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ORIGINAL ARTICLE

Problematic Pornography Use: Can It Be Accurately Measured via the Problematic Pornography Use Scale?

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Abstract

Pornography use has increased its popularity worldwide, raising concerns about potential disordered use. Considering the lack of recognition in diagnostic manuals, conceptual clarification and the validation of robust instruments assessing this problem are much needed. The current study is aimed at assessing the psychometric properties of the Problematic Pornography Use Scale (PPUS). Exploratory and confirmatory analyses (EFA and CFA) were used to assess a four-factor and a bifactor solution. Additionally, this study used latent profile (LPA) and sensitivity analyses to determine suggested cut-off values to identify *at-risk* users. A large sample of adult pornography users completed the PPUS online ($N = 1149$). A four-factor solution as proposed by Kor and colleagues (*Addictive Behaviors*, 39(5), 861-868, Kor et al., Addictive Behaviors 39:861–868, 2014) was identified as the optimal factorial structure. Participants were classified into five profiles, with 3.9% identified as *at-risk* users, 19.9% as moderate to high risk. A cut-off value of 33 was suggested to accurately identify *at-risk* users. The PPUS is a multidimensional instrument, showing good adept ability to detect users at risk of problematic pornography use.

Keywords Addictive behaviors · Problematic pornography use · Disordered Internet use · Psychopathology

Viewing sexually explicit or arousing media online may be considered a normal and popular aspect of Internet use. Nationally representative data from Australian, American, and Polish participants reveal a 70–85% proportion of lifetime prevalence of pornography use (84–85% of males and 54–57% of females; Grubbs et al., 2019; Lewczuk et al., 2020; Rissel et al., 2017). This increased popularity has been attributed to the accessibility, affordability, and anonymity related to online pornography consumption (Cooper, 1998). Although pornography may contribute to consumers' pleasure, sexual education, enhanced sex life, and diverse sexual scenarios for gratification (Hald & Malamuth, 2008; McCormack & Wignall, 2017; McKee, 2007; Weinberg et al., 2010), it has also been claimed to be problematic, compromising one's well-being when used excessively (Alexandraki et al.,

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2018b). The range of adverse outcomes related to problematic pornography use includes unrealistic sexual expectations, relationship difficulties, occupational impairment, diminished behavioral regulation, and psychological distress (Griffiths, 2012; Hald & Malamuth, 2008; Maddox et al., 2011; McKee, 2007; Ross et al., 2012; Twohig et al., 2009). Despite a growing scholarly interest in problematic pornography use, controversies and inconsistencies occur considering its conceptualization (Alexandraki et al., 2018a; Ley et al., 2014).

Past research highlights controversies surrounding pornography, questioning whether this construct should sit within behavioral addictions (Ley et al., 2014). Indeed, pornography addiction has been proposed to lack conceptual sustenance to be recognized as a disorder and instead is formulated within the broader framework of sexual addiction (Duffy et al., 2016; Fernandez and Griffiths, 2019). Additionally, in 2013, hypersexual disorder was not included in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders, despite excessive pornography use being a relatively frequent behavior, as endorsed by 81% of field trial participants (Reid et al., 2012). Nevertheless, the World Health Organization (World Health Organization, 2019) recently adopted the diagnosis of *compulsive sexual behavior disorder* (CSBD; Kraus et al., 2016) under the International Classification of Diseases 11th Revision.

CSBD is characterized by a persistent failure to control intense sexual impulses or urges, resulting in repetitive sexual behavior (Hall, 2019; Kotera & Rhodes, 2019; World Health Organization, 2019). Symptoms may include repetitive sexual activities, such as (i) the use of pornography becoming a central focus of an individual's life, (ii) resulting in functional impairment, (iii) with unsuccessful efforts to reduce the behavior, and (iv) continued behavior despite adverse consequences (World Health Organization, 2019; Wordecha et al., 2018). Interestingly, distress from moral judgments and disapproval about said sexual behavior was deemed insufficient to meet the proposed CSBD diagnostic criteria (World Health Organization, 2019). Therefore, questions remain around whether problematic pornography use should be viewed as an independent condition or a sub-category/symptom of a broader syndrome of disordered sexual activity. Similarly, clarification is required considering the possibility of over-pathologizing pornography consumption (Alexandraki et al., 2018a, 2018b; Allen et al., 2017; George & Koob, 2017; Kraus et al., 2016; Zarate et al., 2022a). Such issues are important, as they underpin the differential diagnosis of the behavior and how this should be best assessed.

Problematic Pornography Use Assessment

One way to clarify such conceptual controversies is through the psychometric examination of scales/instruments commonly used to assess problematic pornography. Researchers have employed several scales to assess disordered CSBD, including the Bergen-Yale Sexual Addiction Scale (BYSAS; Andreassen et al., 2018), the Short Internet Addiction Test (s-IAT; Young, 1998), the Compulsive Sexual Behavior Disorder Scale (CBSD-19; Bőthe et al., 2017), and the Sexual Addiction Screening Test (SAST; Carnes & O'Hara, 1991). Although the scales are helpful in assessing disordered CSBD, they do not focus on assessing problematic online pornography use nor capture broader concepts, such as sex addiction, cybersex, or using the Internet for sex purposes (Carnes & Wilson, 2002; Delmonico & Miller, 2003).

Other instruments have been developed to focus on the narrower concept of problematic pornography use, such as the Problematic Pornography Use Scale (PPUS; Kor et al., 2014) and the Problematic Pornography Consumption Scale (PPCS; Bőthe et al., 2017). The PPUS (12-items) has been widely used due to its coverage of central addiction components (i.e., salience, mood modification, conflict, relapse; Bőthe et al., 2017; Griffiths, 2005) and its significant overlap with diagnostic criteria for the proposed hypersexual disorder (Reid et al., 2012) and CSBD (Kraus et al., 2016). In contrast, the PPCS gages all six factors of addiction (i.e., salience, mood modification, conflict, tolerance, withdrawal, relapse; Griffiths, 2005) and provides a validated cut-off score to differentiate between problematic and non-problematic pornography users. Nonetheless, Fernandez and Griffiths (2019) outline that the PPUS has robust psychometric properties, fewer items, assesses central aspects of conflict (e.g., interpersonal) rather than peripheral (e.g., impact on sex life), and includes questions about "use despite harm," which has been regarded as central to the definition of addiction (Griffiths, 2005). Based on these considerations, the PPUS scale was selected for psychometric evaluation to shed light on assessing problematic pornography use.

The PPUS has been validated and used in Hebrew-speaking Israelis (Kor et al., 2014), Chinese (Chen et al., 2021), and Spanish (Paredes et al., 2021) samples. Exploratory and confirmatory analyses (i.e., EFA and CFA) identified four correlated factors, including (a) distress and functional problems, (b) excessive use, (c) control difficulties, and (d) use for escape/avoid negative emotions (Chen et al., 2021; Kor et al., 2014). Convergent validity was supported through significant positive correlations between the PPUS and motivations for pornography consumption (e.g., emotional avoidance and sexual curiosity). Construct validity was supported by significant associations with depression, anxiety, low self-esteem, emotional insecurity in close relationships, history of trauma, personal distress, functional impairment (Kor et al., 2014), and pornography craving (Chen et al., 2021). Moreover, PPUS total scores were positively associated with being younger, male, and showing higher levels of hypersexuality, Internet addiction (i.e., irrespective of one's application of abuse), and gambling addiction (Kor et al., 2014).

Although the available literature provides initial support for the psychometric properties and factorial structure of the PPUS, some questions remain unanswered. Firstly, while four dimensions are confirmed, the occurrence of a general problematic pornography use syndrome and how this interrelates with the four factors has not been examined. In other words, it remains to be seen if a bi-factor structure (i.e., all items linking with one general dimension and concurrently with their specific factors; Reise et al., 2010) is more informative than a higher order model with its proposed sub-dimensions and the level of cohesion or co-dependence of the four dimensions under this construct (Morin et al., 2015). Investigating the potential for a bifactor model of the PPUS may provide further support for conceptualizing the construct alongside the utility of the specific measure by providing a general score in addition to sub-dimensions. Moreover, no suggested cut-off values have been proposed identifying individuals at-risk of problematic pornography use. Identifying suggested cut-off values is important because it can ease the identification of problematic behaviors, preliminary diagnosis, and prevalence rates while contributing to the larger debate concerning the need to recognize problematic pornography use as an independent behavioral addiction (Zarate et al., 2022a).

The Present Study

The present study is the first to concurrently assess several PPUS factorial structures and identify suggested cut-off values using the responses of a large, normative community sample of pornography consumers. Specifically, this study sought to compare the four-dimensional PPUS structure alongside alternative models, such as the unidimensional and the bi-factor (i.e., the general and four-subdimensions applying better together than independently). Therefore, the study findings are expected to inform the level of usability of the PPUS, as well as the suggested cut-off values identifying individuals at risk of experiencing problematic pornography consumption. To address these aims, the following research questions were formulated:

RQ1—What is the optimum PPUS factorial structure?
RQ2—What is the optimum PPUS cut-off score to identify individuals at-risk of problematic pornography use?

Method

Participants

The sample consisted of 1149 participants recruited from the general community. This exceeds the minimum recommendation of 200 and the general principle of 20 participants per item for EFA/CFA procedures (i.e., 20×12 items on the PPUS = 240). All participants aged 18 years or older were eligible to participate. Participants' age ranged from 18 to 67 years ($M_{age} = 27.01$, SD = 9.15) and included 924 males (80.4%; $M_{age} = 27.21$, SD = 9.39) and 225 females (19.6%; $M_{age} = 26.16$, SD = 8.01). Most participants reported being White/Caucasian (84.2%), straight/heterosexual (70.8%), residing in the USA (53.4%), UK (10.2%), and Australia (12.4%). There were no missing values. All participants reported using Internet pornography within the last 6 months (see Supplementary Tables 1 and 2 for sociodemographic descriptives).

Measures

The *Problematic Pornography Use Scale* (Kor et al., 2014) is a 12-item questionnaire that evaluates problematic pornography use with four subscales: (1) distress and functional problems (DFP; three items; e.g., "using pornography has created significant problems in my personal relationships with other people, in social situations, at work, or in other important aspects of my life"); (2) excessive use (EU; three items; e.g., "I spend too much time planning to and using pornography"); (3) control difficulties (CD; three items; e.g., "I feel I cannot stop watching pornography"); (4) use for escape/avoid negative emotions (ANE; three items; e.g., "I watch pornographic materials when I am feeling despondent"). Items are scored on a Likert-type scale, ranging from 0 (*never true*) to 5 (*almost always true*). Possible total scores range from 0 to 60, with higher scores indicating more problematic pornography use. The PPUS showed acceptable internal consistency in the original (Cronbach's α ranged from 0.79 to 0.92; Kor et al., 2014) and the current study (Cronbach's $\alpha = 0.93$; McDonald's $\omega = 0.93$; see Table 1 for more details).

The *Patient Health Questionnaire* (PHQ-9; Kroenke et al., 2001) is a 9-item tool to assess symptoms of depression. Items are scored on a Likert-type scale, ranging from 0 (*not at all*) to 3 (*nearly every day*), and examples of items include "I have little interest or pleasure in doing things." Total scores, as derived by the accumulation of items' point, range from 0 to 27, with higher scores indicating higher symptom severity. Considering

Table 1 PPUS factorial structure including reliability indices

Items	Factor	Reliability indices	
		α	ω
1. I often think about pornography	F1—excessive use	0.82	0.83
2. I spend too much time being involved in thoughts about pornography			
3. I spend too much time planning to use and using pornography			
4. I feel I cannot stop watching pornography	F2—control difficulties	0.88	0.89
5. I have been unsuccessful in my efforts to reduce or control the frequency I use pornography in my life			
6. I keep watching pornographic materials even though I intend to stop			
7. I use pornographic materials to escape my grief or to free myself from negative feelings	F3—use for escape/avoid negative emotions	0.91	0.91
8. I watch pornographic materials when I am feeling despondent (i.e., hopeless, low-spirited, downhearted)			
9. I have used pornography while experiencing unpleasant or difficult feelings (for example: depression, sorrow, anxiety, boredom, restlessness, shame, or nervousness)			
10. Using pornography has created significant problems in my personal relationships with other people, in social situations, at work or in other important aspects of my life	F4—distress and functional problems	0.81	0.81
11. I risk or put in jeopardy a significant relationship, place of employment, educational or career opportunity because of the use of pornographic materials			
12. I continued using pornography despite the danger of harming myself physically (for example: difficulty getting an erection due to extensive use, difficulty reaching an orgasm in ways that do not include pornography)			

Note: $\alpha = F =$ factor; Cronbach's alpha; $\omega =$ McDonald's omega the current data, the PHQ-9 showed excellent internal consistency (Cronbach's $\alpha = 0.91$; McDonald's $\omega = 0.91$).

The *Generalized Anxiety Disorder* (GAD-7; Spitzer et al., 2006) is a 7-item tool to assess anxiety symptoms. Items are scored on a Likert-type scale, ranging from 0 (*not at all*) to 3 (*nearly every day*), and examples of items include "Feeling nervous, anxious or on edge." Total scores, provided by the accumulation of items, range from 0 to 21, with higher scores indicating higher symptom severity. The GAD-7 showed excellent internal consistency in the current data (Cronbach's $\alpha = 0.92$; McDonald's $\omega = 0.92$).

Procedure

The project received approval from the university ethics board. The study was a cross-sectional, online survey design. Participants were recruited via social networking websites by distributing a survey link. Those who accessed the link were presented with a project information sheet informing them of the study's purpose, risks, and safeguards, alongside information regarding consent and anonymous participation. The study only used participants' responses of those over 18 years. After obtaining consent (via ticking a box), participants were invited to complete demographic questions (i.e., age, sex) followed by the questionnaires. All participants were provided with the contact details of suitable support services pre- and post-completion to assist with any potential discomfort during participation.

Statistical Analyses

To address the outlined aims, a series of statistical processes were employed, including (a) exploratory and confirmatory analyses (EFA/CFA) to evaluate the PPUS latent structure and (b) latent profile (LPA) and sensitivity analyses to identify likely homogeneous groups within the sample, as well as suggested cut-off scores. Finally, *t*-tests were employed to provide evidence of relationships (i.e., external validity arguments/associations) between individuals at-risk of disordered pornographic use and negative psychological consequences (i.e., anxiety and depression).

To answer *RQ1* and assess the PPUS factorial structure, the sample was split evenly to conduct EFA and CFA analyses using RStudio (Lavaan (Rosseel, 2012) and Psych (Revelle, 2022) packages). To ascertain the factorizability of our sample's responses, the Kaiser–Meyer–Olkin test (KMO), matrix determinant, and Bartlett's test of sphericity were employed, with KMO > 0.50, determinant ≠ 0, and significant sphericity ($p < 0.05$) as indicators of acceptable sampling adequacy (Brown, 2015). Subsequently, factors were extracted allowing for orthogonal (VARIMAX) and oblique (Oblimin) rotations to obtain the best possible factorial structure. The optimal number of factors was determined by evaluating eigenvalues and scree plot(s), while factor loadings (λ) > 0.3 were considered appropriate (Brown, 2015). Subsequently, the optimum factorial structure was assessed/confirmed via CFA using the diagonally weighted least squares estimator (DWLS), with RMSEA < 0.10 and CFI/TLI > 0.90 as evidence of appropriate fit (Hu & Bentler, 1999; Zarate et al., 2021). Comparative model evaluation was conducted via the Satorra Bentler Scaled chi-square difference (SBS$\Delta\chi^2$), with $p < 0.05$ as evidence of superior fit (Marsh et al., 2014). Given that χ^2 and $\Delta\chi^2$ are susceptible to showing inflated values, ΔRMSEA and ΔCFI were also considered, with ΔCFI ≤ 0.010 and/or ΔRMSEA ≤ 0.015 as indicative of non-significant differences between models (Chen et al., 2008).

To answer *RQ2* and identify the best cut-off values for detecting individuals at risk of problematic pornography use, a Latent Profile Analysis (LPA) was first conducted using the TidyLPA package in RStudio (Rosenberg et al., 2019). LPA is a statistical approach to identify latent (or unobserved) profiles using a-posteriori likelihood distribution of item responses (i.e., PPUS) by a given sample (Spiliopoulou et al., 2006). TidyLPA uses a Maximum Likelihood Estimator (MLE) to estimate the optimal joint distribution of indicators (including means, variances, and covariances) and thus enables a qualitative description of inter-profile relationships (Masyn, 2013). Supplementary Table 3 describes the possible combinations of variance–covariance structures (i.e., parameterization).

Selecting the optimal number of latent profiles involved a sequential process. Firstly, identification of the best combination of parameters (including (un)constrained profile mean, variance, and covariance) was assessed with the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Approximate Weight of Evidence (AWE) with smaller values indicating better fit (Masyn, 2013). Additionally, the bootstrapped likelihood ratio test (BLRT) was used to compare different models (with k classes) and determine if adding an extra latent class produced a significant increase in fit, with $p<0.05$ as an indication of improved fit (McLachlan, 1987). Moreover, standardized entropy criterion (h) was used to assess heterogeneity levels across latent profiles, with $h=0$ indicating homogenous profiles and $h=1$ indicating heterogenous (i.e., clearly differentiated) profiles (Celeux & Soromenho, 1996). Finally, N min estimated the smallest profile population share, with NMin >0 as justification for selecting k number of profiles (Kovacs et al., 2022).

Traditionally, cut-off values are identified using Item Response Theory (Zarate et al., 2022b, 2023a). However, following the methodology used by Bőthe et al. (2017), a receiver-operator characteristic (ROC) analysis was used to determine the preferred PPUS cut-off points after the identification of "at-risk" users via LPA. The pROC for RStudio (Robin et al., 2011) was used to assess the sensitivity, specificity, and accuracy of selected cut-off values. Sensitivity was calculated as the proportion of true positives (TP; accurate identification of at-risk users), specificity was calculated as the proportion of true negatives (TN; accurate identification of normative users), and accuracy was calculated as (TP + TN)/n (Bőthe et al., 2017).

Results

RQ1—Exploratory (EFA) and Confirmatory Factor Analysis (CFA)

To answer *RQ1* and identify the best factorial structure, EFA and CFA analyses were conducted on two separate samples. Items included in the PPUS show factorizable properties (KMO $=0.917$) and appropriate sphericity ($\chi^2_{[66]}=4632.668$, $p<0.001$). The determinant ($t=0.000$) suggests the possibility of multicollinearity; however, collinearity diagnostics evaluating singular value decomposition showed eigenvalues of 0.087 and a condition index of 10.204 for the smallest dimension. Considering that values remain under acceptable thresholds (i.e., condition index between 10 and 30 indicates moderate collinearity and >30 problematic collinearity; Yu et al., 2015), we proceeded with the EFA to evaluate the PPUS factorial structure.

A principal component extraction method identified a two-factor solution (i.e., eigenvalues >1). However, following suggestions outlined in Kor et al. (2014), a four-factor solution was sought (smallest eigenvalue $=0.701$), explaining 79.6% of the observed variance and component 1 (*control difficulties*) explaining 56.4% of the variance (see Supplementary Fig. 1 and Supplementary Tables 4 and 5). While high inter-component correlations ($r=0.315$ to $r=0.542$) suggest that an oblique rotation should be appropriate, orthogonal (Varimax) and oblique (Oblimin) rotations were performed to evaluate the best pattern structure. Both, orthogonal and oblique rotations produced similar factor loadings, with all items loading saliently on their designated factors ($\lambda>0.3$; see Supplementary Fig. 2; Gomez et al., 2021). The four-factor structure identified 11 out of 12 items in agreement with the proposed factorial structure outlined by Kor et al. (2014), excluding item 12 loading on Factor 1 (instead of Factor 4). All proposed factors demonstrated acceptable reliability indices with Cronbach's α and McDonald's ω ranging from 0.81 to 0.91 (see Table 1 for reliability indices and PPUS items organized by their proposed factors).

Confirmatory Factor Analysis (CFA) was conducted on the second sample to evaluate the structural validity of the model further. The four-factor model proposed by Kor et al. (2014) showed a superior fit in $\Delta\chi^2$, ΔCFI, and ΔRMSEA compared to the unidimensional model and the bifactor model (see Table 2). Additionally, the Kor et al. four-factor model showed an appropriate fit with all items loading saliently and high inter-factor correlations (see Fig. 1).

RQ2—Latent Profile Analysis (LPA)

To answer *RQ2* and identify possible groups of problematic pornography users, LPA was used. The analyses included all four possible parameterization models (Class-varying unrestricted parameterization [CVUP], Class-Invariant Restricted Parameterization [CIRP], Class-Varying Diagonal Parameterization [CVDP], and Class-Invariant Diagonal Parameterization [CIDP]), with two to six possible latent profiles. As seen in Table 3, AIC, BIC, and AWE suggest that the CIRP with five profiles provided the best fit (also see Supplementary Fig. 3). Additionally, the CIRP model with five profiles showed appropriate entropy ($h=0.931$).

PPUS profiles were described considering both raw and standardized reported pornography use to examine their distinct features (see Table 4 and Fig. 2), with significant differences in PPUS scores between each latent profile (*Games-Howell* $p<0.001$; see Supplementary Table 6). Individuals in Profile 1 ($n=45$) represented 3.9% of the sample and scored between + 1.63 and + 2.92 SD across PPUS items with a mean raw total of 42.7. Individuals in this profile scored high across all items and extremely high in *distress and functional problems* (items 10, 11, 12). Thus, Profile 1 was labeled "At-risk users." Individuals in Profile 2 ($n=109$) represented 9.5% of the sample and scored between + 0.38 and + 1.70 SD across PPUS items with a mean raw total of 27.2. Individuals in this profile were therefore considered at "moderate to high risk" of developing problematic pornography use. Individuals in Profile 3 ($n=120$) represented 10.4% of the sample, with a mean raw total of 20.8. These participants scored between + 0.5 and + 1.21 SD in items assessing *excessive use*, *control difficulties*, and *functional problems* and near the mean in items assessing *use for escape*. Accordingly, this profile was labeled "moderate risk with low use for escape.". Individuals in Profile 4 ($n=264$) represented 23% of the sample, with a mean raw total of 11.4. These participants scored near the mean in items assessing *excessive use*, *control difficulties*, and *functional problems* and + 0.5 SD in items assessing *use for escape*. Accordingly, this profile was labeled "normative users with high use for escape." Finally, individuals in Profile 5 ($n=611$) represented 53.2% of the sample with a mean raw total of 4.3. These participants scored around ± 0.5 SD and were thus labeled "normative users."

Table 2 Fit indices for observed factorial models

Model	*df*	χ^2	$\Delta\chi^2$	*p*	CFI	ΔCFI	TLI	RMSEA	ΔRMSEA	AIC	BIC
Unidimensional	54	654.03			.787		.740	.142		18,331.96	18,435.35
4-factors as proposed by Kor et al. (2014)	48	131.61	370.02	< .001	.970	.183	.959	.069	.073	17,486.41	17,615.65
Bifactor model	43	216.08	145.57	< .001	.939	.03	.906	.086	.017	17,629.31	17,780.09

Note: *df*, degrees of freedom; χ^2, chi square; $\Delta\chi^2$ = calculated on Satorra Bentler Scaled (SBS) difference, with comparisons conducted against the immediately preceding model; *p*, significance $\Delta\chi^2$ value; *CFI*, comparative fit index; *TLI*, Tucker–Lewis index; *RMSEA*, root mean square error of approximation; *SRMR*, standardized root mean square residual; *AIC*, Akaike information criterion; *BIC*, Bayesian information criterion

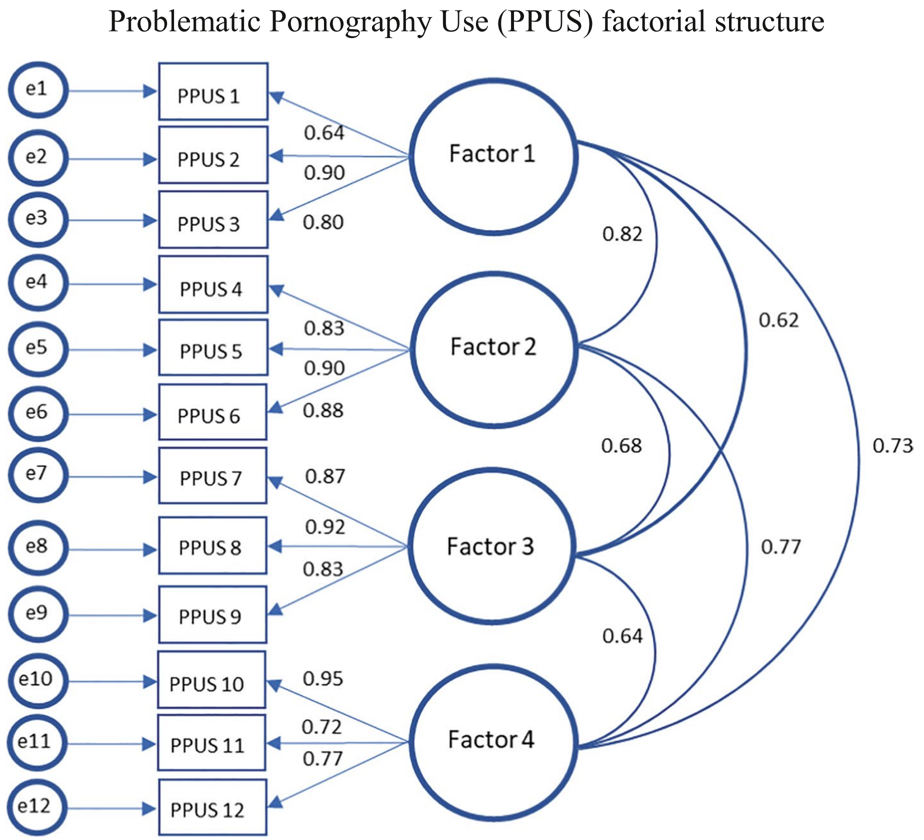

Fig. 1 PPUS optimal factorial structure, including four factors (i.e., "excessive use," "control difficulties," "use for escape/avoiding negative emotions," and "distress and functional problems")

PPUS Cut-Off Points

A receiver-operating characteristic (ROC) analysis was conducted to determine the best possible cut-off points to identify at-risk users. Participants included in the "at-risk" latent profile were considered the benchmark to calculate true-negative (TN) and true-positive cases (TP). As seen in Table 5, a raw score of 33 was the lowest possible threshold with no false negatives and thus suggested as a cut-off score to classify "at risk" pornography users. Most participants (97.8%) were accurately classified as *at-risk* using a cut-off value of 33, with 24 participants (false-positive rate [FPR] = 2.2%) misclassified as being *at-risk* and no participants misclassified as *not-at-risk* users (false-negative rate [FNR] = 0%). At this cut-off value, the positive predictive value (PPV) was 65.2%, and the negative predictive value (NPV) was 100%, suggesting that most participants were correctly classified in their corresponding categories. Moreover, 95% of participants scored below this cut-off value, with individuals exceeding this value falling beyond + 2 SD of the sample distribution (Table 6). Figure 3A shows accuracy values as a function of PPUSS total scores, demonstrating that scores between 28 and 41 showed the highest classification accuracy. Figure 3B shows that the area under the curve (AUC) was 99.9%, indicating that PPUS shows

Table 3 TidyLPA model solutions

Model	Profiles	AIC	BIC	AWE	Log likelihood	Entropy	N Min	BLRT p
CIDP—equal variances, equal covariance	2	39,923.00	40,109.73	40,479.50	– 17,894	0.955	0.172	0.009
	3	38,529.75	38,782.08	39,282.56	– 17,894	0.775	0	0.782
	4	37,773.00	38,090.94	38,722.06	– 17,894	0.740	0	0.535
	5	37,177.30	37,560.85	38,322.53	– 17,475	0.761	0	0.009
	6	36,721.16	37,170.32	38,062.61	– 17,761	0.747	0	0.931
CIRP—equal variances, equal covariances	2	35,993.41	36,513.21	37,546.11	– 19,924	0.974	0.200	0.009
	3	36,019.41	36,604.82	37,768.69	– 19,215	0.926	0.121	0.009
	4	36,045.40	36,696.41	37,990.95	– 18,823	0.906	0.056	0.009
	5	**35,234.54**	**35,951.17**	**37,376.27**	**– 18,513**	**0.931**	**0.039**	**0.009**
	6	35,832.66	36,614.89	38,170.63	– 18,272	0.926	0.034	0.009

Note. This step includes an assessment of possible variance–covariance structures based on AIC, BIC, log likelihood, entropy, number of participants in the smallest profile (N Min), and likelihood ratio test (BLRT) to determine if including an extra profile significantly increases the model fit. Smallest AIC, BIC, AWE, and log likelihood values indicate better fit, largest entropy indicates clearly differentiated profiles, and BLRT $p < .05$ suggests improved information compared to K-1 profiles. Here, AIC, BIC, and AWE suggest CIRP model with 5 profiles as the best fit. Models not converging on a solution were omitted in this table. Bold font indicates the best fitting model

an overall high accuracy of true positive detection of "problematic users." Finally, *at-risk* individuals also scored significantly higher in depression (PHQ-9; Student's $t_{[1147]} = -10.7$, $p < 0.001$; $\text{Mean}_{\text{at-risk}} = 16.8$, $\text{Meann}_{\text{non-at-risk}} = 4$) and anxiety symptoms (GAD-7; Welch's $t_{[46]} = -6.76$, $p < 0.001$; $\text{Mean}_{\text{at-risk}} = 12$, $\text{Meann}_{\text{non-at-risk}} = 4.9$; see Supplementary Fig. 4) compared to the rest of the sample.

Discussion

This study is aimed at examining the PPUS factorial validity and reliability and at identifying suggested cut-off scores to detect individuals *at-risk* of developing disordered pornography use. To address these aims, exploratory (EFA), confirmatory (CFA), latent profiles (LPA), and sensitivity analyses (ROC) were implemented using a large cross-sectional community sample. The results observed here indicate that a four-factor latent structure (as proposed by Kor et al., 2014) best explained the PPUS variance–covariance patterns. Moreover, five significantly different pornography user profiles were observed, with 3.9% of the sample considered at-risk of developing problematic pornography use. Finally, a suggested cut-off PPUS total raw of 33 was proposed to identify at-risk users with a 97.8% detection accuracy. The significance of these evaluations is supported by limited comparative research concerning the factor structure, the latent profiles, and the optimum cut-off point informed by the PPUS responses, representing significant implications for assessing and conceptualizing problematic pornography use.

Table 4 Profile raw scores, standard deviation, and standardized scores (*Z*) across PPUS indicators

Profiles		PPUS1	PPUS2	PPUS3	PPUS4	PPUS5	PPUS6	PPUS7	PPUS8	PPUS9	PPUS10	PPUS11	PPUS12	Mean scores	Range
At-risk users (*n* = 45; 3.9%)	Raw scores	3.73	3.87	3.60	4.22	4.07	4.42	3.89	4.07	4.29	3.73	3.40	3.69	42.7	33–54
	Std scores	*1.63*	*2.43*	*2.23*	*2.17*	*2.24*	*2.33*	*1.86*	*2.01*	*1.71*	*2.87*	*2.92*	*2.05*		
Moderate to high risk (*n* = 109; 9.5%)	Raw scores	2.37	1.94	1.89	2.57	2.59	2.90	3.54	3.63	3.87	2.07	1.37	2.32	27.2	17–40
	Std scores	*0.38*	*0.78*	*0.77*	*1.01*	*1.17*	*1.31*	*1.62*	*1.70*	*1.43*	*1.37*	*0.92*	*1.08*		
Moderate risk with low use for escape (*n* = 120; 10.4%)	Raw scores	2.60	2.18	2.10	2.75	2.64	2.67	1.28	1.02	1.98	1.04	0.72	1.82	20.8	12–35
	Std scores	*0.59*	*0.98*	*0.95*	*1.14*	*1.21*	*1.15*	*0.04*	*−0.16*	*0.16*	*0.44*	*0.29*	*0.72*		
Normative users with high use for escape (*n* = 264; 23%)	Raw scores	2.06	0.93	0.91	0.95	0.75	0.55	2.03	2.06	2.53	0.26	0.20	0.65	11.4	5–23
	Std scores	*0.10*	*−0.09*	*−0.06*	*−0.12*	*−0.17*	*−0.28*	*0.56*	*0.58*	*0.52*	*−0.27*	*−0.23*	*−0.12*		
Normative users (*n* = 611; 53.2%)	Raw scores	1.57	0.49	0.44	0.41	0.24	0.21	0.25	0.30	0.80	0.09	0.09	0.20	4.3	0–14
	Std scores	*−0.35*	*−0.47*	*−0.46*	*−0.51*	*−0.54*	*−0.51*	*−0.68*	*−0.67*	*−0.64*	*−0.42*	*−0.34*	*−0.43*		

Note. It is useful to see how problematic and non-problematic users score differently on the PPUS using raw and standardized scores for comparison purposes. Raw scores represent participant scoring of PPUS items ranging from 1 to 6 (i.e., *never true* to almost always true). Standardized scores (*Z*) allow inferences in terms of how many standard deviations (SD) participant's scores are from the mean. In a *normal* distribution, 68% of participants fall within 1 SD from the mean, and 95% of participants fall within 2 SD from the mean

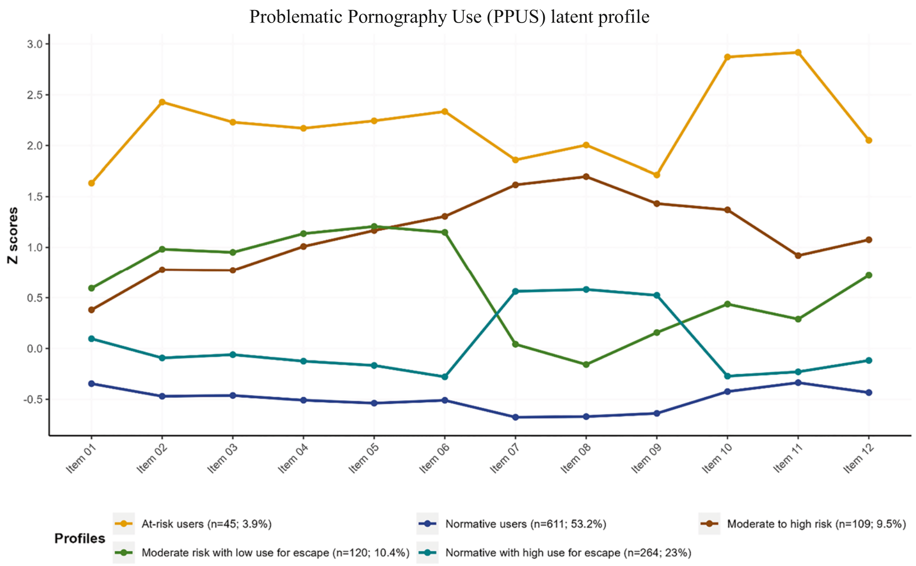

Fig. 2 Standardized PPUS profiles. The two profiles are well differentiated with at-risk users scoring between 0.75 and 2 SD above the mean

Table 5 Calculation of cutoff thresholds for PPUS

Threshold	TN	TP	FN	FP	Specificity (%)	Sensitivity (%)	Accuracy (%)	NPV (%)	PPV (%)
41	1104	23	22	0	100.00	51.11	98.09	98.05	100.00
40	1103	32	13	1	99.91	75.56	98.78	98.84	96.97
39	1103	34	11	1	99.91	75.56	98.96	99.01	97.14
38	1103	37	8	1	99.91	82.22	99.22	99.28	97.37
37	1103	40	5	1	99.91	88.89	99.48	99.55	97.56
36	1103	41	4	1	99.91	91.11	99.56	99.64	97.62
35	1099	41	4	5	99.55	91.11	99.22	99.64	89.13
34	1092	44	1	12	98.91	97.78	98.87	99.91	78.57
33	**1080**	**45**	**0**	**24**	**97.83**	**100.00**	**97.91**	**100.00**	**65.22**
32	1072	45	0	32	97.10	100.00	97.21	100.00	58.44
31	1064	45	0	40	96.38	100.00	96.52	100.00	52.94
30	1058	45	0	46	95.83	100.00	96.00	100.00	49.45
29	1048	45	0	56	94.93	100.00	95.13	100.00	44.55
28	1037	45	0	67	93.93	100.00	94.17	100.00	40.18

Note. Threshold represents composite PPUS scores; *TN*, true negatives; *TP*, true positives; *FN*, false negatives; *FP*, false positives; *Sensitivity*, true positive rate; *Specificity*, true negative rate; *Accuracy*, (specificity + sensitivity)/*n*; *NPV*, negative predictive value; *PPV*, positive predictive value. Bold font highlights the most accurate PPUS total value, and the shaded area represents the 5 most accurate PPUS total values

Table 6 PPUS norms ($N = 1149$)

PPUS total score	Frequency	%	Cumulative %
00	35	3.0	10.7
01	88	7.7	19.2
02	98	8.5	25.6
03	73	6.4	31.9
04	72	6.3	36.9
05	57	5.0	42.8
06	68	5.9	48.5
07	65	5.7	53.1
08	53	4.6	57.5
09	51	4.4	61.5
10	46	4.0	64.6
11	36	3.1	67
12	28	2.4	69.9
13	33	2.9	72.4
14	29	2.5	74.8
15	28	2.4	76.7
16	22	1.9	77.9
17	14	1.2	79.7
18	21	1.8	80.7
19	11	1.0	82.5
20	21	1.8	83.1
21	7	0.6	84.1
22	12	1.0	85.2
23	13	1.1	86.7
24	17	1.5	87.6
25	10	0.9	88.8
26	14	1.2	90.1
27	15	1.3	91.1
28	11	1.0	92
29	10	0.9	92.5
30	6	0.5	93.2
31	8	0.7	93.9
32	8	0.7	95
33	13	1.1	95.9
34	10	0.9	96.2
35	4	0.3	96.3
36	1	0.1	96.6
37	3	0.3	96.9
38	3	0.3	97.1
39	2	0.2	98
40	10	0.9	98
41	0	0.0	98.1
42	1	0.1	98.3
43	2	0.2	98.4
44	1	0.1	98.7
45	4	0.3	98.9

Table 6 (continued)

PPUS total score	Frequency	%	Cumulative %
46	2	0.2	99
47	1	0.1	99.3
48	4	0.3	99.6
49	4	0.3	99.7
50	1	0.1	99.8
51	1	0.1	99.8
52	0	0.0	99.9
53	1	0.1	100
54	1	0.1	10.7

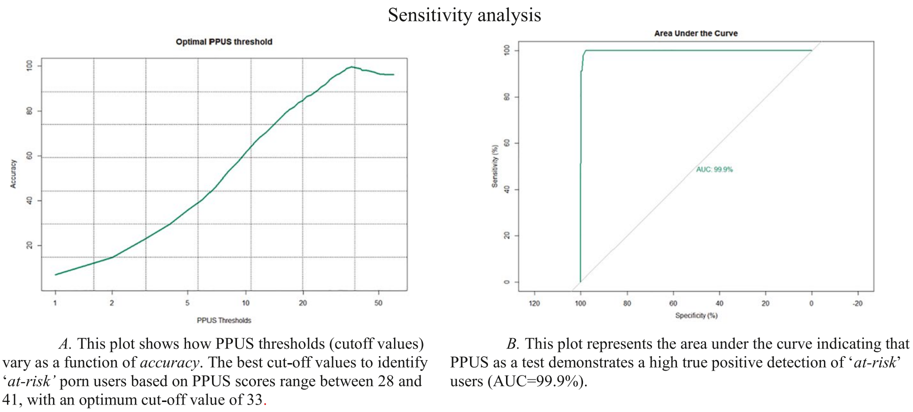

Fig. 3 **A** This plot shows how PPUS thresholds (cutoff values) vary as a function of *accuracy*. The best cut-off values to identify "at-risk" porn users based on PPUS scores range between 28 and 41, with an optimum cut-off value of 33. **B** This plot represents the area under the curve indicating that PPUS as a test demonstrates a high true positive detection of "at-risk" users (AUC = 99.9%)

Exploratory and Confirmatory Factor Analyses

An initial EFA revealed a four-factor solution congruent with Kor and colleagues' (Kor et al., 2014) model explained 79.6% of the variance. Interestingly, Factor 2 (i.e., *excessive use*; see Table 1) accounted for the majority of variance in the data (56.4%; see Supplementary Table 4), emphasizing the importance of such items (i.e., addressing excessive usage experiences) when assessing problematic pornography use. This finding conflicts with Kor and colleagues (Kor et al., 2014) where, in their community sample (only), 21.8% of the variance was accounted for by *excessive use*, with most variance explained by the other factors (i.e., *control difficulties*, *use for escape*, and *distress and functional impairment*). Such differences may reflect the increased accessibility to online porn without necessarily representing an inability to control the use or functional impairment due to excessive use (Stavropoulos et al., 2021).

The three additional factors for the PPUS only accounted for a small percentage of variance, and item 12 loaded concurrently on Factors 4 (*distress and functional problems*) and 1 (*excessive use*; see Supplementary Table 5). Given that research regarding EFAs for the

PPUS is sparse, comparisons for this finding are limited. Nonetheless, this cross-loading may be conceptually supported as item 12 captures *use despite harm*, and this concept may relate to excessive use and functional problems (Fernandez and Griffiths, 2019). Although not considered one of the six core components of addiction, *use despite harm* indirectly reflects key diagnostic criteria for behavioral addictions, thus signifying a PPUS strength (Griffiths, 2005). For example, reflective functioning surrounding harm could inform treatment drives (Binnie & Reavey, 2020). Taken together, the potential benefit of an increased PPUS focus on Factor 2 (i.e., *limited control, tolerance* and *withdrawal*) and Item 12 (i.e., use despite harm) may be of interest to future researchers.

CFA models were compared to assess the optimal PPUS factorial structure, including a unidimensional, a 4-factor solution, and a bifactor model. Except for the unidimensional model, all models demonstrated acceptable fit, supporting the notion that PPUS is a multidimensional construct (Chen et al., 2021). While the bifactor solution was not the strongest fit comparatively, fit indices were still acceptable, suggesting that the PPUS can be reliably interpreted as a general factor with four subdimensions collectively rather than independently. Thus, for assessment purposes and in the context of the bifactor model, the general and sub-factor scores could be used to describe symptom presentations and guide the development of symptom-targeting case formulation plans.

Identifying Users At-Risk of Disordered Pornography Use and PPUS Cut-Off Values

Aiming to identify suggested cut-off PPUS values to differentiate at-risk from normative pornography users, latent profile (LPA) and sensitivity analyses were successively used. The findings indicated five distinct profiles of pornography users in the sample. Most participants (53.2%) fell within normative ranges of PPUS (0 to − 0.5SD), suggesting appropriate pornography use. Interestingly, an additional 23% of participants scored within normative ranges for all PPUS items, except for items related to *use for escape* (Items 7, 8, and 9). This suggests that many individuals engage in pornography consumption to alleviate negative feelings and avoid dealing with unpleasant or difficult experiences, although not within the pathological range. Previous research (Gomez et al., 2018; Stavropoulos et al., 2022) similarly indicated many individuals engage in problematic behaviors, such as disordered pornography use, to *escape* and *avoid* dealing with problems. This maladaptive coping strategy has been associated with the early stages of disordered problematic/addictive behaviors that may result in more significant future problems and may encourage the transition into other types of problematic/addictive behaviors (e.g., disordered gambling, online gaming, or disordered social media use; Zarate et al., 2023b).

The remaining pornography users' latent profiles included individuals experiencing moderate- to high-risk use (9.5%), individuals experiencing moderate- to high-risk use with low use for escape (10.4%), and problematic or *at-risk* users (3.9%). Individuals in the moderate- to high-risk use scored between 0.5 and 1.5SD above the mean across PPUS items, suggesting excessive use, control difficulties, and functional problems. Interestingly, those considered at moderate- to high-risk differed in their use for escape, with some individuals (Profile 3) scoring at mean values in use for escape (Items 7, 8, and 9) and some (Profile 2) scoring at 1.5SD above the mean. This represents an interesting distinction that may require further evaluation and suggests that individuals may engage in disordered pornography use even when they do not use porn to escape their problems (or at least not demonstrating awareness of it). Thus, the latter group may be more resistant to treatment due to their potential lack of awareness regarding their escaping motivations. Finally, individuals at-risk of disordered pornography use scored between 1.5 and 3SD above the mean and represented 3.9% of the sample. These participants also scored significantly higher in depression and anxiety measures, suggesting that those experiencing severe symptoms associated with pornography use also experience comorbid distress-related psychopathologies. Following this classification, a sensitivity analysis determined that a cut-off score of 33 accurately identified individuals considered at-risk of problematic pornography use. Specifically, using this cut-off value, no *at-risk* user was incorrectly classified (i.e., 0 false negatives). This suggests that those exceeding this value show clear signs of disordered pornography use and would be identified as problematic users.

Practical Implications

The findings reported here could have significant clinical and diagnostic implications in evaluating CSBD and further validate the component model in identifying at-risk behavior (Alexandraki et al., 2018a). Specifically, previously outlined CSBD domains (i.e., excessive use, control difficulties, use for escape, distress, and functional problems), in line with the component model of addiction, appear to be accurately captured by the PPUS (Fernandez and Griffiths, 2019). Moreover, the suggested cut-off identified here appears to clearly differentiate *at-risk* individuals from those engaging with online pornography at normative levels. This is important because it disputes the possibility of *over-pathologizing* everyday behaviors (Kraus et al., 2016). In other words, effective measures with validated cut-off scores are much needed to clearly distinguish individuals who may safely engage in online pornography from those who may experience unwanted consequences as a result of disordered use. This notion aligns with the incorporation of different forms of behavioral addictions, such as compulsive shopping and Internet gaming disorder, within the DSM-5 (APA, 2013; Zarate et al., 2023c). In general, a more thorough evaluation of behavioral addictions, which might sometimes receive less focus in mental health practice, such as problematic social media use or disordered sexual behavior, would enable clinicians to diagnose problematic behaviors accurately.

Moreover, the latent profiles observed here represent qualitative differences in *how* users engaged in sex behaviors observed in the current sample. This suggests that clinical assessment of CSBD should be accompanied by considerations aligned with PPUS domains not only to diagnose problematic behaviors but also prevent further problems (Fernandez and Griffiths, 2019). For example, the self-medication hypothesis proposes that distressed individuals may engage in problematic behaviors, such as CSBD, as a maladaptive mechanism to suppress dealing with their emotional issues (Khantzian, 1997). In this context, normative users with *high use for escape* may signal early problematic behaviors that could further develop in diagnosable CSBD.

Limitations, Further Research, and Conclusion

The present study was not without limitations. The community sample used here completed self-report questionnaires captured using a cross-sectional design prone to bias. Thus, longitudinal studies and studies of clinical populations would be useful to assess if the PPUS factorial structure remains time-invariant and group-invariant. Similarly, accurate identification of individuals at-risk of experiencing disordered pornography use may be enhanced with longitudinal examinations of not exclusively self-reported questionnaires but also observatory measures (i.e., mobile monitoring applications capturing one's usage of porn sites). Future research may incorporate these considerations while evaluating the possibility of sequential and progressive problems associated with disordered pornography use. For example, individuals experiencing excessive use may subsequently experience control difficulties leading to distress and functional problems. Moreover, future research may explore the PPUS factorial structure using alternative methodologies, such as structural equation modelling (SEM) and exploratory SEM (ESEM) to address potential lack of model fit due to item cross-loadings.

Despite these limitations, the findings reported here have significant implications regarding the conceptualization, assessment, and prevention of problematic pornography use. Individuals identified at-risk of disordered pornography use also experience high depression and anxiety. This may be taken as indicating (a) the need to recognize problematic pornography use as a unique disorder that may result and/or accompany (in) significant distress and (b) the need to target individuals at-risk of disordered pornography use in primary care, while also addressing their comorbid distress symptoms. Thus, these findings may guide the development of more efficacious treatments targeting disordered/problematic pornography use.

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Data Availability Data and syntax are available in the following link: https://github.com/Daniel28052/PPUS.

Declarations

Ethical Approval and Consent to Participate Ethics approval was granted by the Victoria University Ethics Committee. The current study only involved adult subjects (+ 18 years old), and informed consent was obtained in all cases.

Consent for Publication All authors of the manuscript have read and agreed to its content and are accountable for all aspects of the accuracy and integrity of the manuscript. All methods were carried out in accordance with relevant guidelines and regulations.

Competing Interests The authors declare no competing interests.

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