

Uncovering the most robust predictors of problematic pornography use: A large-scale machine learning study across 16 countries

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Data Sharing Statement:

As the study included data on sensitive topics, we did not make all datasets publicly available. Each collaborator providing datasets can decide whether they would share their own datasets publicly, considering the specific ethical requirements and regulations of their institutions. The first author will work with any academics to obtain access to any of the used datasets in case of reasonable requests.

Conflict of Interest:

The authors declare that they have no conflict of interest. The University of Gibraltar receives funding from the Gibraltar Gambling Care Foundation, an independent, not-for-profit charity. However, this funding source is not related to this study, and the funding institution had no role

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Abstract

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 pre-existing self-report datasets ($N_{participants}=112,397$; $N_{countries}=16$) 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 dataset to examine how different sociodemographic, psychological, and other characteristics predict PPU, and combined the results of all datasets 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 datasets, with the top five being a) pornography use frequency, b) emotional avoidance pornography use motivation, c) stress reduction pornography use motivation, d) moral incongruence towards 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.

Keywords: artificial intelligence; compulsive sexual behavior; machine learning; pornography; problematic pornography use; sex addiction

General Scientific Summary

This study suggests that the top five predictors of problematic pornography use 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.

Uncovering the most robust predictors of problematic pornography use: A large-scale machine learning study across 16 countries

After four decades of clinical attention and a marked increase in scientific studies on out-of-control sexual behaviors (Grubbs, Hoagland, et al., 2020; Grubbs & Kraus, 2021), Compulsive Sexual Behaviour 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% (Bóthe et al., 2023; Bóthe, 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, multi-lab approach with an artificial intelligence-based method (i.e., machine learning).

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% to 94% of adults (Grubbs, Kraus, et al., 2019; Herbenick et al.,

2020; Lewczuk et al., 2020; Rissel et al., 2017) and 42% to 98% of adolescents (Bóthe, 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% to 38% of adults and 5% to 14% of adolescents may experience PPU (Bóthe, Vaillancourt-Morel, Dion, Štulhofer, 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; Bóthe et al., 2023; 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 (Bóthe et al., 2023; Chen 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 (Bóthe et al., 2022; Bóthe, Tóth-Király, et al., 2019; Brand et al., 2022; Castro-Calvo et al., 2022; Kraus et al., 2016; Ley et al., 2014; Rumpf & Montag, 2022; Sassover & Weinstein, 2022).

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, Hoagland, et al., 2020; Grubbs & Kraus, 2021). 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, Hoagland, et al., 2020; Grubbs & Kraus, 2021).

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, WEIRD (i.e., Western, Educated, Industrialized, Rich, and Democratic) samples (Bóthe, Vaillancourt-Morel, et al., 2019; Chen et al., 2022; Grant Weinandy et al., 2023; Grubbs, Hoagland, et al., 2020; Grubbs & Kraus, 2021; Jennings et al., 2021). These limitations call for large datasets 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, machine learning (ML) approaches focus on learning statistical functions from multidimensional datasets, including many potential predictors, and their linear and non-linear 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).

Although conducting ML studies does not necessarily require the use of multiple datasets, 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 datasets 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 pre-existing datasets 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 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 datasets for this study. The [preregistered](#) requirements for eligible datasets 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 datasets ($N_{participants}=112,397$; $N_{countries}=16$) with a codebook describing the study design and all variables (Table 1). The list of all datasets, collaborators, and publications is available in eTable 1. As the study included data on sensitive topics, datasets were not made publicly available.

Preregistration and Related Open Science Materials

The [study design](#) and [analysis plan](#) were preregistered on the Open Science Framework (OSF). Deviations from the preregistered plan are described in the Supplemental Materials. Meta-analytic data, codebooks, complementary analyses, and related materials are available on [OSF](#).

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 (Bóthe et al., 2018; Bóthe, Tóth-Király, Demetrovics, et al., 2021; Bóthe, Vaillancourt-Morel, Dion, Štulhofer, 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-SEM (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 datasets were considered predictor variables. Specific predictors varied from dataset to dataset. We excluded four types of variables from the potential predictors based on pre-established criteria described in the preregistered study design: scales assessing compulsive sexual behavior or any other variant of it, non-validated 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 dataset and its corresponding codebook had been received, the first author 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 dataset to complement the codebook with the missing information. The codebook contained detailed meta-data of the dataset, 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 dataset that the scholars providing the dataset wanted to share. In addition, the codebook included information about all variables in the dataset. 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 dataset and its related codebook, the first author studied all information in the codebook about all variables in each dataset. Then, a systematic coding system was developed based on the identified constructs that were measured across datasets, 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 dataset, the fourth author cross-checked and verified the appropriate use of these common labels. Out of the 3987 variables, a total of 744 predictor categories were identified. The list of all variables and their coded names is available on [OSF](#) (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. To unify the method of dealing with missing data in each dataset, only data from participants who did not have missing data on the PPU scale were used, as each dataset 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 dataset with

the PPU score as the dependent/outcome variable^a, a machine learning 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 VSURF 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^b 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 ten 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 pre-established 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 ten datasets and that emerged as significant predictors in at least 50% of the datasets.

Results

^aWhen 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 (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 datasets; 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 Supplemental Materials). Therefore, we used the first data collection waves from the longitudinal datasets as cross-sectional data, and conducted the same analyses on these datasets as on the cross-sectional ones.

^bFor 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 dataset, 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 datasets.

Descriptive information for each dataset and the results of the random forest models are presented in Table 1. On average, datasets included 43 potential predictors (ranging between four to 260 predictors across datasets), of which 11 were included in the final models. The explained variances ranged from 6.54% to 85.17% across the datasets.^c The meta-analytic results ($Q(79)=6194.1, p<.001; \tau^2=0.07; I^2=98.70%; H^2=74.65%$) showed that the predictors explained 45.84% (95% CI: 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 ten datasets and that emerged as significant predictors in at least 50% of the datasets) are presented in Table 2.^d The top five predictors were frequency of use, emotional avoidance pornography use motivation, stress reduction pornography use motivation, moral incongruence towards 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 ten pre-established meta-analytic moderators, only the number of variables in the dataset and the number of predictors selected in the final model had significant effects on the results (Table 3). Having more variables ($F(1,82)=5.55, p=.021, \tau^2=0.07, I^2=98.75%$) and having more predictors in the final model ($F(1,82)=16.86, p<.001, \tau^2=0.06, I^2=98.63%$) contributed to heterogeneity, although the size of these contributions was negligible. These

^c 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 $n_{tree} = 1000, n_{tree} = 1500, n_{tree} = 2000,$ and $n_{tree} = 5000$. Details of the conducted analysis can be found in the supplemental materials. The findings suggested that the different n_{tree} values might not have affected the results substantially, corroborating the robustness of the results.

^d The predictive power of the variables that were included in at least ten datasets (not restricted to those that were predictors in at least 50% of the datasets) and the predictive power of all variables (without any restrictions) are available on OSF in the Supplemental Materials:

https://osf.io/b2wa5/?view_only=59746e81e01d420c8b39fdcc79cd95db.

results suggest that the datasets' characteristics (e.g., country of data collection) did not play a crucial role in the heterogeneity and predictive power of the models.^e

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 towards 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 ($F(3,80)=10.52, p<.001, \tau^2=0.05, I^2=98.35\%$), only blaming others ($B=0.39, SE=0.11, p<.001$) contributed significantly. Yet, similar to the results with the meta-analytic moderators, these variables' effect on heterogeneity was small.

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

^e We used the cut-off 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 cut-off of 30% of missing data would result in changes in the results. We conducted all the analyses with only datasets that had less than 30% of missing data. Details of the conducted analysis can be found in the supplemental materials. The findings suggested that the level of missing data might not have affected the results substantially, corroborating the robustness of the results.

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, 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 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 symptom of PPU compared to other symptoms (Bóthe, 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) (Bóthe, Lonza, et al., 2020; Bóthe, Tóth-Király, et al., 2020; Chen et al., 2021; 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 (Bóthe, Lonza, et al., 2020; Bóthe, Tóth-Király, et al., 2020; Chen et al., 2021; 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 (Bóthe, 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 5th revision of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (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 ICD-11 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 datasets 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 (Bóthe, Koós, Nagy, Kraus, et al., 2021). In addition, samples from specific countries (e.g., China, Hungary, the US) 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 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, Hoagland, et al., 2020; Grubbs & Kraus, 2021).

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, Hoagland, et al., 2020; Grubbs & Kraus, 2021). 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).

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Table 1. Characteristics of the Datasets included in the Study and the Results of the Random Forest Models on each Dataset

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 - mean (%)	Missing data - min. (%)	Missing data - max. (%)
1	15137	PPCS	community sample	adult sample	Hungary	published	92	11	48.17	172.57	0.85	0.00	6.25
2	6165	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	1285	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	1002	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	1090	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	1873	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	6023	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	1400	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	1016	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	1158	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
60	1109	PPUS	community sample	adult sample	international / not specified	published	20	10	74.27	36.69	0.00	0.00	0.00
61	2491	PPCS	community sample	adult sample	United States	not published	15	11	51.81	0.92	0.10	0.00	0.40
75	4035	PPUS	community sample	adult sample	Israel	published	33	16	37.65	37.78	0.02	0.00	0.32
78	1461	BPS	community sample	adult sample	United States	published	20	9	47.41	3.63	0.07	0.00	1.23
79	1526	BPS	community sample	adult sample	United States	not published	44	18	14.26	6.79	0.05	0.00	0.33
33a	9263	BPS	treatment-seeking sample	adult sample	China	published	18	14	36.51	5.61	0.00	0.00	0.00
33b	9263	PPCS	treatment-seeking sample	adult sample	China	published	18	14	58.37	287.62	0.00	0.00	0.00
33c	9263	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	1174	CPUI	community sample	adult sample	United States	published	32	14	38.55	1.50	0.01	0.00	0.17
58b	1171	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	1384	CPUI	community sample	adult sample	United States	not published	56	30	75.17	0.80	1.42	0.00	7.44
71b	1371	CPUI	community sample	adult sample	United States	not published	56	30	85.17	0.49	1.42	0.00	7.44

72a	1070	CPUI	community sample	adult sample	United States	not published	97	29	77.88	1.45	2.98	0.00	22.71
77a	1634	PPCS	community sample	adolescent sample	international / not specified	not published	7	4	14.71	136.27	0.00	0.00	0.00
77b	1634	PPCS	community sample	adolescent sample	international / not specified	not published	7	4	16.70	20.68	0.00	0.00	0.00
80a	1143	CPUI	community sample	adult sample	United States	published	48	12	43.91	1.15	1.93	0.00	36.13
80b	1124	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 dataset 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 datasets (see details in the Supplemental Materials). As a negative explained variance is not interpretable, these datasets were not included in the interpretation and meta-analysis steps of the study. MSE=mean squared error; 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; CIUS-SEM=Compulsive Internet Use Scale-SEM; CPCS=Compulsive Pornography Consumption Scale. Missing Data - Min = minimum of missing data across predictors per dataset; Missing Data - Max. = maximum of missing data across predictors per dataset. a=At the time of data solicitation.

Table 2. The Most Robust Predictors of Problematic Pornography Use.

Variables	Included in datasets (out of 84)	Significant predictor in % of the datasets 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 towards 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 datasets and that emerged as significant predictors in at least 50% of the datasets 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.

Table 3. Results of the Meta-Regression and Subgroup Analyses with the Preregistered Meta-Analytic Moderators

Variables	k	Explained variance	95% CI	p-value	I ²	95% CI	p-value	Adjusted p-value
PPU scale used^a							0.265	1.000
PPCS	28	45.45%	38.43%, 52.12%	<0.001	98.87%	98.70%, 99.02%		
BPS	14	40.27%	31.01%, 49.19%	<0.001	96.83%	95.78%, 97.62%		
CPUI	31	48.79%	40.69%, 56.33%	<0.001	98.54%	98.31%, 98.74%		
PPUS	9	52.34%	40.34%, 62.89%	<0.001	98.03%	97.30%, 98.56%		
Timeframe of asking about PPU^b							0.761	1.000
No timeframe specified	33	47.06%	38.75%, 54.84%	<0.001	98.61%	98.40%, 98.79%		
Past 6 months	50	45.66%	40.93%, 50.23%	<0.001	98.63%	98.47%, 98.78%		
Who completed the PPU scale^c							0.399	1.000
No timeframe specified	28	41.45%	35.04%, 47.67%	<0.001	98.31%	98.01%, 98.56%		
Past 6 months users	17	52.38%	35.04%, 47.67%	<0.001	98.96%	98.75%, 99.13%		
Past 12 months users	15	44.86%	34.48%, 54.55%	<0.001	98.97%	98.75%, 99.15%		
Lifetime users	22	46.64%	38.29%, 54.48%	<0.001	97.63%	97.09%, 98.07%		
Country of data collection^d							0.271	1.000
International/not specified	7	36.46%	14.86%, 57.49%	0.001	99.10%	98.81%, 99.32%		
Canada	5	34.60%	8.20%, 61.44%	0.008	98.68%	98.06%, 99.10%		
China	8	49.72%	41.14%, 57.63%	<0.001	98.57%	98.07%, 98.94%		
Hungary	18	42.98%	33.95%, 51.55%	<0.001	98.80%	98.56%, 99.00%		
United States of America	30	50.63%	42.33%, 58.27%	<0.001	98.83%	98.66%, 98.99%		
Publication status^e							0.967	1.000
Unpublished	48	45.77%	39.44%, 51.82%	<0.001	98.61%	98.43%, 98.76%		
≥ 1 publication	36	45.94%	40.2%, 51.45%	<0.001	98.75%	98.58%, 98.90%		
Sample type 1				<0.001			0.102	0.815
Community sample	76	46.81%	42.32%, 51.15%	<0.001	98.64%	98.51%, 98.75%		
Treatment-seeking sample	8	36.32%	22.01%, 50.31%	<0.001	98.92%	98.58%, 99.18%		
Sample type 2^f							NA	NA
Adult sample	77	47.09%	42.75%, 51.29%	<0.001	98.58%	98.44%, 98.70%		
Study design							0.631	1.000
Cross-sectional	74	46.15%	41.46%, 50.68%	<0.001	98.77%	98.66%, 98.88%		
Longitudinal	10	43.63%	32.64%, 53.91%	<0.001	96.39%	94.85%, 97.48%		
	k	estimate	standard error	t-value	degrees of freedom		p-value	
Year of data collection (start date)								
Intercept	84	-39.18	24.83	-1.58	82		0.118	
Value	84	0.02	0.01	1.61	82		0.111	
Year of data collection (end date)								
Intercept	84	-30.31	25.70	-1.18	82		0.241	
Value	84	0.02	0.01	1.21	82		0.229	

Number of predictors used in the random forests model						
Intercept	84	0.75	0.04	17.28	82	<0.001
Value	84	<0.01	<0.01	2.36	82	0.021
Number of predictors selected in the final random forests model						
Intercept	84	0.63	0.05	11.69	82	<0.001
Value	84	0.02	<0.01	4.10	82	<0.001

Note. When a model ID includes a letter (e.g., 33a, 33b), it represents that the dataset included more than one PPU measure, and thus all PPU measures were considered outcome variables in separate models. a=*p*-values adjusted using the Holm-method (*n*=8 tests). 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. a=It was not possible to include the Compulsive Internet Use Scale-SEM (CIUS-SEM) and the Compulsive Pornography Consumption Scale (CPCS) in this analysis as fewer than 5 studies used them. b=It was not possible to include the category “past three months” in this analysis as fewer than 5 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 5 studies used them. d=It was not possible to include Bangladesh, Germany, Iran, Israel, Malaysia, Netherlands, Poland, Portugal, Slovakia, and Spain in this analysis as fewer than 5 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 5 studies were conducted in these populations.

Table 4. Exploratory Results of Subgroup Analyses with the Most Robust Predictor Variables and the Level of Missing Data.

Variables	k	Explained variance (%)	95% CI	p-value	R ²	95% CI	p-value	Adjusted p-value ^a
Gender							0.021	0.349
Not predictor	44	50.25%	43.76%, 56.34%	<0.001	98.91%	98.78%, 99.02%		
Predictor	40	40.82%	35.67%, 45.86%	<0.001	97.63%	97.24%, 97.96%		
Pornography use frequency							0.082	1.000
Not predictor	23	39.96%	31.65%, 48.00%	<0.001	98.71%	98.48%, 98.91%		
Predictor	61	48.00%	43.01%, 52.78%	<0.001	98.44%	98.27%, 98.60%		
Duration of pornography use per occasion							0.096	1.000
Not predictor	58	43.38%	38.39%, 48.22%	<0.001	98.24%	98.03%, 98.43%		
Predictor	26	51.15%	42.88%, 58.75%	<0.001	98.97%	98.81%, 99.10%		
Emotional avoidance pornography use motivation							0.004	0.060
Not predictor	73	43.90%	39.27%, 48.40%	<0.001	98.42%	98.25%, 98.56%		
Predictor	11	57.91%	48.56%, 66.10%	<0.001	98.37%	97.88%, 98.75%		
Stress reduction pornography use motivation							0.027	0.453
Not predictor	76	44.72%	40.13%, 49.17%	<0.001	98.47%	98.32%, 98.61%		
Predictor	8	55.98%	45.13%, 65.43%	<0.001	98.11%	97.37%, 98.64%		
Fantasy pornography use motivation							0.014	0.245
Not predictor	75	44.28%	39.75%, 48.68%	<0.001	98.41%	98.25%, 98.56%		
Predictor	9	58.02%	46.13%, 68.10%	<0.001	98.62%	98.17%, 98.95%		
Moral incongruence towards pornography use							<0.001	0.008
Not predictor	57	41.03%	35.97%, 45.98%	<0.001	98.56%	98.39%, 98.70%		
Predictor	27	55.39%	48.70%, 61.53%	<0.001	98.75%	98.54%, 98.92%		
Self-perceived addiction to pornography							0.021	0.352
Not predictor	77	44.75%	40.22%, 49.15%	<0.001	98.49%	98.34%, 98.62%		
Predictor	7	57.08%	45.14%, 67.27%	<0.001	99.19%	98.94%, 99.38%		
Treatment-seeking for pornography use							0.082	1.000
Not predictor	78	44.78%	40.39%, 49.04%	<0.001	98.39%	98.23%, 98.53%		
Predictor	6	58.70%	38.22%, 74.24%	<0.001	97.52%	96.20%, 98.38%		
Sexual function							0.224	1.000
Not predictor	79	46.48%	42.10%, 50.71%	<0.001	98.70%	98.58%, 98.81%		
Predictor	5	35.30%	11.64%, 58.8%	0.004	97.64%	96.24%, 98.52%		
Sexual shame							0.003	0.058
Not predictor	73	42.97%	38.86%, 46.98%	<0.001	98.39%	98.22%, 98.54%		
Predictor	11	62.99%	48.77%, 74.18%	<0.001	98.46%	98.01%, 98.81%		
Anxiety symptoms							0.008	0.139
Not predictor	69	42.35%	38.47%, 46.15%	<0.001	97.60%	97.31%, 97.86%		
Predictor	15	60.23%	46.51%, 71.39%	<0.001	99.24%	99.09%, 99.36%		
Depression symptoms							0.002	0.026

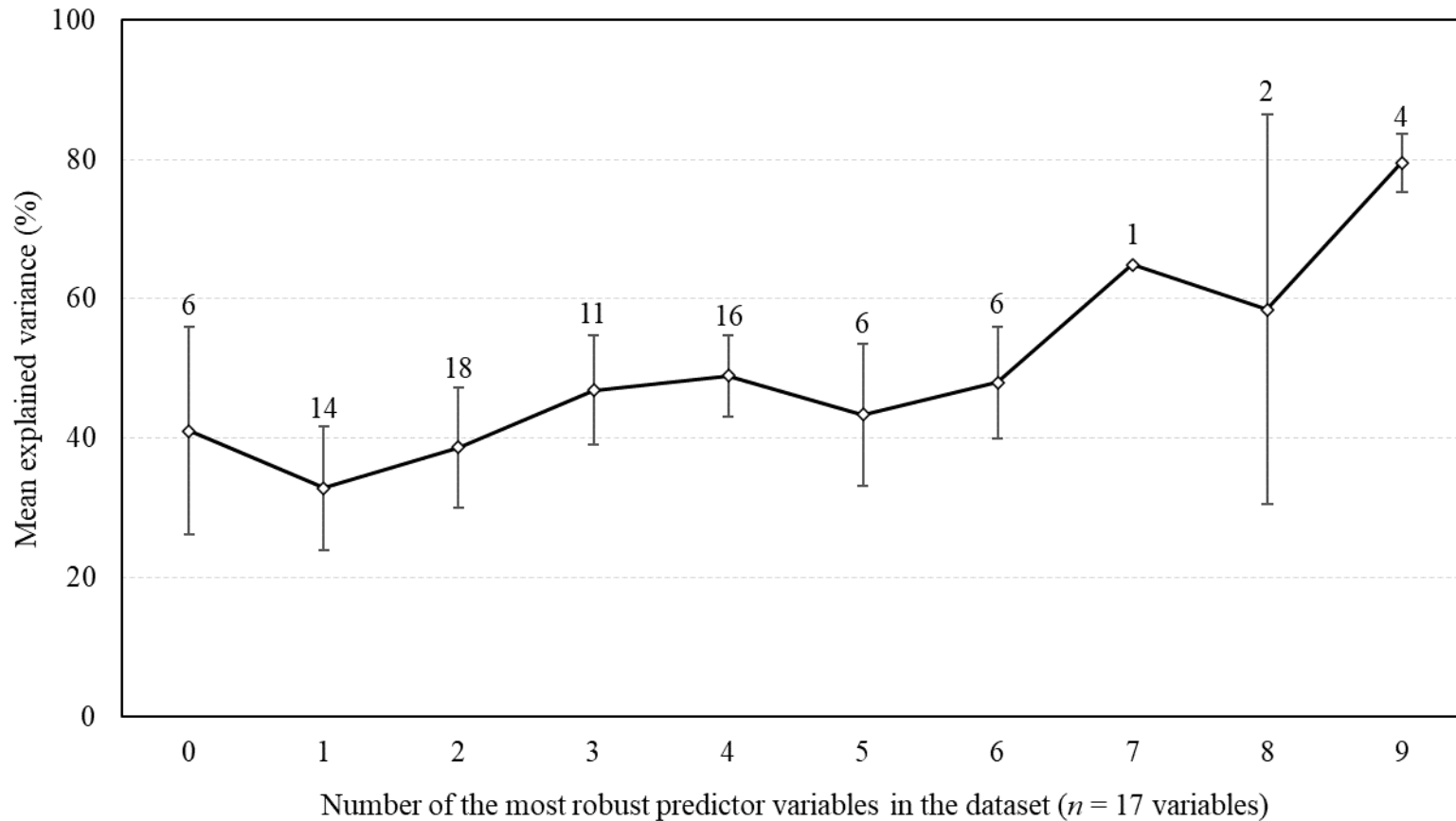
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Not predictor	70	42.83%	38.39%, 47.15%	<0.001	98.54%	98.40%, 98.68%		
Predictor	14	59.77%	49.43%, 68.60%	<0.001	98.82%	98.55%, 99.04%		
Guilt							0.046	0.785
Not predictor	76	44.05%	39.86%, 48.13%	<0.001	98.46%	98.30%, 98.60%		
Predictor	8	61.28%	41.08%, 76.22%	<0.001	98.97%	98.65%, 99.21%		
Blaming others							<0.001	0.001
Not predictor	77	43.02%	39.1%, 46.85%	<0.001	98.31%	98.14%, 98.47%		
Predictor	7	71.41%	56.17%, 82.10%	<0.001	98.13%	97.33%, 98.68%		
Attachment anxiety							0.298	1.000
Not predictor	76	44.94%	40.59%, 49.17%	<0.001	98.64%	98.51%, 98.76%		
Predictor	8	54.11%	33.06%, 70.84%	<0.001	98.84%	98.46%, 99.12%		
Loneliness							0.150	1.000
Not predictor	75	44.34%	40.16%, 48.41%	<0.001	98.41%	98.25%, 98.55%		
Predictor	9	57.41%	36.36%, 73.53%	<0.001	99.42%	99.29%, 99.53%		
	k	estimate	standard error	t-value	degrees of freedom		p-value	
Missing data								
Intercept	84	0.80	0.04	21.46	82		<.001	
Value	84	0.02	0.02	0.99	82		0.324	

Note. α =p-values adjusted using the Holm-method ($n=17$ tests).

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 datasets with the given number of predictor variables is shown above the error bars. No dataset included more than nine of the most robust predictors.