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Uncovering the Most Robust Predictors of Problematic Pornography Use: A Large-Scale Machine Learning Study Across 16 Countries

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The findings of this study have not been published previously, but parts of the results have been presented at the 47th Annual Meeting of the International Academy of Sex Research and at the Seventh International Conference on Behavioral Addictions. Detailed information on the individual data sets' data use and publication status can be found in eTable 1 in the online supplemental materials. Beáta Bőthe was supported by a postdoctoral fellowship from the SCOUP Team–Sexuality and Couples–Fonds de recherche du Québec, Société et Culture during the preparation of the study and by the Banting Postdoctoral Fellowship (Social Sciences and Humanities Research Council [SSHRC]) during the data solicitation and the preparation of the first draft of the article. Marie-Pier Vaillancourt-Morel was supported by a Research Chair from the Université du Québec à Trois-Rivières and a career award from the Fonds de recherche du Québec–Santé. Sophie Bergeron was supported by a Tier I Canada Research Chair and grants from the Canadian Institutes of Health Research and SSHRC. Shane W. Kraus was supported by grants from the Kindbridge Research Institute and the International Center for

Problematic pornography use (PPU) is the most common manifestation of the newly introduced compulsive sexual behavior disorder diagnosis in the 11th revision of the International Classification of Diseases. Research related to PPU has proliferated in the past two decades, but most prior studies were characterized by several shortcomings (e.g., using homogenous, small samples), resulting in crucial knowledge gaps and a limited understanding concerning empirically based risk factors for PPU. This study aimed to identify the most robust risk factors for PPU using a preregistered study design. Independent laboratories' 74 preexisting self-report data sets ($N_{\text{participants}} = 112{,}397$; $N_{\text{countries}} = 16$) were combined to identify which factors can best predict PPU using an artificial intelligence-based method (i.e., machine learning). We conducted random forest models on each data set to examine how different sociodemographic, psychological, and other characteristics predict PPU, and combined the results of all data sets using random-effects meta-analysis with meta-analytic moderators (e.g., community vs. treatment-seeking samples). Predictors explained 45.84% of the variance in PPU scores. Out of the 700+ potential predictors, 17 variables emerged as significant predictors across data sets, with the top five being (a) pornography use frequency, (b) emotional avoidance pornography use motivation, (c) stress reduction pornography use motivation, (d) moral incongruence toward pornography use, and (e) sexual shame. This study is the largest and most integrative data analytic effort in the field to date. Findings contribute to a better understanding of PPU's etiology and may provide deeper insights for developing more efficient, cost-effective, empirically based directions for future research as well as prevention and intervention programs targeting PPU.

General Scientific Summary

This study suggests that the top five predictors of problematic pornography use (PPU) were frequency of use, emotional avoidance pornography use motivation, stress reduction pornography use motivation, moral incongruence, and sexual shame. These findings provide empirically based key insights to develop effective, scientifically driven prevention and intervention programs for PPU that are currently absent from the literature and health care systems.

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Beáta Bőthe served as lead for conceptualization, project administration, supervision, validation, writing–original draft, and writing–review and editing and contributed equally to data curation, funding acquisition, methodology, and resources. Marie-Pier Vaillancourt-Morel served in a supporting role for conceptualization, data curation, funding acquisition, investigation, methodology, resources, and writing–review and editing. Sophie Bergeron served in a supporting role for conceptualization, data curation, funding acquisition, investigation, methodology, resources, and writing–review and editing. Zsombor Hermann served as lead for formal analysis and visualization and served in a supporting role for data curation, investigation, methodology, resources, software, validation, and writing–review and editing. Krisztián Ivaskevics served in a supporting role for data curation, formal analysis, investigation, methodology, resources, software, and writing–review and editing. Shane W. Kraus served in a supporting role for conceptualization, data curation, investigation, methodology, resources, supervision, and writing–review and editing. Joshua B. Grubbs served in a supporting role for conceptualization, data curation, investigation, methodology, resources, supervision, and writing–review and editing. Marie-Pier Vaillancourt-Morel and Sophie Bergeron contributed equally to supervision. Members of the Problematic Pornography Use Machine Learning Study Consortium served in supporting roles for data curation, investigation, resources, and writing–review and editing.

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After four decades of clinical attention and a marked increase in scientific studies on out-of-control sexual behaviors (Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020), compulsive sexual behavior disorder (CSBD) has now been included in the 11th revision of the International Classification of Diseases (Kraus et al., 2018; World Health Organization, 2022). CSBD is defined as a persistent pattern of uncontrollable sexual impulses, urges, and behaviors, resulting in clinically significant distress and adverse consequences, with prevalence estimates ranging between 2% to 10% (Bőthe et al., 2023; Bőthe, Nagy, et al., 2024; Bőthe, Potenza, et al., 2020; Briken et al., 2022; Dickenson et al., 2018; Grubbs, Reid, et al., 2023; Kraus et al., 2018; Lewczuk, Wizła, et al., 2022; World Health Organization, 2022). The most common behavioral manifestation of CSBD is problematic pornography use (PPU) (Reid et al., 2012), defined as a persistent pattern of uncontrollable pornography use along with significant distress and functional impairment (Kraus et al., 2018; World Health Organization, 2022). Despite the introduction of the official CSBD diagnosis, some key questions have yet to be addressed due to previous studies' theoretical and methodological limitations (e.g., small, homogenous samples) (Grubbs, Hoagland, et al., 2020). One such key question pertains to potential risk factors for PPU. In the present study, we aimed to identify risk factors contributing to PPU using an innovative, multilab approach with an artificial intelligence-based method (i.e., machine learning [ML]).

Past literature suggests that PPU is likely to be present in more than 80% of individuals with CSBD, potentially due to widespread internet access (Grubbs, Hoagland, et al., 2020; Reid et al., 2012). Based on web traffic data, pornography use has increased by 310% since the early 2000s (Lewczuk, Wójcik, et al., 2022). Nationally representative and large-scale studies suggest that, in the past 20 years, 70%–94% of adults (Grubbs, Kraus, et al., 2019; Herbenick et al., 2020; Lewczuk et al., 2020; Rissel et al., 2017) and 42%–98% of adolescents (Bőthe, Vaillancourt-Morel, et al., 2020; Donevan et al., 2022; Wolak et al., 2007; Wright et al., 2020) reported using pornography.

However, pornography use qualifies as PPU only for a small subset of users, resulting in significant distress and legal, financial, or relationship issues (Grubbs, Kraus, et al., 2019; Lewczuk et al., 2020; Rissel et al., 2017; Sniewski & Farvid, 2020). Recent estimates suggest that 1%–38% of adults and 5%–14% of adolescents may experience PPU (Bőthe, Vaillancourt-Morel, et al., 2021; Grubbs, Kraus, et al., 2019; Lewczuk et al., 2020; Rissel et al., 2017; Štulhofer et al., 2020; Svedin et al., 2011). These varying prevalence estimates may stem from real group differences (e.g., PPU may be higher in some cultures or among specific populations, such as samples including only men; Ahorsu et al., 2023; Bőthe et al., 2023; Bőthe, Nagy, et al., 2024; Grubbs, Hoagland, et al., 2020). However, they may also derive from the different conceptualizations and measurements of PPU, leading to even higher prevalence estimates for PPU than for CSBD in some cases (Bőthe et al., 2023; Bőthe, Nagy, et al., 2024; Chen, Jiang, Wang, et al., 2022; Fernandez & Griffiths, 2021). There is a long-standing debate on the classification and symptomatology of PPU, with some suggesting that PPU may be best conceptualized as a behavioral addiction, while others consider it as an impulse control or a compulsivity-related disorder (Bőthe et al., 2022; Bőthe, Tóth-Király, et al., 2019; Brand et al., 2020; Castro-Calvo et al., 2022; Kraus et al., 2016; Ley et al., 2014; Rumpf & Montag, 2022; Sassover & Weinstein, 2020).

Nevertheless, even at the lowest ends of these prevalence estimates, PPU may be as common as well-established mental health issues such as mood disorders (Polanczyk et al., 2015; Steel et al., 2014); yet, it has received significantly less scientific attention to date (Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020). Consequences of mental disorders as well as of PPU might be prevented and treated, reducing potential public health impacts, if sufficient scientific evidence was available to develop cost-effective, evidence-based prevention and intervention programs (Grubbs, Floyd, et al., 2023; Grubbs, Hoagland, et al., 2020; Nelson & Rothman, 2020). In line with this notion, one crucial step to achieve this goal is to better understand which risk factors are related to PPU (Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020).

Several theoretical models have been developed to describe the potential etiology of PPU (e.g., the interaction of person-affect-cognition-execution model, the moral incongruence model; Brand et al., 2019; Grubbs, Perry, et al., 2019). These models are similar in that they propose several different factors contributing to the development of PPU, and potential interactions between structural, situational, psychological, and biological characteristics. In the past two decades, more than 120 empirical studies examined PPU, among which many tested theoretical models, and examined potential risk and protective factors (Grubbs, Hoagland, et al., 2020). Still, a key challenge for the field has been to draw clear inferences from diverse findings and available data and make this knowledge cumulative. One crucial obstacle these studies have faced is the limited number of participants and number of variables that could be included in one study (e.g., the cost of studies increases as more participants and variables are included) and the lack of analytical methods to handle such complex models (Grubbs, Hoagland, et al., 2020). Another important shortcoming is the focus on small, homogenous, Western, educated, industrialized, rich, and democratic (WEIRD) samples (Bőthe, Vaillancourt-Morel, et al., 2019; Chen, Jiang, Wang, et al., 2022; Grant Weinandy et al., 2023; Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020; Jennings et al., 2021). These limitations call for large data sets with a wide range of variables, and the application of novel statistical methods that can handle the simultaneous consideration of hundreds of factors to provide accurate predictions concerning individuals' PPU and related risk factors.

Artificial intelligence-based data analytic methods represent an effective approach for developing algorithms capable of solving these complex problems and outperform traditional regression methods in predictive tasks (e.g., predicting suicidal risk) (Dwyer et al., 2018; Walsh et al., 2017, 2018). Specifically, ML approaches focus on learning statistical functions from multidimensional data sets, including many potential predictors, and their linear and nonlinear interactions, to make generalizable predictions about individuals, providing crucial information about potential risk factors. Therefore, ML can produce meaningful, accurate, replicable, and generalizable models that can improve current theoretical models and be easily integrated into clinical care (Dwyer et al., 2018; Orrù et al., 2020; Yarkoni & Westfall, 2017).

Table 1
Characteristics of the Data Sets Included in the Study and the Results of the Random Forest Models on Each Data Set

Model ID	Valid *N*	PPU scale used	Sample Type 1	Sample Type 2	Country	Publication status[a]	No. of potential predictors	No. of included predictors	Explained variance in the model (%)	*MSE*	Missing data—*M* (%)	Missing data—min. (%)	Missing data—max. (%)
1	15,137	PPCS	Community sample	Adult sample	Hungary	Published	92	11	48.17	172.57	0.85	0.00	6.25
2	6,165	PPCS	Community sample	Adult sample	Hungary	Published	65	16	72.73	13.09	2.36	0.00	11.65
3	363	PPCS	Community sample	Adult sample	Hungary	Published	23	2	50.55	27.29	0.65	0.00	6.61
4	1,285	CPUI	Community sample	Adult sample	Hungary	Published	28	20	37.34	84.58	0.03	0.00	0.70
5	772	PPCS	Community sample	Adult sample	Hungary	Published	45	16	28.32	215.32	0.33	0.00	2.59
6	304	CPUI	Community sample	Adult sample	Hungary	Published	45	6	21.14	91.64	0.26	0.00	2.96
7	550	CPUI	Community sample	Adult sample	Hungary	Published	15	5	18.76	99.13	0.00	0.00	0.00
8	1,002	PPCS	Treatment-seeking sample	Adult sample	International/ not specified	Published	23	10	22.68	412.61	0.20	0.00	1.50
9	756	PPCS	Community sample	Adult sample	Hungary	Published	66	12	63.20	134.00	1.69	0.00	12.43
10	1,090	PPCS	Community sample	Adult sample	Hungary	Published	53	11	54.81	141.59	0.68	0.00	11.38
11	171	PPCS	Community sample	Adult sample	Hungary	Not published	73	5	54.52	98.46	1.11	0.00	6.43
12	366	PPCS	Community sample	Adult sample	Hungary	Not published	60	9	57.38	114.28	1.50	0.00	11.20
13	466	PPCS	community sample	Adult sample	Hungary	Not published	17	2	13.31	325.55	0.48	0.00	7.08
14	558	PPCS	Community sample	Adult sample	Hungary	Not published	41	9	36.47	156.43	5.33	0.00	28.67
15	518	PPCS	Community sample	Adult sample	Hungary	Not published	38	13	21.43	250.42	4.31	0.00	22.01
16	201	PPCS	Community sample	Adult sample	Hungary	Not published	23	9	52.34	124.68	1.75	0.00	36.32
19	233	CPUI	Community sample	Adult sample	Hungary	Not published	16	2	37.48	74.05	0.00	0.00	0.00
20	225	PPCS	Treatment-seeking sample	Adult sample	International/ not specified	Not published	37	9	34.28	152.54	0.04	0.00	0.89
21	699	PPCS	Community sample	Adult sample	Hungary	Not published	157	7	39.09	17.58	1.76	0.00	27.47
22	580	PPCS	Community sample	Adult sample	Hungary	Not published	260	25	53.22	19.27	2.93	0.00	37.24
23	822	CPUI	Community sample	Adult sample	Canada	Published	32	9	24.91	0.48	5.44	0.00	15.69
24	658	CPUI	Community sample	Young adult sample (16–29 years)	Canada	Not published	39	15	28.53	0.51	0.60	0.00	15.20
25	1,873	PPCS	Community sample	Adolescent sample	Canada	Published	102	15	62.48	0.21	5.60	0.00	39.72
28	158	CPUI	Community sample	Young adult sample (16–29 years)	Canada	Published	36	6	49.53	81.76	0.32	0.00	10.13
29	6,023	BPS	Community sample	Adult sample	Bangladesh	Not published	27	20	43.89	3.47	0.00	0.00	0.00
30	316	CPUI	Treatment-seeking sample	Adult sample	Canada	Not published	14	4	7.59	0.50	3.05	0.00	19.62
31	299	PPUS	Treatment-seeking sample	Adult sample	International/ not specified	Not published	22	8	34.92	94.85	1.14	0.00	25.08
32	1,400	CPUI	Community sample	Adult sample	United States	Published	32	14	50.00	8.66	0.04	0.00	0.21
34	134	PPUS	Treatment-seeking sample	Adult sample	International/ not specified	Published	26	10	51.35	87.15	0.00	0.00	0.00
35	330	PPCS	Community sample	Adult sample	Portugal	Not published	12	6	66.19	142.81	0.03	0.00	0.30
36	431	PPCS	Community sample	Adult sample	Germany	Not published	21	7	60.25	101.61	3.48	0.00	18.10
37	241	BPS	Community sample	Adult sample	Israel	Not published	26	8	47.31	0.07	3.93	0.00	25.31
38	241	CIUS-SEM	Community sample	Adolescent sample	Netherlands	Published	71	9	12.40	0.31	1.54	0.00	34.44
39	653	BPS	Community sample	Adult sample	Poland	Not published	12	2	28.23	5.82	5.42	0.00	23.89
40	519	CPUI	Community sample	Adult sample	United States	Published	21	12	62.72	54.49	0.28	0.00	2.12
41	1,016	BPS	Community sample	Adult sample	Poland	Published	69	12	56.35	2.25	1.30	0.00	33.46
42	760	BPS	Community sample	Adult sample	Poland	Not published	26	9	39.78	4.01	0.08	0.00	0.26
43	261	BPS	Community sample	Adult sample	Israel	Not published	18	3	59.27	0.11	11.03	0.00	36.78
45	866	PPUS	Community sample	Adult sample	United States	Not published	21	6	64.23	0.30	0.24	0.00	1.73
48	808	PPUS	Community sample	Young adult sample (16–29 years)	China	Published	4	3	36.66	51.72	0.00	0.00	0.00
49	1,158	CPCS	Community sample	Adult sample	United States	Published	25	13	13.03	42.92	2.30	0.00	21.50
50	275	PPUS	Community sample	Adult sample	United States	Not published	21	7	54.12	0.29	2.86	0.00	10.18
52	377	PPCS	Community sample	Adult sample	Slovakia	Not published	27	11	28.81	220.23	1.17	0.00	13.00
56	401	PPCS	Community sample	Adult sample	Iran	Published	6	4	35.41	293.15	0.00	0.00	0.00
57	512	PPCS	Community sample	Adult sample	Spain	Not published	61	6	37.69	11.82	5.42	0.00	31.45
59	749	CPUI	Community sample	Adult sample	United States	Published	42	8	51.62	0.95	4.87	0.00	37.25

(*table continues*)

Table 1 (*continued*)

Model ID	Valid *N*	PPU scale used	Sample Type 1	Sample Type 2	Country	Publication status[a]	No. of potential predictors	No. of included predictors	Explained variance in the model (%)	*MSE*	Missing data—*M* (%)	Missing data—min. (%)	Missing data—max. (%)
60	1,109	PPUS	Community sample	Adult sample	International/not specified	Published	20	10	74.27	36.69	0.00	0.00	0.00
61	2,491	PPCS	Community sample	Adult sample	United States	Not published	15	11	51.81	0.92	0.10	0.00	0.40
75	4,035	PPUS	Community sample	Adult sample	Israel	Published	33	16	37.65	37.78	0.02	0.00	0.32
78	1,461	BPS	Community sample	Adult sample	United States	Published	20	9	47.41	3.63	0.07	0.00	1.23
79	1,526	BPS	Community sample	Adult sample	United States	Not published	44	18	14.26	6.79	0.05	0.00	0.33
33a	9,263	BPS	Treatment-seeking sample	Adult sample	China	Published	18	14	36.51	5.61	0.00	0.00	0.00
33b	9,263	PPCS	Treatment-seeking sample	Adult sample	China	Published	18	14	58.37	287.62	0.00	0.00	0.00
33c	9,263	PPUS	Treatment-seeking sample	Adult sample	China	Published	18	8	45.42	114.44	0.00	0.00	0.00
46a	640	BPS	Community sample	Adult sample	China	Published	10	6	47.37	5.17	0.33	0.00	3.28
46b	640	PPCS	Community sample	Adult sample	China	Published	10	6	57.56	208.73	0.33	0.00	3.28
47a	316	BPS	Community sample	Adult sample	China	Published	10	10	52.02	2.86	0.00	0.00	0.00
47b	316	PPUS	Community sample	Adult sample	China	Published	10	6	62.60	41.89	0.00	0.00	0.00
54a	305	BPS	Community sample	Adult sample	Malaysia	Not published	81	7	46.95	4.02	0.72	0.00	28.85
54b	305	PPCS	Community sample	Adult sample	Malaysia	Not published	81	12	58.25	175.92	0.72	0.00	28.85
54c	305	CPUI	Community sample	Adult sample	Malaysia	Not published	81	14	54.89	1.04	0.72	0.00	28.85
58a	1,174	CPUI	Community sample	Adult sample	United States	Published	32	14	38.55	1.50	0.01	0.00	0.17
58b	1,171	BPS	Community sample	Adult sample	United States	Published	32	12	39.05	0.16	0.01	0.00	0.17
62a	366	CPUI	Community sample	Adult sample	United States	Not published	61	9	32.24	1.29	1.93	0.00	13.93
62b	361	CPUI	Community sample	Adult sample	United States	Not published	61	5	36.50	0.61	1.93	0.00	13.57
63a	648	CPUI	Community sample	Adult sample	United States	Not published	30	17	40.99	1.37	2.16	0.00	6.17
63b	621	CPUI	Community sample	Adult sample	United States	Not published	30	7	42.93	0.72	2.08	0.00	5.96
65a	152	CPUI	Community sample	Adult sample	United States	Not published	85	23	44.21	0.92	2.82	0.00	31.58
65b	152	CPUI	Community sample	Adult sample	United States	Not published	85	15	49.38	0.94	2.82	0.00	31.58
68a	900	CPUI	Community sample	Adult sample	United States	Not published	79	13	53.82	0.71	1.42	0.00	30.11
68b	896	CPUI	Community sample	Adult sample	United States	Not published	79	8	59.80	0.45	1.42	0.00	30.13
69a	394	CPUI	Community sample	Adult sample	United States	Not published	49	11	40.51	1.28	2.99	0.00	28.93
69b	384	CPUI	Community sample	Adult sample	United States	Not published	49	11	64.87	0.59	2.94	0.00	28.39
70a	624	CPUI	Community sample	Adult sample	United States	Not published	64	7	60.09	1.01	3.14	0.00	30.77
70b	618	CPUI	Community sample	Adult sample	United States	Not published	64	17	79.92	0.49	3.10	0.00	30.74
71a	1,384	CPUI	Community sample	Adult sample	United States	Not published	56	30	75.17	0.80	1.42	0.00	7.44
71b	1,371	CPUI	Community sample	Adult sample	United States	Not published	56	30	85.17	0.49	1.42	0.00	7.44
72a	1,070	CPUI	Community sample	Adult sample	United States	Not published	97	29	77.88	1.45	2.98	0.00	22.71
77a	1,634	PPCS	Community sample	Adolescent sample	International/not specified	Not published	7	4	14.71	136.27	0.00	0.00	0.00
77b	1,634	PPCS	Community sample	Adolescent sample	International/not specified	Not published	7	4	16.70	20.68	0.00	0.00	0.00
80a	1,143	CPUI	Community sample	Adult sample	United States	Published	48	12	43.91	1.15	1.93	0.00	36.13
80b	1,124	CPUI	Community sample	Adult sample	United States	Published	48	15	59.12	0.73	1.93	0.00	36.21
81a	308	CPUI	Community sample	Adult sample	United States	Not published	13	8	23.20	63.50	0.72	0.00	6.49
81b	308	BPS	Community sample	Adult sample	United States	Not published	13	7	6.54	6.29	0.72	0.00	6.49

Note. When a model ID includes a letter (e.g., 33a, 33b), it represents that the data set included more than one PPU measure, and thus, all PPU measures were considered outcome variables in separate models. When conducting the random forest models, the model showed a negative explained variance in the case of seven data sets (see details in the online supplemental materials). As a negative explained variance is not interpretable, these data sets were not included in the interpretation and meta-analysis steps of the study. ID = identification number; PPU = problematic pornography use; *MSE* = mean-squared error; missing data—min. = minimum of missing data across predictors per data set; missing data—max. = maximum of missing data across predictors per data set; PPCS = long or short version of the Problematic Pornography Consumption Scale; CPUI = long or short version of the Cyber-Pornography Use Inventory; BPS = Brief Pornography Screen; PPUS = Problematic Pornography Use Scale; CPCS = Compulsive Pornography Consumption Scale; CIUS-SEM = Compulsive Internet Use Scale–SEM; SEM = sexually explicit media.
[a] At the time of data solicitation.

Although conducting ML studies does not necessarily require the use of multiple data sets, a collectivistic approach involving several research laboratories and data collection efforts is beneficial for identifying risk factors for PPU. It provides greater statistical power due to the larger sample size; a high number of measured variables; and a greater generalizability of findings to diverse populations as data sets from different cultures, gender, age, and treatment-seeking groups can be included in a study (Joel et al., 2020). In the present study, we combined data from preexisting data sets from multiple independent laboratories, and used preregistered ML and meta-analytic methods to document the most robust predictors of PPU. Given that this study was exploratory in nature and ML is a data-driven method, there were no a priori hypotheses.

Method

Technical details of the method and results sections can be found in the online supplemental materials.

Data Solicitation, Data Eligibility, and Data Availability

Using the reference list of the most recent overarching systematic review on CSBD and PPU (Grubbs, Hoagland, et al., 2020), we contacted all researchers who might have collected data including a PPU measure, as well as others who might have access to eligible data. Overall, we contacted 98 researchers and laboratories worldwide between the fall of 2020 and spring of 2021 to provide available data sets for this study. The preregistered requirements for eligible data sets were as follows: PPU was assessed with a clinical interview or a well-validated scale; the study used a cross-sectional or longitudinal design; the study collected self-report or behavioral data from adolescent or adult populations; and the data were published or unpublished. Studies with experimental or dyadic designs were excluded. Overall, we received 74 eligible data sets ($N_{\text{participants}} =$ 112,397; $N_{\text{countries}} = 16$) with a codebook describing the study design and all variables (Table 1). The list of all data sets, collaborators, and publications is available in eTable 1 in the online supplemental materials. As the study included data on sensitive topics, data sets were not made publicly available.

Preregistration and Related Open Science Materials

The study design (https://osf.io/jqkzr/) and analysis plan (https://osf.io/xaek2/?view_only=801f387a797043cf9aae5485c6e6ef29) were preregistered on the Open Science Framework (OSF) (project's main page: https://osf.io/jaemx/; Bőthe, Vaillancourt-Morel, et al., 2024). Deviations from the preregistered plan are described in the online supplemental materials. Meta-analytic data, codebooks, complementary analyses, and related materials are available on the OSF (https://osf.io/b2wa5/?view_only=59746e81e01d420c8b39fdcc79cd95db).

Measures

The PPU score was the outcome variable, assessed by different, well-validated scales. The long and short versions of the Problematic Pornography Consumption Scale (Bőthe et al., 2018; Bőthe, Tóth-Király, Demetrovics, et al., 2021; Bőthe, Vaillancourt-Morel, et al., 2021) measure PPU based on the six-component model of addiction (Griffiths, 2005), including salience, tolerance, mood modification, conflict, relapse, and withdrawal symptoms. The long and short versions of the Cyber Pornography Use Inventory (Grubbs et al., 2010, 2015; Grubbs & Gola, 2019) assess addictive/compulsive use of pornography, access efforts (i.e., efforts made to be able to view pornography), and emotional distress due to pornography use. The Brief Pornography Screen (Kraus et al., 2020) was developed as a screener to assess impaired control over pornography use and related negative emotions (e.g., guilt after use). The Problematic Pornography Use Scale (Kor et al., 2014) was developed based on four common characteristics of substance use disorders and behavioral addictions, including excessive use, control difficulties, pornography use to avoid negative emotions, and distress and functional problems due to pornography use. The Compulsive Internet Use Scale-sexually explicit media (Downing et al., 2014) was developed on the basis of the addiction framework, and assesses loss of control, coping/mood modification, conflict, preoccupation, and withdrawal symptoms. Finally, the Compulsive Pornography Consumption Scale (Noor et al., 2014) measures obsessive thoughts about pornography and its compulsive use based on the characteristics of obsessive–compulsive disorder (American Psychiatric Association, 2013).

All other variables in the data sets were considered predictor variables. Specific predictors varied from data set to data set. We excluded four types of variables from the potential predictors based on preestablished criteria described in the preregistered study design: scales assessing compulsive sexual behavior or any other variant of it, nonvalidated author-constructed scales, scales or items assessing the consequences of pornography use, and open-ended questions.

Adopting the approaches of prior work (Joel et al., 2020), when a data set and its corresponding codebook had been received, Beáta Bőthe and two research assistants studied these materials, identified any information that was missing from the codebook, and requested the scholar(s) who had provided the data set to complement the codebook with the missing information. The codebook contained detailed metadata of the data set, including the sample size, any inclusion and exclusion criteria, nationality of participants, description of the population (i.e., adult vs. adolescent sample, community vs. treatment-seeking sample), dates of data collection, type of the study (i.e., cross-sectional vs. longitudinal design), type and timeframe of PPU assessment, whether the data had already been published, how missing data were coded, and any other distinguishing features of the data set that the scholars providing the data set wanted to share. In addition, the codebook included information about all variables in the data set. This information included all variables' names; a brief description of them; the names, abbreviations, number of items, and factors comprising a scale; the references of the scales; the scoring of each variable; and any notes that the scholars wanted to share. After ensuring that all necessary information was available in the data set and its related codebook, Beáta Bőthe studied all information in the codebook about all variables in each data set. Then, a systematic coding system was developed based on the identified constructs that were measured across data sets, and each variable was labeled using a common code (e.g., different measures of impulsivity were labeled as "impulsivity"). After finalizing the coding of all variables in each data set, Zsombor Hermann cross-checked and verified the appropriate use of these common labels. Out of the 3,987 variables, a total of 744 predictor categories were identified. The list of all variables and their coded names is available on the OSF (https://osf.io/b2wa5/?view_only=59746e81e01d420c8b39fdcc79cd95db) (codebook of variables tab of the Excel sheet). This coded list of variables was used to assess the predictive success rate of each construct.

Statistical Analyses

All analyses were conducted in R (V4.2.2) (R Core Team, 2022), and the used packages are listed in eTable 2 in the online supplemental materials. To unify the method of dealing with missing data in each data set, only data from participants who did not have missing data on the PPU scale were used, as each data set used different inclusion criteria for participation and assessing PPU among participants. We used the MissForest (Stekhoven & Bühlmann, 2012) random forest imputation algorithm to handle missing data on predictor variables (Lang & Little, 2018; Newman, 2014; Stekhoven & Bühlmann, 2012). Following previous work (Joel et al., 2020), we used random forest models on each data set with the PPU score as the dependent/outcome variable,[1] an ML method that builds on classification and regression trees to test the strength of each available predictor with a recursive partitioning process (Berk, 2010; Breiman, 2001). The variable selection using random forests package was used for variable selection, as it is able to select only those predictors that meaningfully contribute to the model (Genuer et al., 2010, 2015). Briefly, the results of this analysis show how much variance of the outcome variable could be predicted by the predictor variables, and which variables made the greatest contributions.

Following prior work (Joel et al., 2020), the results from the 84 models[2] were combined using random-effects meta-analysis (Hedges & Vevea, 1998) by transforming the percentage of explained variance in the outcome variable from the random forest models into effect size indicators (Harrer et al., 2021). Then, the results of the meta-analysis were transformed back into explained variance. Following the preregistered analysis plan, we examined 10 meta-analytic moderators (e.g., PPU scale used, community vs. treatment-seeking sample). Given the high level of heterogeneity in the meta-analysis that could not be explained by the preestablished meta-analytic moderators, we conducted exploratory subgroup analyses. We examined the importance of the contribution of those predictor variables that were included in at least 10 data sets and that emerged as significant predictors in at least 50% of the data sets.

Results

Descriptive information for each data set and the results of the random forest models are presented in Table 1. On average, data sets included 43 potential predictors (ranging between four to 260 predictors across data sets), of which 11 were included in the final models. The explained variances ranged from 6.54% to 85.17% across the data sets.[3] The meta-analytic results, $Q(79) = 6{,}194.1$, $p < .001$, $\tau^2 = .07$; $I^2 = 98.70\%$, $H^2 = 74.65\%$, showed that the predictors explained 45.84% (95% confidence interval [41.57%, 49.98%]) of the variance in the PPU scores. The most robust predictors of PPU (i.e., 17 variables that were included in at least 10 data sets and that emerged as significant predictors in at least 50% of the data sets) are presented in Table 2.[4] The top five predictors were frequency of use, emotional avoidance pornography use motivation, stress reduction pornography use motivation, moral incongruence toward pornography use, and sexual shame. As demonstrated in Figure 1, predictive power increased as the number of identified predictors included in the model increased.

Out of the 10 preestablished meta-analytic moderators, only the number of variables in the data set and the number of predictors selected in the final model had significant effects on the results (Table 3). Having more variables, $F(1, 82) = 5.55$, $p = .021$, $\tau^2 = .07$, $I^2 = 98.75\%$, and having more predictors in the final model, $F(1, 82) = 16.86$, $p < .001$, $\tau^2 = .06$, $I^2 = 98.63\%$, contributed to heterogeneity, although the size of these contributions was negligible. These results suggest that the data sets' characteristics (e.g., country of data collection) did not play a crucial role in the heterogeneity and predictive power of the models.[5]

Given considerable heterogeneity, we conducted exploratory, post hoc subgroup analyses to explore whether this heterogeneity could be explained by the presence of the most robust predictors included in the models (i.e., the variable is not a predictor vs. the variable is a predictor) or the level of missing data (Table 4). Results suggested that one pornography use-related characteristics (i.e., moral incongruence toward pornography use) and two negative emotions-related characteristics (i.e., depression symptoms and blaming others: transferring blame from self to others) contributed significantly to the heterogeneity of the results (Table 4). However, when all these variables were included in one model, $F(3, 80) = 10.52$, $p < .001$, $\tau^2 = .05$, $I^2 = 98.35\%$, only blaming others, $B = .39$, $SE = 0.11$, $p < .001$, contributed significantly. Yet, similar to the results with the meta-analytic moderators, these variables' effect on heterogeneity was small.

[1] When starting the study, the aim was not only to examine the predictors of PPU using cross-sectional data, but also the predictors of change in PPU over time using longitudinal datasets (https://osf.io/jqkzr). However, during data preparation and analysis, major issues were identified that made it impossible to conduct the preregistered longitudinal analyses. These issues included the low number of longitudinal data sets; high levels of missing data in the different waves of data collections; no longitudinal changes in PPU over time in several datasets; and when changes were present, they were not linear (see eFigure 1 in the online supplemental materials). Therefore, we used the first data collection waves from the longitudinal data sets as cross-sectional data and conducted the same analyses on these data sets as on the cross-sectional ones.

[2] For the sake of comprehensiveness, in cases when more than one PPU measure (e.g., both the Brief Pornography Screen and the Cyber-Pornography Use Inventory) were included in a given data set, we conducted the analysis using each PPU measure as an outcome variable in separate models. Therefore, the total number of models is greater than the total number of data sets.

[3] We used the hyperparameter of $n_{tree} = 500$ in the original version of the manuscript. During the review process, it was requested to test if the use of different n_{tree} values would result in changes in prediction quality. We tested the random forest models with $n_{tree} = 1{,}000$, $n_{tree} = 1{,}500$, $n_{tree} = 2{,}000$, and $n_{tree} = 5{,}000$. Details of the conducted analysis can be found in the online supplemental materials. The findings suggested that the different n_{tree} values might not have affected the results substantially, corroborating the robustness of the results.

[4] The predictive power of the variables that were included in at least 10 data sets (not restricted to those that were predictors in at least 50% of the data sets) and the predictive power of all variables (without any restrictions) are available on OSF in the online supplemental materials (https://osf.io/b2wa5/?view_only=59746e81e01d420c8b39fdcc79cd95db).

[5] We used the cutoff of 40% of missing data in the original version of the manuscript (i.e., when more than 40% were missing on a given variable or when a participant had more than 40% of missing data, these variables or participants were removed from the analyses, respectively). During the review process, it was requested to test if the use of a more conservative cutoff of 30% of missing data would result in changes in the results. We conducted all the analyses with only data sets that had less than 30% of missing data. Details of the conducted analysis can be found in the online supplemental materials. The findings suggested that the level of missing data might not have affected the results substantially, corroborating the robustness of the results.

Table 2
The Most Robust Predictors of Problematic Pornography Use

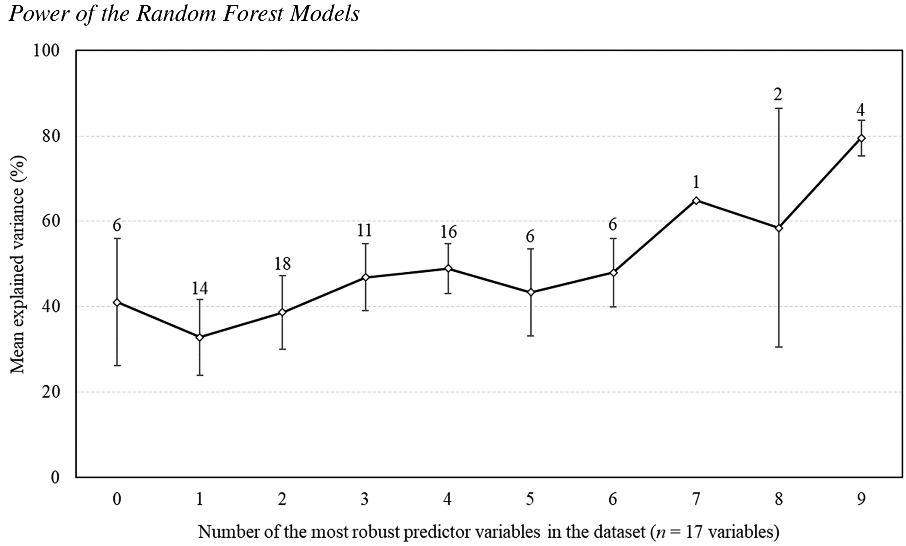
Variable	Included in data sets (out of 84)	Significant predictor in % of the data sets it was included
1. Pornography use frequency	65	93.85
2. Emotional avoidance pornography use motivation	13	84.62
3. Sexual shame	13	84.62
4. Moral incongruence toward pornography use	33	81.82
5. Stress reduction pornography use motivation	10	80.00
6. Fantasy pornography use motivation	12	75.00
7. Duration of pornography use per occasion	40	65.00
8. Blaming others	11	63.64
9. Anxiety symptoms	24	62.50
10. Guilt	13	61.54
11. Treatment seeking for pornography use	10	60.00
12. Self-perceived addiction to pornography	12	58.33
13. Depression symptoms	26	53.85
14. Gender[a]	76	52.63
15. Loneliness	18	50.00
16. Attachment anxiety	16	50.00
17. Sexual function	10	50.00

Note. This table includes all variables that were included in at least 10 data sets and that emerged as significant predictors in at least 50% of the data sets in which they were included.
[a] Studies included in the present analyses either assessed participants' sex assigned at birth or gender identity, depending on the study design, aims of the study, and the sociocultural context in which the study was conducted. Therefore, for the sake of parsimony and statistical power, we included both the sex assigned at birth and the gender identity in the "gender" variable in the present analyses.

Discussion

The present study is the largest collaborative and most integrative data analytic effort to date in the field of CSBD research to identify risk factors that consistently contribute to PPU. Out of more than 700 potential variables, the final list of risk factors included characteristics specifically related to pornography use (e.g., moral incongruence) as well as more general factors (e.g., depressive symptoms). Not only do the present findings contribute to the refinement of current theoretical models but can also provide empirically based knowledge to develop effective, scientifically based prevention and intervention programs targeting PPU, which are currently missing from the literature and clinical care (Antons et al., 2022; Borgogna et al., 2022; Grubbs, Hoagland,

Figure 1
Visual Presentation of the Most Robust Predictors' Additive Contribution to the Predictive Power of the Random Forest Models



Note. Error bars represent the 95% confidence intervals. The number of data sets with the given number of predictor variables is shown above the error bars. No data set included more than nine of the most robust predictors.

Table 3
Results of the Metaregression and Subgroup Analyses With the Preregistered Meta-Analytic Moderators

Variable	*k*	Explained variance (%)	95% CI	*p*	I^2 (%)	95% CI	*p*	Adjusted *p*
PPU scale used[a]							.265	1.000
PPCS	28	45.45	[38.43%, 52.12%]	<.001	98.87	[98.70%, 99.02%]		
BPS	14	40.27	[31.01%, 49.19%]	<.001	96.83	[95.78%, 97.62%]		
CPUI	31	48.79	[40.69%, 56.33%]	<.001	98.54	[98.31%, 98.74%]		
PPUS	9	52.34	[40.34%, 62.89%]	<.001	98.03	[97.30%, 98.56%]		
Timeframe of asking about PPU[b]							.761	1.000
No timeframe specified	33	47.06	[38.75%, 54.84%]	<.001	98.61	[98.40%, 98.79%]		
Past 6 months	50	45.66	[40.93%, 50.23%]	<.001	98.63	[98.47%, 98.78%]		
Who completed the PPU scale[c]							.399	1.000
No timeframe specified	28	41.45	[35.04%, 47.67%]	<.001	98.31	[98.01%, 98.56%]		
Past 6 months users	17	52.38	[35.04%, 47.67%]	<.001	98.96	[98.75%, 99.13%]		
Past 12 months users	15	44.86	[34.48%, 54.55%]	<.001	98.97	[98.75%, 99.15%]		
Lifetime users	22	46.64	[38.29%, 54.48%]	<.001	97.63	[97.09%, 98.07%]		
Country of data collection[d]							.271	1.000
International/not specified	7	36.46	[14.86%, 57.49%]	.001	99.10	[98.81%, 99.32%]		
Canada	5	34.60	[8.20%, 61.44%]	.008	98.68	[98.06%, 99.10%]		
China	8	49.72	[41.14%, 57.63%]	<.001	98.57	[98.07%, 98.94%]		
Hungary	18	42.98	[33.95%, 51.55%]	<.001	98.80	[98.56%, 99.00%]		
United States of America	30	50.63	[42.33%, 58.27%]	<.001	98.83	[98.66%, 98.99%]		
Publication status[e]							.967	1.000
Unpublished	48	45.77	[39.44%, 51.82%]	<.001	98.61	[98.43%, 98.76%]		
≥ 1 publication	36	45.94	[40.2%, 51.45%]	<.001	98.75	[98.58%, 98.90%]		
Sample Type 1				<.001			.102	0.815
Community sample	76	46.81	[42.32%, 51.15%]	<.001	98.64	[98.51%, 98.75%]		
Treatment-seeking sample	8	36.32	[22.01%, 50.31%]	<.001	98.92	[98.58%, 99.18%]		
Sample Type 2[f]							NA	NA
Adult sample	77	47.09	[42.75%, 51.29%]	<.001	98.58	[98.44%, 98.70%]		
Study design							.631	1.000
Cross-sectional	74	46.15	[41.46%, 50.68%]	<.001	98.77	[98.66%, 98.88%]		
Longitudinal	10	43.63	[32.64%, 53.91%]	<.001	96.39	[94.85%, 97.48%]		

Variable	*k*	Estimate	*SE*	*t*	*df*	*p*
Year of data collection (start date)						
Intercept	84	−39.18	24.83	−1.58	82	.118
Value	84	0.02	0.01	1.61	82	.111
Year of data collection (end date)						
Intercept	84	−30.31	25.70	−1.18	82	.241
Value	84	0.02	0.01	1.21	82	.229
Number of predictors used in the random forests model						
Intercept	84	0.75	0.04	17.28	82	<.001
Value	84	<0.01	<0.01	2.36	82	.021
Number of predictors selected in the final random forests model						
Intercept	84	0.63	0.05	11.69	82	<.001
Value	84	0.02	<0.01	4.10	82	<.001

Note. When a model ID includes a letter (e.g., 33a, 33b), it represents that the data set included more than one PPU measure, and thus, all PPU measures were considered outcome variables in separate models. *p* values adjusted using the Holm method ($n = 8$ tests). CI = confidence interval; PPU = problematic pornography use; PPCS = long or short version of the Problematic Pornography Consumption Scale; BPS = Brief Pornography Screen; CPUI = long or short version of the Cyber-Pornography Use Inventory; PPUS = Problematic Pornography Use Scale; NA = not applicable; CIUS-SEM = Compulsive Internet Use Scale–SEM; CPCS = Compulsive Pornography Consumption Scale; SEM = sexually explicit media.
[a] It was not possible to include the CIUS-SEM and the CPCS in this analysis as fewer than five studies used them. [b] It was not possible to include the category "past 3 months" in this analysis as fewer than five studies used it. [c] It was not possible to include the categories "past week users" and "past month users" in this analysis as fewer than five studies used them. [d] It was not possible to include Bangladesh, Germany, Iran, Israel, Malaysia, the Netherlands, Poland, Portugal, Slovakia, and Spain in this analysis as fewer than five studies were conducted in these countries. [e] At the time of data solicitation. [f] It was not possible to include the categories "adolescents" and "young adults (16–29 years)," defined by the original study, in this analysis as fewer than five studies were conducted in these populations.

et al., 2020; Turner et al., 2022; Yarkoni & Westfall, 2017). Given the abundance of examined variables, we focused on the constructs that may have the strongest effect on the current understanding of PPU and public health.

Eight out of the 17 predictors of PPU were related to pornography use characteristics, with pornography use frequency having the strongest predictive power. These results are consistent with the findings of a recent meta-analysis, suggesting that the frequency of pornography use may be an indicator of PPU, given the moderate, positive association (Chen, Jiang, Wang, et al., 2022). However, it might not be a crucial predictor of PPU in itself as prior studies reported that pornography use frequency might be a peripheral

Table 4

Exploratory Results of Subgroup Analyses With the Most Robust Predictor Variables and the Level of Missing Data

Variable	k	Explained variance (%)	95% CI	p	I^2 (%)	95% CI	p	Adjusted p[a]
Gender							.021	.349
Not predictor	44	50.25	[43.76%, 56.34%]	<.001	98.91	[98.78%, 99.02%]		
Predictor	40	40.82	[35.67%, 45.86%]	<.001	97.63	[97.24%, 97.96%]		
Pornography use frequency							.082	1.000
Not predictor	23	39.96	[31.65%, 48.00%]	<.001	98.71	[98.48%, 98.91%]		
Predictor	61	48.00	[43.01%, 52.78%]	<.001	98.44	[98.27%, 98.60%]		
Duration of pornography use per occasion							.096	1.000
Not predictor	58	43.38	[38.39%, 48.22%]	<.001	98.24	[98.03%, 98.43%]		
Predictor	26	51.15	[42.88%, 58.75%]	<.001	98.97	[98.81%, 99.10%]		
Emotional avoidance pornography use motivation							.004	.060
Not predictor	73	43.90	[39.27%, 48.40%]	<.001	98.42	[98.25%, 98.56%]		
Predictor	11	57.91	[48.56%, 66.10%]	<.001	98.37	[97.88%, 98.75%]		
Stress reduction pornography use motivation							.027	.453
Not predictor	76	44.72	[40.13%, 49.17%]	<.001	98.47	[98.32%, 98.61%]		
Predictor	8	55.98	[45.13%, 65.43%]	<.001	98.11	[97.37%, 98.64%]		
Fantasy pornography use motivation							.014	.245
Not predictor	75	44.28	[39.75%, 48.68%]	<.001	98.41	[98.25%, 98.56%]		
Predictor	9	58.02	[46.13%, 68.10%]	<.001	98.62	[98.17%, 98.95%]		
Moral incongruence toward pornography use							<.001	.008
Not predictor	57	41.03	[35.97%, 45.98%]	<.001	98.56	[98.39%, 98.70%]		
Predictor	27	55.39	[48.70%, 61.53%]	<.001	98.75	[98.54%, 98.92%]		
Self-perceived addiction to pornography							.021	.352
Not predictor	77	44.75	[40.22%, 49.15%]	<.001	98.49	[98.34%, 98.62%]		
Predictor	7	57.08	[45.14%, 67.27%]	<.001	99.19	[98.94%, 99.38%]		
Treatment seeking for pornography use							.082	1.000
Not predictor	78	44.78	[40.39%, 49.04%]	<.001	98.39	[98.23%, 98.53%]		
Predictor	6	58.70	[38.22%, 74.24%]	<.001	97.52	[96.20%, 98.38%]		
Sexual function							.224	1.000
Not predictor	79	46.48	[42.10%, 50.71%]	<.001	98.70	[98.58%, 98.81%]		
Predictor	5	35.30	[11.64%, 58.8%]	.004	97.64	[96.24%, 98.52%]		
Sexual shame							.003	.058
Not predictor	73	42.97	[38.86%, 46.98%]	<.001	98.39	[98.22%, 98.54%]		
Predictor	11	62.99	[48.77%, 74.18%]	<.001	98.46	[98.01%, 98.81%]		
Anxiety symptoms							.008	0.139
Not predictor	69	42.35	[38.47%, 46.15%]	<.001	97.60	[97.31%, 97.86%]		
Predictor	15	60.23	[46.51%, 71.39%]	<.001	99.24	[99.09%, 99.36%]		
Depression symptoms							.002	.026
Not predictor	70	42.83	[38.39%, 47.15%]	<.001	98.54	[98.40%, 98.68%]		
Predictor	14	59.77	[49.43%, 68.60%]	<.001	98.82	[98.55%, 99.04%]		
Guilt							.046	.785
Not predictor	76	44.05	[39.86%, 48.13%]	<.001	98.46	[98.30%, 98.60%]		
Predictor	8	61.28	[41.08%, 76.22%]	<.001	98.97	[98.65%, 99.21%]		
Blaming others							<.001	.001
Not predictor	77	43.02	[39.1%, 46.85%]	<.001	98.31	[98.14%, 98.47%]		
Predictor	7	71.41	[56.17%, 82.10%]	<.001	98.13	[97.33%, 98.68%]		
Attachment anxiety							.298	1.000
Not predictor	76	44.94	[40.59%, 49.17%]	<.001	98.64	[98.51%, 98.76%]		
Predictor	8	54.11	[33.06%, 70.84%]	<.001	98.84	[98.46%, 99.12%]		
Loneliness							.150	1.000
Not predictor	75	44.34	[40.16%, 48.41%]	<.001	98.41	[98.25%, 98.55%]		
Predictor	9	57.41	[36.36%, 73.53%]	<.001	99.42	[99.29%, 99.53%]		

Variable	k	Estimate	SE	t	df	p
Missing data						
Intercept	84	0.80	0.04	21.46	82	<.001
Value	84	0.02	0.02	0.99	82	.324

Note. CI = confidence interval.
[a] p values adjusted using the Holm method ($n = 17$ tests).

symptom of PPU compared to other symptoms (Bőthe, Lonza, et al., 2020). In particular, high-frequency pornography use may appear without PPU (e.g., due to strong sexual desire), and self-perceived PPU may be present even with low-frequency pornography use (e.g., due to moral incongruence and disapproval of pornography) (Bőthe, Lonza, et al., 2020; Bőthe, Tóth-Király, et al., 2020; Chen, Jiang, Luo, et al., 2022; Grubbs, Lee, et al., 2020; Jiang et al., 2022). Therefore, it is recommended to inquire about an individual's pornography use frequency when assessing PPU, but solely relying on the quantity (e.g., frequency) of use to determine PPU can induce biases (Bőthe, Lonza, et al., 2020; Bőthe, Tóth-Király, et al., 2020; Chen, Jiang, Luo, et al., 2022; Grubbs, Lee, et al., 2020; Jiang et al., 2022).

Another category of predictors that emerged was related to negative emotions (e.g., guilt, sexual shame, emotional avoidance pornography use motivation). Corroborating prior work, these findings suggest that individuals with PPU may experience more negative emotions and turn to pornography as a means of coping with them (Bőthe, Tóth-Király, Bella, et al., 2021; Floyd & Grubbs, 2022; Lew-Starowicz et al., 2020; Volk et al., 2019). These findings are of special clinical interest as the previously proposed (but ultimately rejected) hypersexual disorder diagnosis for the fifth revision of the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013, 2022) included engagement in sexual activities as a response to negative emotions and stress as a diagnostic criterion. In contrast, the current CSBD diagnostic guidelines in the 11th revision of the International Classification of Diseases do not consider sexual activities as a response to negative emotions or stress as a criterion (Gola et al., 2022; Kraus et al., 2018; Lew-Starowicz et al., 2020; World Health Organization, 2022). Future studies are essential to examine the roles of general (e.g., anxiety) and pornography-related negative emotions (e.g., moral incongruence), emotion dysregulation, and the use of pornography as a coping strategy to delineate whether the inclusion of coping with negative emotions and/or stress are warranted as a diagnostic criterion (Grubbs, Reid, et al., 2023). These findings also highlight the importance of assessing anxiety, depression, and negative emotions when diagnosing or treating PPU, as mood disorders have been shown to be highly comorbid with PPU and CSBD in general (Grant Weinandy et al., 2023; Kraus et al., 2015).

From a public health perspective, psychiatric disorders are associated with a high economic burden (Vigo et al., 2016; Whiteford et al., 2015). With the identification of the strongest, most consistent, and generalizable predictors of PPU, we provide knowledge concerning reliable risk factors for PPU, which in turn, may contribute to the development of more efficient, scientifically based, cost-effective prevention and intervention programs. In addition, this study reported empirical evidence about the relative importance of PPU risk factors, providing potential guidelines for future studies concerning which variables might be important to assess, reducing cost and participant fatigue.

Limitations and Future Directions

As the study used data from self-report surveys, biases related to this design may be present (e.g., recall bias). Despite the inclusion of all accessible data sets at the time of data solicitation, studies from WEIRD countries were still overrepresented, limiting generalizability to other populations. Recent initiatives specifically aimed at making CSBD and PPU research more inclusive (e.g., International Sex Survey) are ongoing and thus were not included in this work (Bőthe, Koós, et al., 2021). In addition, samples from specific countries (e.g., China, Hungary, and the United States) were overrepresented in the study, which might have biased the findings. Cultural differences concerning pornography use and PPU are documented in the literature, suggesting that, for example, individuals in more conservative cultures (e.g., China) may report higher self-perceived PPU due to stricter sexual values (Ahorsu et al., 2023; Chen, Jiang, Wang, et al., 2022; Lewczuk et al., 2020; Vaillancourt-Morel & Bergeron, 2019). Therefore, future studies among more diverse populations are warranted, considering potential cultural differences.

Given considerable unexplained heterogeneity in the study, future work should further explore potential contributing factors. For example, previous findings suggest that different scales aiming to assess the same construct (e.g., depression) may demonstrate low levels of content overlap in the symptoms they assess (i.e., different scales may capture different aspects of the heterogeneous symptoms of depression). Thus, it is possible that the selection of a particular scale may bias the results as well as the generalizability and replicability of findings (Fried, 2017). Yet, it is important to note our findings suggested that the use of different PPU scales (i.e., the outcomes in the random forest models) did not contribute to the heterogeneity of the results. Future studies are encouraged to examine the potential role of using different scales to assess predictors in random forest models and related biases.

Future research would also benefit from the use of observational and clinical data as well as medical records to examine the utility of more objective data in predicting PPU (Dwyer et al., 2018; Walsh et al., 2018). Although the study originally sought to examine the predictors of change in PPU over time using longitudinal samples, it was not possible to do so given the relatively low number of studies, the high levels of missing data, and the lack of (linear) change in PPU over time. Further long-term longitudinal studies with several assessment waves, especially among adolescents, clinical samples, and couples, are warranted (Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020).

Conclusion

Despite the proliferation of research on PPU and CSBD, knowledge of risk factors has been severely limited due to the theoretical and methodological shortcomings of prior studies (Griffin et al., 2021; Grubbs & Kraus, 2021; Grubbs, Hoagland, et al., 2020). Synthesizing a large and diverse body of data related to PPU, the present study identified crucial risk factors for PPU, providing a better understanding of PPU's etiology and an empirical basis for the refinement of current theoretical models as well as scientifically based prevention and treatment targets (Yarkoni & Westfall, 2017).

References

Ahorsu, D. K., Adjorlolo, S., Nurmala, I., Ruckwongpatr, K., Strong, C., & Lin, C. Y. (2023). Problematic porn use and cross-cultural differences: A brief review. *Current Addiction Reports*, *10*(3), 572–580. https://doi.org/10.1007/S40429-023-00505-3

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.).

American Psychiatric Association. (2022). *Diagnostic and statistical manual of mental disorders* (5th ed., text rev.).

Antons, S., Engel, J., Briken, P., Krüger, T. H. C., Brand, M., & Stark, R. (2022). Treatments and interventions for compulsive sexual behavior disorder with a focus on problematic pornography use: A preregistered systematic review. *Journal of Behavioral Addictions*, *11*(3), 643–666. https://doi.org/10.1556/2006.2022.00061

Berk, R. (2010). An introduction to statistical learning from a regression perspective. In A. R. Piquero & D. Weisburd (Eds.), *Handbook of quantitative criminology* (pp. 725–740). Springer. https://doi.org/10.1007/978-0-387-77650-7_34

Borgogna, N. C., Garos, S., Meyer, C. L., Trussell, M. R., & Kraus, S. W. (2022). A review of behavioral interventions for compulsive sexual behavior disorder. *Current Addiction Reports*, *9*(3), 99–108. https://doi.org/10.1007/s40429-022-00422-x

Bőthe, B., Koós, M., & Demetrovics, Z. (2022). Contradicting classification, nomenclature, and diagnostic criteria of Compulsive Sexual Behavior Disorder (CSBD) and future directions •: Commentary to the debate: "Behavioral addictions in the ICD-11". *Journal of Behavioral Addictions*, *11*(2), 204–209. https://doi.org/10.1556/2006.2022.00030

Bőthe, B., Koós, M., Nagy, L., Kraus, S. W., Demetrovics, Z., Potenza, M. N., Michaud, A., Ballester-Arnal, R., Batthyány, D., Bergeron, S., Billieux, J., Briken, P., Burkauskas, J., Cárdenas-López, G., Carvalho, J., Castro-Calvo, J., Chen, L., Ciocca, G., Corazza, O., … Vaillancourt-Morel, M.-P. (2023). Compulsive sexual behavior disorder in 42 countries: Insights from the International Sex Survey and introduction of standardized assessment tools. *Journal of Behavioral Addictions*, *12*(2), 393–407. https://doi.org/10.1556/2006.2023.00028

Bőthe, B., Koós, M., Nagy, L., Kraus, S. W., Potenza, M. N., & Demetrovics, Z. (2021). International Sex Survey: Study protocol of a large, cross-cultural collaborative study in 45 countries. *Journal of Behavioral Addictions*, *10*(3), 632–645. https://doi.org/10.1556/2006.2021.00063

Bőthe, B., Lonza, A., Štulhofer, A., & Demetrovics, Z. (2020). Symptoms of problematic pornography use in a sample of treatment considering and treatment non-considering men: A network approach. *Journal of Sexual Medicine*, *17*(10), 2016–2028. https://doi.org/10.1016/j.jsxm.2020.05.030

Bőthe, B., Nagy, L., Koós, M., Demetrovics, Z., Potenza, M. N., Kraus, S. W., & International Sex Survey Consortium. (2024). Problematic pornography use across countries, genders, and sexual orientations: Insights from the International Sex Survey and comparison of different assessment tools. *Addiction*, *119*(5), 928–950. https://doi.org/10.1111/add.16431

Bőthe, B., Potenza, M. N., Griffiths, M. D., Kraus, S. W., Klein, V., Fuss, J., & Demetrovics, Z. (2020). The development of the Compulsive Sexual Behavior Disorder Scale (CSBD-19): An ICD-11 based screening measure across three languages. *Journal of Behavioral Addictions*, *9*(2), 247–258. https://doi.org/10.1556/2006.2020.00034

Bőthe, B., Tóth-Király, I., Bella, N., Potenza, M. N., Demetrovics, Z., & Orosz, G. (2021). Why do people watch pornography? The motivational basis of pornography use. *Psychology of Addictive Behaviors*, *35*(2), 172–186. https://doi.org/10.1037/adb0000603

Bőthe, B., Tóth-Király, I., Demetrovics, Z., & Orosz, G. (2021). The short version of the Problematic Pornography Consumption Scale (PPCS-6): A reliable and valid measure in general and treatment-seeking populations. *Journal of Sex Research*, *58*(3), 342–352. https://doi.org/10.1080/00224499.2020.1716205

Bőthe, B., Tóth-Király, I., Potenza, M. N., Griffiths, M. D., Orosz, G., & Demetrovics, Z. (2019). Revisiting the role of impulsivity and compulsivity in problematic sexual behaviors. *Journal of Sex Research*, *56*(2), 166–179. https://doi.org/10.1080/00224499.2018.1480744

Bőthe, B., Tóth-Király, I., Potenza, M. N., Orosz, G., & Demetrovics, Z. (2020). High-frequency pornography use may not always be problematic. *Journal of Sexual Medicine*, *17*(4), 793–811. https://doi.org/10.1016/j.jsxm.2020.01.007

Bőthe, B., Tóth-Király, I., Zsila, Á., Griffiths, M. D., Demetrovics, Z., & Orosz, G. (2018). The development of the Problematic Pornography Consumption Scale (PPCS). *Journal of Sex Research*, *55*(3), 395–406. https://doi.org/10.1080/00224499.2017.1291798

Bőthe, B., Vaillancourt-Morel, M.-P., Bergeron, S., & Demetrovics, Z. (2019). Problematic and non-problematic pornography use among LGBTQ adolescents: A systematic literature review. *Current Addiction Reports*, *6*(4), 478–494. https://doi.org/10.1007/s40429-019-00289-5

Bőthe, B., Vaillancourt-Morel, M.-P., Bergeron, S., Hermann, Z., Ivaskevics, K., Kraus, S. W., & Grubbs, J. B. (2024, March 8). *Uncovering the most robust predictors of problematic pornography use (PPU) with machine learning*. https://doi.org/10.17605/OSF.IO/JAEMX

Bőthe, B., Vaillancourt-Morel, M.-P., Dion, J., Štulhofer, A., & Bergeron, S. (2021). Validity and reliability of the short version of the Problematic Pornography Consumption Scale (PPCS-6-A) in adolescents. *Psychology of Addictive Behaviors*, *35*(4), 486–500. https://doi.org/10.1037/adb0000722

Bőthe, B., Vaillancourt-Morel, M.-P., Girouard, A., Štulhofer, A., Dion, J., & Bergeron, S. (2020). A large-scale comparison of Canadian sexual/gender minority and heterosexual, cisgender adolescents' pornography use characteristics. *Journal of Sexual Medicine*, *17*(6), 1156–1167. https://doi.org/10.1016/j.jsxm.2020.02.009

Brand, M., Rumpf, H. J., Demetrovics, Z., Müller, A., Stark, R., King, D. L., Goudriaan, A. E., Mann, K., Trotzke, P., Fineberg, N. A., Chamberlain, S. R., Kraus, S. W., Wegmann, E., Billieux, J., & Potenza, M. N. (2020). Which conditions should be considered as disorders in the International Classification of Diseases (ICD-11) designation of "other specified disorders due to addictive behaviors"? *Journal of Behavioral Addictions*, *11*(2), 150–159. https://doi.org/10.1556/2006.2020.00035

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews*, *104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Briken, P., Wiessner, C., Štulhofer, A., Klein, V., Fuß, J., Reed, G. M., & Dekker, A. (2022). Who feels affected by "out of control" sexual behavior? Prevalence and correlates of indicators for ICD-11 Compulsive Sexual Behavior Disorder in the German Health and Sexuality Survey (GeSiD). *Journal of Behavioral Addictions*, *11*(3), 900–911. https://doi.org/10.1556/2006.2022.00060

Castro-Calvo, J., Flayelle, M., Perales, J. C., Brand, M., Potenza, M. N., & Billieux, J. (2022). Compulsive Sexual Behavior Disorder should not be classified by solely relying on component/symptomatic features •: Commentary to the debate: "Behavioral addictions in the ICD-11". *Journal of Behavioral Addictions*, *11*(2), 210–215. https://doi.org/10.1556/2006.2022.00029

Chen, L., Jiang, X., Luo, X., Kraus, S. W., & Bőthe, B. (2022). The role of impaired control in screening problematic pornography use: Evidence from cross-sectional and longitudinal studies in a large help-seeking male sample. *Psychology of Addictive Behaviors*, *36*(5), 537–546. https://doi.org/10.1037/adb0000714

Chen, L., Jiang, X., Wang, Q., Bőthe, B., Potenza, M. N., & Wu, H. (2022). The association between the quantity and severity of pornography use: A meta-analysis. *Journal of Sex Research*, *59*(6), 704–719. https://doi.org/10.1080/00224499.2021.1988500

Dickenson, J. A., Gleason, N., Coleman, E., & Miner, M. H. (2018). Prevalence of distress associated with difficulty controlling sexual urges, feelings, and behaviors in the United States. *JAMA Network Open*, *1*(7), Article e184468. https://doi.org/10.1001/jamanetworkopen.2018.4468

Donevan, M., Jonsson, L., Bladh, M., Priebe, G., Fredlund, C., & Svedin, C. G. (2022). Adolescents' use of pornography: Trends over a ten-year period in Sweden. *Archives of Sexual Behavior*, *51*(2), 1125–1140. https://doi.org/10.1007/s10508-021-02084-8

Downing, M. J., Antebi, N., & Schrimshaw, E. W. (2014). Compulsive use of Internet-based sexually explicit media: Adaptation and validation of the Compulsive Internet Use Scale (CIUS). *Addictive Behaviors*, *39*(6), 1126–1130. https://doi.org/10.1016/j.addbeh.2014.03.007

Dwyer, D. B., Falkai, P., & Koutsouleris, N. (2018). Machine learning approaches for clinical psychology and psychiatry. *Annual Review of Clinical Psychology*, *14*(1), 91–118. https://doi.org/10.1146/annurev-clinpsy-032816-045037

Fernandez, D. P., & Griffiths, M. D. (2021). Psychometric instruments for problematic pornography use: A systematic review. *Evaluation and the Health Professions*, *44*(2), 111–141. https://doi.org/10.1177/0163278719861688

Floyd, C. G., & Grubbs, J. B. (2022). Context matters: How religion and morality shape pornography use effects. *Current Sexual Health Reports*, *14*(3), 82–98. https://doi.org/10.1007/s11930-022-00329-8

Fried, E. I. (2017). The 52 symptoms of major depression: Lack of content overlap among seven common depression scales. *Journal of Affective Disorders*, *208*, 191–197. https://doi.org/10.1016/J.JAD.2016.10.019

Genuer, R., Poggi, J. M., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, *31*(14), 2225–2236. https://doi.org/10.1016/J.PATREC.2010.03.014

Genuer, R., Poggi, J.-M., Tuleau-Malot, C., & Tuleau, C. (2015). VSURF: An R package for variable selection using random forests. *The R Journal*, *7*(2), 19–33. https://doi.org/10.32614/RJ-2015-018

Gola, M., Lewczuk, K., Potenza, M. N., Kingston, D. A., Grubbs, J. B., Stark, R., & Reid, R. C. (2022). What should be included in the criteria for compulsive sexual behavior disorder? *Journal of Behavioral Addictions*, *11*(2), 160–165. https://doi.org/10.1556/2006.2020.00090

Grant Weinandy, J. T., Lee, B., Hoagland, K. C., Grubbs, J. B., & Bőthe, B. (2023). Anxiety and compulsive sexual behavior disorder: A systematic review. *Journal of Sex Research*, *60*(4), 545–557. https://doi.org/10.1080/00224499.2022.2066616

Griffin, K. R., Way, B. M., & Kraus, S. W. (2021). Controversies and clinical recommendations for the treatment of compulsive sexual behavior disorder. *Current Addiction Reports*, *8*(4), 546–555. https://doi.org/10.1007/s40429-021-00393-5

Griffiths, M. D. (2005). A "components" model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Grubbs, J. B., Floyd, C. G., & Kraus, S. W. (2023). Pornography use and public health: Examining the importance of online sexual behavior in the health sciences. *American Journal of Public Health*, *113*(1), 22–26. https://doi.org/10.2105/AJPH.2022.307146

Grubbs, J. B., & Gola, M. (2019). Is pornography use related to erectile functioning? Results from cross-sectional and latent growth curve analyses. *Journal of Sexual Medicine*, *16*(1), 111–125. https://doi.org/10.1016/j.jsxm.2018.11.004

Grubbs, J. B., Hoagland, C., Lee, B., Grant, J., Davison, P. M., Reid, R., & Kraus, S. W. (2020). Sexual addiction 25 years on: A systematic and methodological review of empirical literature and an agenda for future research. *Clinical Psychology Review*, *82*, Article 101925. https://doi.org/10.1016/j.cpr.2020.101925

Grubbs, J. B., & Kraus, S. W. (2021). Pornography use and psychological science: A call for consideration. *Current Directions in Psychological Science*, *30*(1), 68–75. https://doi.org/10.1177/0963721420979594

Grubbs, J. B., Kraus, S. W., & Perry, S. L. (2019). Self-reported addiction to pornography in a nationally representative sample: The roles of use habits, religiousness, and moral incongruence. *Journal of Behavioral Addictions*, *8*(1), 88–93. https://doi.org/10.1556/2006.7.2018.134

Grubbs, J. B., Lee, B. N., Hoagland, K. C., Kraus, S. W., & Perry, S. L. (2020). Addiction or transgression? Moral incongruence and self-reported problematic pornography use in a nationally representative sample. *Clinical Psychological Science*, *8*(5), 936–946. https://doi.org/10.1177/2167702620922966

Grubbs, J. B., Perry, S. L., Wilt, J. A., & Reid, R. C. (2019). Pornography problems due to moral incongruence: An integrative model with a systematic review and meta-analysis. *Archives of Sexual Behavior*, *48*(2), 397–415. https://doi.org/10.1007/s10508-018-1248-x

Grubbs, J. B., Reid, R. C., Bőthe, B., Demetrovics, Z., Coleman, E., Gleason, N., Miner, M. H., Fuss, J., Klein, V., Lewczuk, K., Gola, M., Fernandez, D. P., Fernandez, E. F., Carnes, S., Lew-Starowicz, M., Kingston, D., & Kraus, S. W. (2023). Assessing compulsive sexual behavior disorder: The development and international validation of the compulsive sexual behavior disorder-diagnostic inventory (CSBD-DI). *Journal of Behavioral Addictions*, *12*(1), 242–260. https://doi.org/10.1556/2006.2023.00005

Grubbs, J. B., Sessoms, J., Wheeler, D. M., & Volk, F. (2010). The cyber-pornography use inventory: The development of a new assessment instrument. *Sexual Addiction and Compulsivity*, *17*(2), 106–126. https://doi.org/10.1080/10720161003776166

Grubbs, J. B., Volk, F., Exline, J. J., & Pargament, K. I. (2015). Internet pornography use: Perceived addiction, psychological distress, and the validation of a brief measure. *Journal of Sex and Marital Therapy*, *41*(1), 83–106. https://doi.org/10.1080/0092623X.2013.842192

Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2021). Doing meta-analysis in R: A hands-on guide. In M. Harrer, P. Cuijpers, T. Furukawa, & D. Ebert (Eds.), *Doing meta-analysis with R: A hands-on guide*. Chapman & Hall/CRC Press. https://www.routledge.com/Doing-Meta-Analysis-with-R-A-Hands-On-Guide/Harrer-Cuijpers-Furukawa-Ebert/p/book/9780367610074

Hedges, L. V., & Vevea, J. L. (1998). Fixed- and random-effects models in meta-analysis. *Psychological Methods*, *3*(4), 486–504. https://doi.org/10.1037/1082-989X.3.4.486

Herbenick, D., Fu, T.-C., Wright, P., Paul, B., Gradus, R., Bauer, J., & Jones, R. (2020). Diverse sexual behaviors and pornography use: Findings from a nationally representative probability survey of Americans aged 14 to 60 years. *Journal of Sexual Medicine*, *17*(4), 623–633. https://doi.org/10.1016/j.jsxm.2020.01.013

Jennings, T. L., Lyng, T., Gleason, N., Finotelli, I., & Coleman, E. L. I. (2021). Compulsive sexual behavior, religiosity, and spirituality: A systematic review. *Journal of Behavioral Addictions*, *10*(4), 854–878. https://doi.org/10.1556/2006.2021.00084

Jiang, X., Wu, Y., Zhang, K., Bőthe, B., Hong, Y., & Chen, L. (2022). Symptoms of problematic pornography use among help-seeking male adolescents: Latent profile and network analysis. *Journal of Behavioral Addictions*, *11*(3), 912–927. https://doi.org/10.1556/2006.2022.00065

Joel, S., Eastwick, P. W., Allison, C. J., Arriaga, X. B., Baker, Z. G., Bar-Kalifa, E., Bergeron, S., Birnbaum, G. E., Brock, R. L., Brumbaugh, C. C., Carmichael, C. L., Chen, S., Clarke, J., Cobb, R. J., Coolsen, M. K., Davis, J., de Jong, D. C., Debrot, A., DeHaas, E. C., … Wolf, S. (2020). Machine learning uncovers the most robust self-report predictors of relationship quality across 43 longitudinal couples studies. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(32), 19061–19071. https://doi.org/10.1073/pnas.1917036117

Kor, A., Zilcha-Mano, S., Fogel, Y. A., Mikulincer, M., Reid, R. C., & Potenza, M. N. (2014). Psychometric development of the Problematic Pornography Use Scale. *Addictive Behaviors*, *39*(5), 861–868. https://doi.org/10.1016/j.addbeh.2014.01.027

Kraus, S. W., Gola, M., Grubbs, J. B., Kowalewska, E., Hoff, R. A., Lew-Starowicz, M., Martino, S., Shirk, S. D., & Potenza, M. N. (2020). Validation of a brief pornography screen across multiple samples. *Journal of Behavioral Addictions*, *9*(2), 259–271. https://doi.org/10.1556/2006.2020.00038

Kraus, S. W., Krueger, R. B., Briken, P., First, M. B., Stein, D. J., Kaplan, M. S., Voon, V., Abdo, C. H. N. N., Grant, J. E., Atalla, E., & Reed, G. M. (2018). Compulsive sexual behaviour disorder in the ICD-11. *World Psychiatry*, *17*(1), 109–110. https://doi.org/10.1002/wps.20499

Kraus, S. W., Potenza, M. N., Martino, S., & Grant, J. E. (2015). Examining the psychometric properties of the Yale-Brown Obsessive-Compulsive Scale in a sample of compulsive pornography users. *Comprehensive Psychiatry*, *59*, 117–122. https://doi.org/10.1016/j.comppsych.2015.02.007

Kraus, S. W., Voon, V., & Potenza, M. N. (2016). Should compulsive sexual behavior be considered an addiction? *Addiction*, *111*(12), 2097–2106. https://doi.org/10.1111/add.13297

Lang, K. M., & Little, T. D. (2018). Principled missing data treatments. *Prevention Science*, *19*(3), 284–294. https://doi.org/10.1007/s11121-016-0644-5

Lewczuk, K., Glica, A., Nowakowska, I., Gola, M., & Grubbs, J. B. (2020). Evaluating pornography problems due to moral incongruence model. *Journal of Sexual Medicine*, *17*(2), 300–311. https://doi.org/10.1016/j.jsxm.2019.11.259

Lewczuk, K., Wizła, M., Glica, A., Potenza, M. N., Lew-Starowicz, M., & Kraus, S. W. (2022). Withdrawal and tolerance as related to compulsive sexual behavior disorder and problematic pornography use–Preregistered study based on a nationally representative sample in Poland. *Journal of Behavioral Addictions*, *11*(4), 979–993. https://doi.org/10.1556/2006.2022.00076

Lewczuk, K., Wójcik, A., & Gola, M. (2022). Increase in the prevalence of online pornography use: Objective data analysis from the period between 2004 and 2016 in Poland. *Archives of Sexual Behavior*, *51*(2), 1157–1171. https://doi.org/10.1007/s10508-021-02090-w

Lew-Starowicz, M., Lewczuk, K., Nowakowska, I., Kraus, S. W., & Gola, M. (2020). Compulsive sexual behavior and dysregulation of emotion. *Journal of Sexual Medicine*, *8*(2), 191–205. https://doi.org/10.1016/j.sxmr.2019.10.003

Ley, D., Prause, N., & Finn, P. (2014). The emperor has no clothes: A review of the "pornography addiction" model. *Current Sexual Health Reports*, *6*(2), 94–105. https://doi.org/10.1007/s11930-014-0016-8

Nelson, K. M., & Rothman, E. F. (2020). Should public health professionals consider pornography a public health crisis? *American Journal of Public Health*, *110*(2), 151–153. https://doi.org/10.2105/AJPH.2019.305498

Newman, D. A. (2014). Missing data: Five practical guidelines. *Organizational Research Methods*, *17*(4), 372–411. https://doi.org/10.1177/1094428114548590

Noor, S. W., Rosser, B. R. S., & Erickson, D. J. (2014). A brief scale to measure problematic sexually explicit media consumption: Psychometric properties of the Compulsive Pornography Consumption (CPC) Scale among men who have sex with men. *Sexual Addiction & Compulsivity*, *21*(3), 240–261. https://doi.org/10.1080/10720162.2014.938849

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., & Sartori, G. (2020). Machine learning in psychometrics and psychological research. *Frontiers in Psychology*, *10*, Article 2970. https://doi.org/10.3389/fpsyg.2019.02970

Polanczyk, G. V., Salum, G. A., Sugaya, L. S., Caye, A., & Rohde, L. A. (2015). Annual research review: A meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *56*(3), 345–365. https://doi.org/10.1111/jcpp.12381

R Core Team. (2022). *R: A language and environment for statistical computing* (Version V4.2.2) [Computer software]. R Foundation for Statistical Computing, https://www.R-project.org

Reid, R. C., Carpenter, B. N., Hook, J. N., Garos, S., Manning, J. C., Gilliland, R., Cooper, E. B., Mckittrick, H., Davtian, M., & Fong, T. (2012). Report of findings in a DSM-5 field trial for hypersexual disorder. *Journal of Sexual Medicine*, *9*(11), 2868–2877. https://doi.org/10.1111/j.1743-6109.2012.02936.x

Rissel, C., Richters, J., de Visser, R. O., McKee, A., Yeung, A., & Caruana, T. (2017). A profile of pornography users in Australia: Findings from the second Australian study of health and relationships. *Journal of Sex Research*, *54*(2), 227–240. https://doi.org/10.1080/00224499.2016.1191597

Rumpf, H. J., & Montag, C. (2022). Where to put Compulsive Sexual Behavior Disorder (CSBD)? Phenomenology matters •: Commentary to the debate: "Behavioral addictions in the ICD-11". *Journal of Behavioral Addictions*, *11*(2), 230–233. https://doi.org/10.1556/2006.2022.00039

Sassover, E., & Weinstein, A. (2020). Should compulsive sexual behavior (CSB) be considered as a behavioral addiction? A debate paper presenting the opposing view. *Journal of Behavioral Addictions*, *11*(2), 166–179. https://doi.org/10.1556/2006.2020.00055

Sniewski, L., & Farvid, P. (2020). Hidden in shame: Heterosexual men's experiences of self-perceived problematic pornography use. *Psychology of Men and Masculinity*, *21*(2), 201–212. https://doi.org/10.1037/men0000232

Steel, Z., Marnane, C., Iranpour, C., Chey, T., Jackson, J. W., Patel, V., & Silove, D. (2014). The global prevalence of common mental disorders: A systematic review and meta-analysis 1980-2013. *International Journal of Epidemiology*, *43*(2), 476–493. https://doi.org/10.1093/ije/dyu038

Stekhoven, D. J., & Bühlmann, P. (2012). Missforest—non-parametric missing value imputation for mixed-type data. *Bioinformatics*, *28*(1), 112–118. https://doi.org/10.1093/BIOINFORMATICS/BTR597

Štulhofer, A., Rousseau, A., & Shekarchi, R. (2020). A two-wave assessment of the structure and stability of self-reported problematic pornography use among male Croatian adolescents. *International Journal of Sexual Health*, *32*(2), 151–164. https://doi.org/10.1080/19317611.2020.1765940

Svedin, C. G., Åkerman, I., & Priebe, G. (2011). Frequent users of pornography. A population based epidemiological study of Swedish male adolescents. *Journal of Adolescence*, *34*(4), 779–788. https://doi.org/10.1016/j.adolescence.2010.04.010

Turner, D., Briken, P., Grubbs, J., Malandain, L., Mestre-Bach, G., Potenza, M. N., & Thibaut, F. (2022). The World Federation of Societies of Biological Psychiatry guidelines on the assessment and pharmacological treatment of compulsive sexual behaviour disorder. *Dialogues in Clinical Neuroscience*, *24*(1), 10–69. https://doi.org/10.1080/19585969.2022.2134739

Vaillancourt-Morel, M.-P., & Bergeron, S. (2019). Self-perceived problematic pornography use: Beyond individual differences and religiosity. *Archives of Sexual Behavior*, *48*(2), 437–441. https://doi.org/10.1007/s10508-018-1292-6

Vigo, D., Thornicroft, G., & Atun, R. (2016). Estimating the true global burden of mental illness. *The Lancet Psychiatry*, *3*(2), 171–178. https://doi.org/10.1016/S2215-0366(15)00505-2

Volk, F., Floyd, C. G., Bohannon, K. E., Cole, S. M., McNichol, K. M., Schott, E. A., & Williams, Z. D. R. (2019). The moderating role of the tendency to blame others in the development of perceived addiction, shame, and depression in pornography users. *Sexual Addiction & Compulsivity*, *26*(3–4), 239–261. https://doi.org/10.1080/10720162.2019.1670301

Walsh, C. G., Ribeiro, J. D., & Franklin, J. C. (2017). Predicting risk of suicide attempts over time through machine learning. *Clinical Psychological Science*, *5*(3), 457–469. https://doi.org/10.1177/2167702617691560

Walsh, C. G., Ribeiro, J. D., & Franklin, J. C. (2018). Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *59*(12), 1261–1270. https://doi.org/10.1111/jcpp.12916

Whiteford, H. A., Ferrari, A. J., Degenhardt, L., Feigin, V., & Vos, T. (2015). The global burden of mental, neurological and substance use disorders: An analysis from the global burden of disease study 2010. *PLoS ONE*, *10*(2), Article e0116820. https://doi.org/10.1371/JOURNAL.PONE.0116820

Wolak, J., Mitchell, K., & Finkelhor, D. (2007). Unwanted and wanted exposure to online pornography in a national sample of youth Internet users. *Pediatrics*, *119*(2), 247–257. https://doi.org/10.1542/peds.2006-1891

World Health Organization. (2022). *International statistical classification of diseases and related health problems* (11th ed.). https://icd.who.int/

Wright, P. J., Herbenick, D., & Paul, B. (2020). Adolescent condom use, parent-adolescent sexual health communication, and pornography: Findings from a U. S. probability sample. *Health Communication*, *35*(13), 1576–1582. https://doi.org/10.1080/10410236.2019.1652392

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393

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