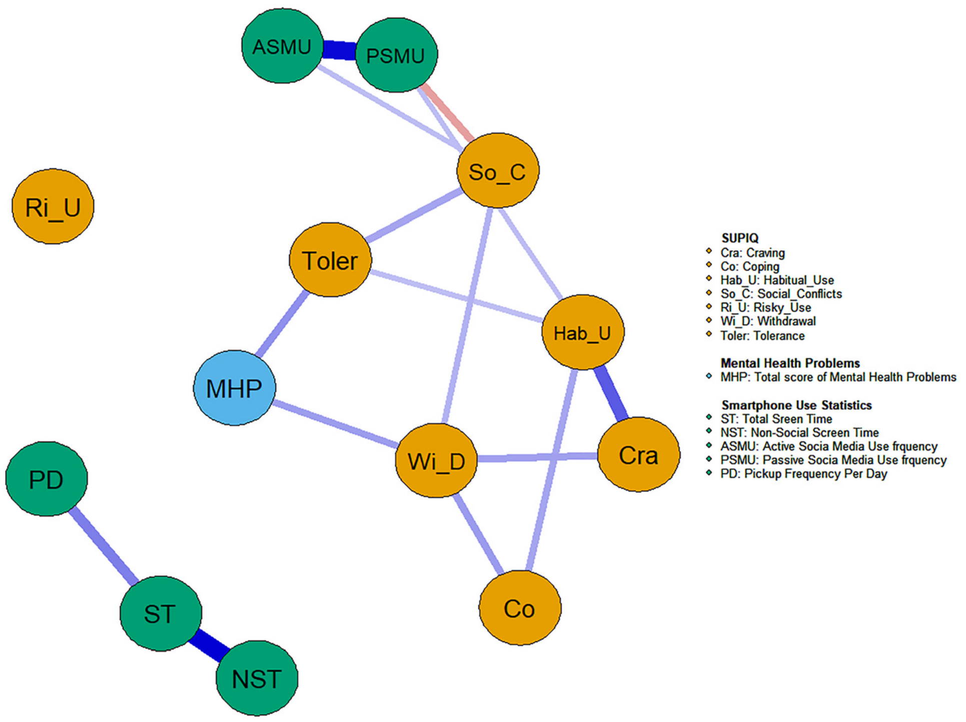

Fig. 1. The network analysis including all the sum scores of the SUPIQ factors, mental health problems and all smartphone use indicators (regularized model) with the university community sample ($N = 292$)

Note. The color (blue = positive, red = negative) and thickness of the edges indicate the strength of association. The nodes have been colored according to the domain that they belong to. SUPIQ = The Smartphone Use Problems Identification Questionnaire.

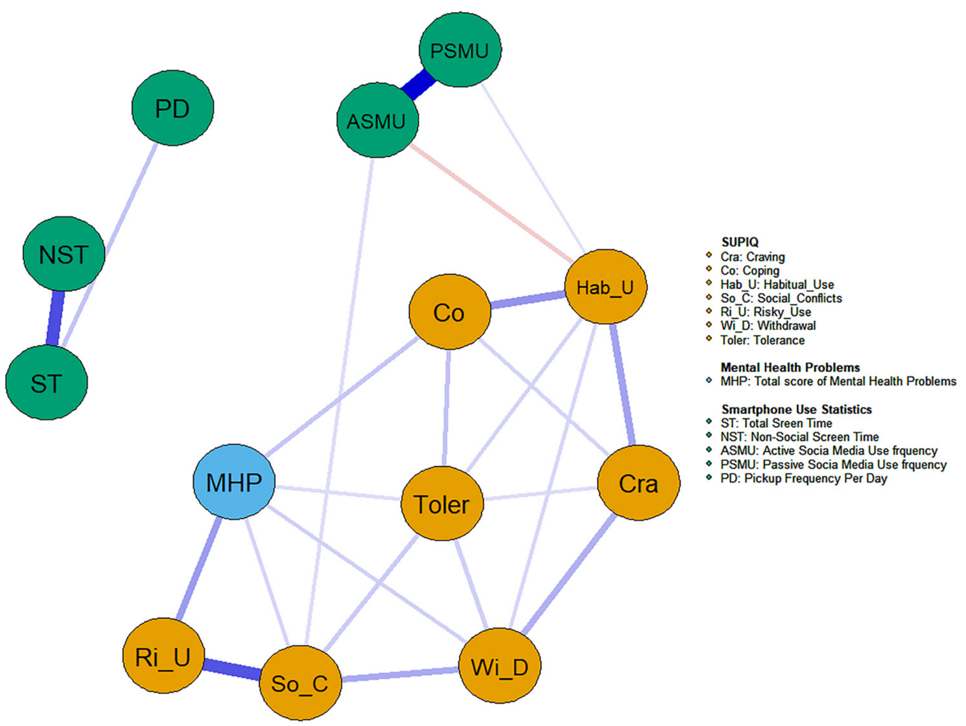

Fig. 2. The network analysis including all the sum scores of the SUPIQ factors, mental health problems and all smartphone use indicators (regularized model) with the general population sample ($N = 397$)

Note. The color (blue = positive, red = negative) and thickness of the edges indicate the strength of association. The nodes have been colored according to the domain that they belong to. SUPIQ = The Smartphone Use Problems Identification Questionnaire.

Table 7. Hierarchical multiple regression results with the two samples

Independent variables	University community sample (N = 292)				General population sample (N = 397)			
	B	β	R^2	SE	B	β	R^2	SE
Step 1			0.210					
SAS-SV	0.576***	0.458***		0.066	1.192***	0.714***	0.510	0.059
Step 2			0.277				0.642	
SAS-SV	0.179	0.142		0.099	0.453***	0.272***		0.079
SUPIQ	0.314***	0.409***		0.060	0.539***	0.573***		0.045

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire; SAS-SV = the short version of smartphone addiction scale. Dependent variable = mental health problems. The possible multicollinearity problems have been checked by VIF (variance inflation factor), the VIF values of SAS-SV and SUPIQ were 2.474 for the university community sample and 2.481 for the general population sample. These values are lower than the universal criterion of 10 when detecting multicollinearity (Vatcheva, Lee, McCormick, & Rahbar, 2016). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8. Relative importance and 95% confidence interval indicated by relative contribution percentages (%) of the SAS-SV and the SUPIQ in the regression model of step 2

Attribute	University community sample (N = 292)				General population sample (N = 397)			
	LMG	LAST	FIRST	PRATT	LMG	LAST	FIRST	PRATT
SAS-SV	39.30 [27.42, 52.53]	10.82 [0.04,61.91]	43.80 [35.19, 51.44]	23.52 [−5.75, 56.70]	42.02 [36.87, 47.06]	18.36 [6.30,36.32]	45.44 [42.24, 48.35]	30.20 [18.12, 42.20]
SUPIQ	60.70 [47.47, 72.58]	89.18 [38.09, 99.96]	56.20 [48.56, 64.81]	76.48 [43.30, 105.75]	57.98 [52.94, 63.13]	81.64 [63.68, 93.70]	54.56 [51.65, 57.76]	69.80 [57.80, 81.88]

Note. SUPIQ = the Smartphone Use Problems Identification Questionnaire; SAS-SV = the short version of smartphone addiction scale. Dependent variable = mental health problems, n of bootstrap = 2000. LMG, LAST, FIRST, PTATT are the four different estimation methods offered by package "relaimpo". 27.7% and 64.24% of mental health problems' variances could be explained in university community and general population samples separately.

at different ages (c.f., White & Labouvie, 1989). Results showed that the strength of the relationships between items and the underlying construct like the factor loadings of the SUPIQ, differed across the two samples.

Regarding convergent validity, the linear correlation analyses showed that the SUPIQ and its factors were positively correlated with mental health problems, the SAS-SV, indicating the good convergent validity of the SUPIQ. The partial correlation network analyses showed that mental health problems were positively correlated with Withdrawal and Tolerance in both samples and positively correlated with Coping, Social Conflicts, and Risky Use in the general population sample. Such results are consistent with previous studies (see a review, S. Sohn, Rees, Wildridge, Kalk, & Carter, 2019). These results suggest that Habitual Use and Craving might not be key factors in defining PSU or central symptoms of PSU (e.g., Fournier et al., 2023). Total screen time, nonsocial screen time, and pickup frequency were not correlated with the SUPIQ factors, contrary to prior research (see a review, Ryding & Kuss, 2020). This discrepancy may be due to our inclusion of mental health problems in the analyses, which was not common in previous studies (see a review, Ryding & Kuss, 2020). Active social media use was positively correlated with Social Conflicts in both samples and negatively correlated with Habitual Use in the general population sample. Passive social media use was positively correlated with Habitual Use in both samples and negatively correlated with Social Conflicts in the university community sample. These results align with former studies (e.g., Su et al., 2022), suggesting different roles of active and passive social media use in relation to the PSU. Regarding explanatory power, the SUPIQ outperformed the SAS-SV in the regression models where the mental health problems were the outcome variables for both samples.

Limitations and future study directions

While our study provides valuable insights into the initial psychometric features of the SUPIQ, there is a need for further investigation to deepen our understanding of PSU. We comprehensively examined construct and convergent validity, reliability, measurement invariance, and explanatory power using samples primarily from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) countries. However, the volunteerism of participants and the focus on WEIRD countries with English as the primary survey language impacted the representativeness of the samples. To address this limitation, future research should target larger and more diverse samples, including clinical samples, while considering the different languages to assess the broader applicability of the SUPIQ globally (Billieux, Philippot, et al., 2015; Billieux, Schimmenti, et al., 2015; Flayelle et al., 2022; Lopez-Fernandez, 2017). Further refinements are warranted, particularly in the items of Craving, Coping, and Tolerance. The tailoring of the SUPIQ for different populations is crucial, and assessing the relative significance of different factors in defining PSU remains an important avenue for future research. Additionally, the test-retest reliability can also be further investigated with future studies and a short form of the SUPIQ should be generated to ensure the feasibility of usage and compare the short form with the SAS-SV in future studies (c.f. Kwon, Kim, et al., 2013).

In our study, we tested the SUPIQ's convergent validity with smartphone use statistics, mental health problems, and the SAS-SV. Future research could explore the overlap between the SUPIQ and other behavioral and substance-related addictions (e.g., Andrade et al., 2022; Kwon, Lee, et al., 2013) or the possible correlations between the SUPIQ and other variables like personality traits (Giustiniani et al., 2022) and childhood trauma (Fan et al., 2023). We have also tested the explanatory power of the SUPIQ in comparison to the SAS-SV (Kwon, Kim, et al., 2013), while future studies would benefit from employing the full versions of the PMPUQ (Billieux et al., 2008) and SAS (Kwon, Lee, et al., 2013) to confirm the predictive power of the complete SUPIQ. Additionally, individual differences in the SUPIQ warrant investigation through person-centered analyses, such as latent profile analysis with cross-sectional data (e.g., Yue et al., 2021) and growth mixture modeling with longitudinal data (e.g., Lai et al., 2022), to identify the problematic subgroups.

CONCLUSIONS

To conclude, we tested the psychometric quality of a newly developed instrument to measure problematic smartphone use, namely the Smartphone Use Problems Identification Questionnaire (SUPIQ). Throughout this process, the SUPIQ underwent refinements in different aspects, including the adaptation of items within factors like Craving and Coping, identification of pivotal negative consequences related to Social Conflicts and Risky Use, expanded measurements for Risky Use, Withdrawal, and Tolerance factors, and the introduction of a novel factor-Habitual Use. The SUPIQ shows good reliability and validity, and it is a valuable tool for evaluating contemporary and severe smartphone use problems rooted in users' everyday behaviors. The SUPIQ stands as an updated and robust tool, aiming to contribute significantly to the nuanced assessment of problematic smartphone use.

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SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2024.00010.

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