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THE USE OF MACHINE LEARNING TO IMPROVE THE IDENTIFICATION AND ASSESSMENT OF INTERNET-RELATED DISORDERS

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To my grandparents.

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As far as I can remember, the Internet took a specific place in my life. Thanks to its use, I could learn so many things, interact with so many people, and have so much fun. I don’t count the nights where I stayed awake till very (very) late being on the Internet, not seeing the time passing, just because I had a sudden interest in a specific topic or because I just discovered a new type of video game that allowed me to play online. It is also thanks to the Internet that I started to be fascinated by psychological science, research, statistics, and programming. It won’t be exaggerated to claim that the Internet is even the reason why I decided to study psychological science. During my studies, I discovered the field of cyberpsychology in psychological research and I immediately knew it would be a great match between us! This is how I contacted Professor Joël Billieux and crossed my fingers to be able to do my master's thesis under his supervision. This decision was one of the best that I ever took in my life.

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Abstract

The Internet's growing significance has raised global concerns about Internet-related disorders. Organizations like the American Psychological Association (APA) and the World Health Organization (WHO) have already highlighted the potential negative effects of excessive Internet use on mental health. Since the inclusion of gaming disorder as a condition for further study in the DSM-5 and its recognition as a mental disorder in ICD-11, research on the problematic use of the Internet (PUI) become a topic of even greater significance.

The present PhD thesis aims to address two key research priorities in the field of PUI, formulated by the European Network for PUI, related to (a) contributing to their conceptualization and (b) improving their assessment. In this regard, four different studies targeting gaming disorder and cyberchondria, a condition characterized by excessive and uncontrollable searching for health-related information on the Internet, were deployed. This thesis centrally focuses on using machine learning (ML) and traditional statistics to reach these objectives.

In *Study 1*, the levels of cyberchondria during the pandemic were investigated and compared with the retrospectively assessed pre-pandemic levels. It also identified psychological factors that could predict the level of cyberchondria during the pandemic. In *Study 2*, different gamer groups based on their profiles of passion for gaming were identified. It also observed how gaming disorder symptoms, assessed within the substance use disorder and gambling frameworks (e.g., tolerance, withdrawal, preoccupation, mood modification), are linked to harmonious and/or an obsessive passion for gaming. *Study 3* used gaming disorder criteria to predict depression and well-being levels. It also identified predictors of gaming disorder level and their importance in the prediction of each DSM-5 criterion proposed for Internet

gaming disorder. Finally, *Study 4* warns against the misuse of algorithm-generated data in ML analyses and its negative impact on the conceptualization and assessment of a PUI.

Results from the studies suggest that cyberchondria and gaming disorder can be understood within the same general framework. Nevertheless, additional models specific to each condition can enhance their understanding and provide important insights for their treatment and prevention interventions. Regarding their assessment, the thesis supports the idea of a possible transdiagnostic nature of the criteria proposed by the ICD-11 for the assessment of gaming disorder and their potential capacity to address the various forms of PUI. The thesis also demonstrates that ML methodologies offer a helpful and convenient instrument for psychological research topics such as the PUI.

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List of Abbreviations

ADHD	Attention-Deficit / Hyperactivity Disorder
AI	Artificial Intelligence
APA	American Psychiatric Association
AUC	Area Under the ROC Curve
BR	Battle Royale
CH	Calinski-Harabasz
CI	Confidence Interval
COVID-19	Coronavirus disease 2019
CSS	Cyberchondria Severity Scale
CV	Cross-Validation
DF	Degrees of freedom
DSM-5	5th edition of the Diagnostic and Statistical Manual of Mental Disorders
DT	Decision Tree
EN	Elastic Net
FPS	First Person Shooters
GASA	Game Addiction Scale for Adolescents
GD	Gaming disorder
ICD-11	11th International Classification of Diseases
IGD-20	Internet Gaming Disorder Test
I-PACE	Interaction of Person-Affect-Cognition-Execution
IUS-SH	Intolerance of Uncertainty Scale-Short Form
K-NN	K-Nearest Neighbors
LASSO	Least Absolute Shrinkage Selection Operator
LR	Logistic Regression
MAC-RF	Multidimensional Assessment of COVID-19-Related Fears

MAE	Mean Absolute Error
Mdn	Median
ML	Machine Learning
MMORPGs	Massively Multiplayer Online Role-Playing Games
MOBA	Multiplayer Online Battles Arenas
MOGQ	Motives for Online Gaming Questionnaire
NB	Naïve Bayes
NN	Neural Network
OCD	Obsessive-Compulsive Disorder
OSF	Open Science Framework
PHQ	Patient Health Questionnaire
PUI	Problematic Use of the Internet
RF	Random Forests
RMSE	Root Mean Square Error
RQ	Relationship Questionnaires
RTS	Real Time Strategy
SD	Standard Deviation
SHAI	Short Health Anxiety Inventory
SMOTE	Synthetic Minority Oversampling Technique
SUD	Substance Use Disorder
SVM	Support Vector Machine
UAB	User-Avatar Bond
UAB-Q	User-Avatar Bond Questionnaire
UPPS-P	Urgency (negative), Premeditation (lack of), Perseverance (lack of), Sensation Seeking, Urgency (positive), Impulsive Behavior Scale
WHO	World Health Organization
XGB	X Gradient Boosting

1. Theoretical framework

1.1. The problematic use of Internet

From 2000 to 2023, the world's Internet usage grew by 1392% (*Internet World Stats*, 2024), leading to 5.35 billion of users worldwide as of January 2024 (*Statista*, 2024). Nowadays, the Internet can serve different purposes, such as searching for information, navigation, video games, and social networking, and is easily and immediately accessible thanks to smartphones and other devices. Despite its undeniable benefits, an overuse of the Internet is associated with detrimental effects including low academic performance, fatigue, and psychopathological symptoms (Moreno et al., 2013; Spada, 2014; Young, 1996). For this reason, the World Health Organization (WHO, 2015) considers the problematic use of the Internet (PUI), which is described as "*Internet use that is risky, excessive or impulsive in nature leading to adverse life consequences, specifically physical, emotional, social or functional impairment*" (Moreno et al., 2013), as a relevant public health concern in modern societies. In the literature, several terms are used to refer to the problematic use of Internet, for example "*Internet addiction"*, "*Internet use disorder",* "*compulsive Internet use"*, "*Internet overuse",* or *"pathological Internet use"* (Fienberg et al., 2022; Montag et al., 2021; Moreno et al., 2013). The current work will use the term of PUI, which is considered to be a broader term (Moreno et al., 2013) and does not assume the nosology or underlying causative mechanisms of the different forms of PUI (Fineberg et al., 2022). The term PUI has the advantage that it can be used as an umbrella term that regroups all the potential problematic behaviors related to Internet use (Fineberg et al., 2022). Before the pandemic, various meta-analyses (e.g., Buneviciene & Bunevicius, 2021; Pan et al., 2020) found prevalence rates of PUI to range from 6% to 9.7% (Burkauskas et al., 2022). Nevertheless, due to notable variations in methodology and cultural backgrounds, determining the prevalence of PUI remains a challenge, resulting in varying prevalence estimates worldwide (Burkauskas et al., 2022). Regarding comorbidities, suicidal thoughts, violent behavior, depression, social anxiety, ADHD, and autistic spectrum disease have all been linked to PUI as potential predictors and outcomes, for both younger and older age groups (Fineberg et al., 2022).

In the current thesis, we decided to focus on two specific types of problematic online behaviors, namely problematic video game involvement and cyberchondria. The problematic use of video games is the only PUI present in both the 11th International Classification of Diseases (ICD-11, WHO, 2019), and the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5, American Psychiatric Association [APA], 2013). In 2013, the APA included a condition called "*Internet Gaming Disorder*" in Section 3 (emerging measures and models) of the DSM-5. Later, in 2019, the WHO integrated it into the ICD-11 with the label "*Gaming Disorder*". Its recognition as a mental disorder in the next version of the DSM is still unclear since no changes have been made in the DSM-5-TR (First et al., 2022). Another reason is that this disorder affects a broad population, including children, teenagers, and adults (Darvesh et al., 2020). Finally, its prevalence is significant and equal to that of Substance Use Disorder (SUD) and Obsessive-Compulsive Disorder (OCD) (Stevens et al., 2021). Conversely, cyberchondria is an example of a PUI that is not yet recognized as a disorder, neither by the DSM-5 nor the ICD-11, and its conceptualization is still in the early stages of its development (Mestre-Bach & Potenza, 2023). Given the COVID-19 pandemic, it became a PUI of high interest since its occurrence might have increased during the pandemic (Mestre-Bach & Potenza, 2023; Starcevic et al., 2021). Due to the context of the pandemic crisis, this PhD project had the unique opportunity to investigate this PUI at its possibly highest level of expression and prevalence, leading to potentially optimal circumstances for investigating its mechanisms and conceptualization. Another reason pertains to the proposition that, while some kinds of PUI may share risk factors (e.g., psychological dimensions or personality traits) with behavioral addictions (e.g., gaming disorder), other forms may more strongly resemble social anxiety, impulse control disorders, or

OCD (e.g., cyberchondria) (Fineberg et al., 2018). Thus, focusing on cyberchondria and gaming disorder is a way of attempting to characterize the variety of behaviors and disorders that are included under the umbrella PUI forms. Accordingly, in addition to its relevance due to the public health concerns worldwide during the COVID-19 crisis, cyberchondria is also a relevant condition in addition to gaming disorder. For these reasons, and because tackling all PUI forms was not possible, the present work will focus on these two specific forms of PUI.

1.1.1. Gaming disorder

As discussed previously, gaming disorder is the first form of PUI incorporated in both the DSM-5 and ICD-11. It is acknowledged as a mental disorder in the ICD-11 under the "*disorders due to substance use or addictive behaviours*" section by the WHO (WHO, 2019), while it is present in section III "*emerging measures and models: Conditions for further study*" of the DSM-5 and thus not recognized yet by the APA team (APA, 2013). The status of gaming disorder differs in both systems, underscoring the debated nature of this disorder (Aarseth et al., 2017; Castro-Calvo et al., 2021).

DMS-5 vs ICD-11

In the DSM-5, nine distinct criteria are proposed to assess gaming disorder, or Internet gaming disorder as mentioned in the DSM-5. The criteria mentioned in the DSM-5 are: (1) "*preoccupation with the Internet*" (preoccupation); (2) "*withdrawal symptoms when Internet gaming is taken away*" (withdrawal); (3) "*the need to spend increasing amounts of time engaged in Internet games*" (tolerance); (4) "*unsuccessful attempts to control the participation in Internet games*" (loss of control); (5) "*Loss of interests in previous hobbies and entertainment as a result of, and with the exception of, Internet games*" (loss of interest); (6) "*continued excessive use of Internet games despite knowledge of psychosocial problems*" (continued overuse); (7) "*has deceived family members, therapists, or others regarding the *amount of Internet gaming*" (deceiving); (8) "*use of Internet games to escape or relieve a negative mood*" (escape of negative feelings); and (9) "*has jeopardized or lost a significant relationship, job, or educational or career opportunity because of participation in Internet games*" (conflict/interference) (APA, 2013). It is important to note that these criteria consist of a mixture of criteria used for gambling disorder (e.g., preoccupation, deceiving) and SUD disorder (e.g., withdrawal, tolerance) (Petry et al., 2014). To detect clinical impairment according to the DSM-5, it is necessary to present at least five of the proposed criteria during the last 12 month. The DSM-5 considers offline gaming as a subtype of Internet gaming disorder (APA, 2013).

In the ICD-11, the hallmarks of gaming disorder include the simultaneous presence of three criteria: (1) "*impaired control over gaming (e.g., onset, frequency, intensity, duration, termination, context)*" (loss of control); (2) "*increasing priority given to gaming to the extent that gaming takes precedence over other life interests and daily activities"* (loss of interest)*;* and (3) *"continuation or escalation of gaming despite the occurrence of negative consequences"* (continued overuse). To be diagnosed with the disorder, all criteria must be met during the last 12 months and result in significant functional impairment in areas such as work, social life, or family relationships (WHO, 2019). If all criteria are not met for diagnosis, the ICD-11 proposes the term "hazardous gaming" to refer to risky behavior with potential health consequences (WHO, 2019).

Diagnoses based on the DSM-5 and the ICD-11 diverge in terms of the prevalence of gaming disorder. In a recent study assessing gaming disorder among a sizable sample of teenagers from Spain (N=41,507), the authors found a prevalence of 3.1% when using the DSM-5, and a prevalence of 1.8% when using the ICD-11 (Nogueira-López et al., 2023). Similar difference have been found in a sample of 1429 gamers in Germany, where a prevalence of 3.28% was found using the ICD-11, compared to 5.7% when using the DSM-5 (Montag et al., 2019). A more noticeable difference in prevalence rates between both diagnostic systems has been found by Borges et al. (2019) when assessing gaming disorder in a large sample of Mexican university students (N= 7,022), where a prevalence of 5.3% was obtained using the DSM-5, as opposed to 2.7% when using the ICD-11. Overall, it seems that participant demographics and study methods affect the prevalence rates of gaming disorder. A number of variables, including age, location, culture, sampling techniques, and assessment instruments, can have a significant impact on gaming disorder prevalence rates (Kim et al., 2022).

The more conservative assessment according to the ICD-11 seems to result in more realistic prevalence rates (Nogueira-López et al., 2023). Moreover, in comparison to the DSM-5, which includes criteria related to SUD that imply physiological aspects such as withdrawal and tolerance, the ICD-11 focuses on functional impairment (Jo et al., 2019).

High engagement or problematic use?

In 2007, Charlton & Danforth (2007) conducted a study that emphasized the limitations of using a substance addiction approach to conceptualize and assess addictive behaviors. Their study identified two types of criteria related to behavioral addiction. The first type, labelled as core criteria, directly relates to pathological use and includes withdrawal, conflict/interference, and loss of control. The second type, labelled as peripheral criteria, is not necessarily related to pathological use and might reflect intensive but healthy involvement. It includes cognitive salience, euphoria (i.e., a positive feeling due to the activity), and tolerance (Charlton & Danforth, 2007).

More recently, a Delphi study, regrouping 29 international experts on gaming disorder examined the capacity of the DSM-5 and ICD-11 criteria to make the distinction between a normal and a pathological use of video games (clinical utility) (Castro-Calvo et al., 2021). A Delphi study is a structured and iterative method used to achieve a consensus among experts on a particular topic. The process involves multiple rounds where feedback is given to the expert, who can change their answer after being made aware of their colleagues' answers. The study continues until a consensus is reached or no further changes are expected in the subsequent round (Castro-Calvo et al., 2021). Regarding the clinical utility of the DSM-5 criteria, consensus was reached on excluding three criteria (tolerance, deception, escape negative feelings) and including three criteria reached (loss of control, continued overuse, conflict/interference). There was no consensus on the remaining criteria (i.e., preoccupation, withdrawal, loss of interest). In contrast, none of the criteria present in the ICD-11 reached a consensus for exclusion. Most of them were considered relevant (loss of control, continued overuse, functional impairment), and only one (loss of interest) did not reach a consensus for its inclusion or exclusion (Castro-Calvo et al., 2021).

While the conservative approach of the ICD-11 might essentially detect the more severe forms of gaming disorder, missing the less severe ones (Borges et al., 2021), it cannot be excluded that the DSM-5 over-pathologizes (i.e., false positive cases) by including criteria that lack clinical utility. The DSM-5 gives the same importance to all criteria which could lead, with the use of a cutoff score, to incorrectly identifying highly engaged but healthy gamers as presenting a gaming disorder (Billieux et al., 2019). To refrain from unnecessarily pathologizing and becoming overly concerned about video game use, it is crucial to efficiently differentiate highly engaged but healthy gamers from gamers presenting a problematic engagement toward video games. In that regard, Vallerand's dualistic model of passion is a relevant theoretical framework (Vallerand, 2015).

The dualistic model of Passion

The dualistic model of Passion proposed by Vallerand (2015) posits two distinct types of passion, namely harmonious and obsessive ones. Harmonious passion occurs when a person internalizes (autonomously) a certain activity into their identity. This results in a strong connection with the activity, but the activity does not interfere with other areas of life. Harmonious passion is characterized by mindful engagement instead of uncontrolled urges. People with harmonious passion perform the activity with a secure sense of self-esteem, openness, and flexibility (Vallerand, 2015). Harmonious passion has been found to be linked with numerous benefits associated with gaming. People who experience harmonious passion for gaming tend to have better energy levels after playing games, and they enjoy the games more (Przybylski et al., 2009). They also report higher levels of satisfaction with their lives (Przybylski et al., 2009), higher levels of well-being and lower levels of loneliness (Mandryk et al., 2020). Additionally, having a harmonious passion for gaming seems to act as a shield against any potential negative consequences of gaming (Przybylski et al., 2009).

Obsessive passion, on the other side, is characterized by controlled internalization that can occur due to various pressures (intra and/or interpersonal), such as social acceptance, self-esteem, or because the activity produces uncontrollable excitement. Obsessive passions tend to dominate the lives of individuals and can lead to a passive attitude, making people feel controlled by their passion and unable to regulate their engagement. Once this happens, the activity can often conflict with other areas of life, such as work or social relationships (Vallerand, 2015). Obsessive passion has been linked to a tendency to play to escape daily life struggles (Bertran & Chamarro, 2016), and negative outcomes (Bertran & Chamarro, 2016; Mills et al., 2018), notably lower levels of well-being and higher levels of loneliness (Mandryk et al., 2020).

1.1.2. Cyberchondria

Cyberchondria is a condition characterized by excessive and uncontrollable searching for health-related information on the Internet, subsequently causing increased health anxiety and other negative consequences. This behavior can lead to psychological distress, functional impairment, and abnormal healthcare utilization patterns (Starcevic et al., 2021). It is important to distinguish between cyberchondria and hypochondriasis. While it may seem like cyberchondria is a new form of hypochondriasis in today's digital age, the presence of hypochondriasis is not a requirement for the development of cyberchondria. Curiosity about unfamiliar bodily sensations, coupled with the abundance of online health information that can sometimes be confusing or unreliable, could lead to increased health anxiety and excessive searching for health-related information online (Mestre-Bach & Potenza, 2023). A major common symptom of individuals with cyberchondria is spending an unreasonable amount of time conducting these searches (Starcevic, 2017).

Between 2003 and 2019, there were less than 20 published manuscripts per year about cyberchondria on Pubmed or Scopus. Since the COVID-19 pandemic, however, the number of published manuscripts per year on cyberchondria has significantly increased, tripling from 2019 to 2022. It also has been argued that the COVID-19 pandemic may have increased the prevalence of cyberchondria, with some persons being more susceptible than others due to their anxiety related to health (Mestre-Bach & Potenza, 2023). Also, females, younger people, people living alone, and those with medical or mental health conditions are the groups who have been shown to report increased levels of cyberchondria during the COVID-19 pandemic (Vismara et al., 2022). Cyberchondria is becoming a growing concern in need of further research, and a consensus on its definition and conceptualization is necessary to improve its development, assessment, and treatment.

Its conceptualization and assessment

Cyberchondria is a construct that includes several dimensions, which can be evaluated using the Cyberchondria Severity Scale (CSS). This assessment tool measures the severity of the disorder with 33 items, using a 5-point Likert scale to determine the frequency of the individual's behavior, ranging from "*Never*" (1) to "*Always*" (5) (McElroy & Shevlin, 2014). The dimensions conceptualized and assessed by the CSS are: (1) excessiveness, which means that a person excessively uses the Internet to find health-related content; (2) compulsiveness, which refers to online search behavior that interferes with the person's daily activities; (3) distress, which describes the worry and discomfort that a person feels due to their Internet searches; (4) reassurance, which represents the person's need for reassurance from medical experts after finding information on the Internet; and (5) mistrust, which illustrates the tension that a person feels when deciding whether to trust their own research and self-diagnosis or to trust a medical expert (McElroy & Shevlin, 2014; Schenkel et al., 2021). Nevertheless, the relevance of the last dimension (mistrust) is debated regarding the conceptualization of cyberchondria. Some results suggest that a bifactor model with four independent dimensions and a generic factor of cyberchondria (meaning a total score) is a better fit for the data (Schenkel et al., 2021).

Cyberchondria has been proposed as a potential transdiagnostic component in a number of clinical illnesses, including hypochondriasis, OCD, and health-related anxiety that might manifest as generalized anxiety disorder (Mestre-Bach & Potenza, 2023). It also correlates with stress, depression, somatic symptoms, and healthcare use (Schenkel et al., 2021). To date, the prevalence of cyberchondria in the population remains unclear (Infanti, Starcevic, et al., 2023). Nevertheless, it has been argued that the COVID-19 context has increased its occurrence (Starcevic et al., 2021). Strategies based on improving online health information literacy have been proposed to protect vulnerable profiles and prevent the apparition of cyberchondria, while online cognitive-behavior therapy seems to be effective for its treatment (Starcevic, 2023; Vismara et al., 2022).

The context of COVID-19

Starcevic et al. (2021) proposed that cyberchondria occurrence or level increased due to the COVID-19 pandemic and have proposed a new model of cyberchondria in a pandemic context. The authors identified several reasons for this exacerbation. Firstly, the newly discovered and poorly understood disease has increased people's perception of threat and fear. Secondly, the ambiguity surrounding the pandemic and the effectiveness of various measures, such as lockdowns and vaccinations, has made it harder for people to cope with the situation. Thirdly, the lack of authoritative and trustworthy health information based on evidence further hinders coping strategies. Fourthly, the abundance of contradictory, unverified, and constantly changing information creates confusion. Lastly, engaging in excessive online health information seeking does not necessarily provide the necessary information one needs to make informed decisions. These reasons may heighten feelings of anxiety and discomfort, which in turn may increase the sense of danger, consequently diminishing the ability to effectively manage uncertainty and sustaining searches for health information on the Internet (Starcevic et al., 2021).

1.2. Key research priorities for the problematic use of Internet and aims of the present work

In 2018, a group of international experts from Europe identified nine key research priorities that are necessary to advance the field of PUI (Fineberg et al., 2018). These key research priorities are: (1) the production of conceptualizations based on consensus regarding PUI with the inclusion of brain-based mechanisms, specifiers, comorbidities, and phenotypes that must be developed reliably; (2) assessment tools appropriate for age and culture to diagnose and assess severity of PUI; (3) characterizing and quantifying the impact of various PUI forms on quality of life, but also health; (4) describing the clinical paths of the different types of PUI; (5) clarifying the eventual roles of personality features and genetics; (6) clarifying the eventual role of social factors in its development; (7) interventions to prevent and treat PUI and its different forms should be generated and validated; (8) improved early detection and both therapeutic and preventative interventions via identifying biomarkers, including digital markers; and finally, (9) diminish the obstacles for timely recognition and interventions (Fineberg et al., 2018).

The current project will directly address two of these key research priorities: (1) the need for a consensus regarding the conceptualization of two forms of PUI (i.e., cyberchondria and gaming disorder), and (2) the improvement of their assessment. To do so, we aim to capitalize on Machine learning (ML) analyses in addition to traditional statistics. The use of ML in psychological research is of growing interest, and some authors recommend and encourage its use in addition to traditional statistics (Dehghan et al., 2022; Orrù et al., 2020; Rajula et al., 2020; Rosenbusch et al., 2021). Moreover, the present PhD thesis is part of the Doctoral Training Unit on Data-driven Computational Modelling and Applications (DRIVEN), funded by the Fonds National de la Recherche (FNR), which aims to connect data-driven approaches with their applications in various areas. Thus, this thesis also aims to explore how machine learning techniques can help to address the two key research priorities outlined above.

1.3. Machine learning

There are three distinct methods of ML : supervised, unsupervised, and reinforcement (Mak et al., 2019) (**Table 1**). Supervised learning, also known as supervised ML, is the most frequently used type of ML in research related to psychological and medical research. It involves predicting values with a known output, such as the presence of a disorder or the level of symptoms (Shatte et al., 2019). In supervised ML analyses, there are two main types of tasks: classification and regression. In the classification task, the goal is to predict the belonging to a category or a label using several predictors. For example, one might try to predict whether an image contains a cat or a dog. In contrast, the regression task involves predicting a continuous value such as the price of a product. In this method, the model is task-driven and uses features (independent variables or predictors) to predict a target (dependent variable or output) (Mak et al., 2019). In unsupervised learning (also named unsupervised ML), the model is data-driven, does not have a known outcome, and is used to either create clusters (or groups) or to reduce the dimensionality of a dataset (Mak et al., 2019). Finally, in reinforcement learning the model is based on a trial-and-error logic where it gets feedback from the environment and is goal-oriented (e.g., a robot learning how to walk) (Mak et al., 2019).

Table 1

The different methods of Machine Learning

	Supervised		Unsupervised	Reinforcement
Characteristic	Task-driven		Data-driven	Goal-oriented
Goal	Predict the value of a variable that can be continuous or categorical		Find underlying patterns in the data	Interacting with the environment to achieve a specific goal
Data	Labelled data		Unlabeled data	Generated by the model during the trials
Type	Regression	Classification	Clustering	Exploitation / Exploration*
Example of use	Predict the temperature of a wheel.	Predict if an image contains a dog or a cat.	Create different profiles of online shoppers	Making a robot able to walk.

*Note. *Exploration*: trying new strategies to achieve the goal; *Exploitation*: exploiting the strategies discovered during the exploration

The use of ML in psychological research is of growing interest and some authors recommend and encourage its use in addition to traditional statistics (Dehghan et al., 2022; Orrù et al., 2020; Rajula et al., 2020; Rosenbusch et al., 2021). Thus, the purpose is not to replace traditional statistics but to bring new insights and output by using ML. This approach has been applied in the studies reported in *chapters 2, 3, and 4*. In this chapter, we will focus on supervised and unsupervised ML method and their use in psychological research.

1.3.1. The workflow of machine learning

ML terminologies and methodology are not easy to grasp for a non-initiated person. As a first step, it is necessary to understand its terminologies and workflow (procedures). The terminologies of ML will be tackled through its workflow represented in **Figure 1**.

Figure 1

Machine Learning analysis workflow

Step 1: Preprocessing

The first step of ML, after the data collection, is to ensure data quality. For that purpose, *data preprocessing* is necessary. This procedure consists of preparing the original data for further analysis. This involves several steps (Fan et al., 2021): (a) data cleaning, where missing values and outliers are handled; (b) data reduction, where the purpose is to reduce the dimensions of the data by, for example, removing redundant data; (c) data scaling, which aims to set the variables on analogous ranges; (d) data transformation, which consists of adapting the data's values or format according to further analyses; and (e) data partitioning which, for example, aims to summarize a group of variables into categories (Fan et al., 2021).

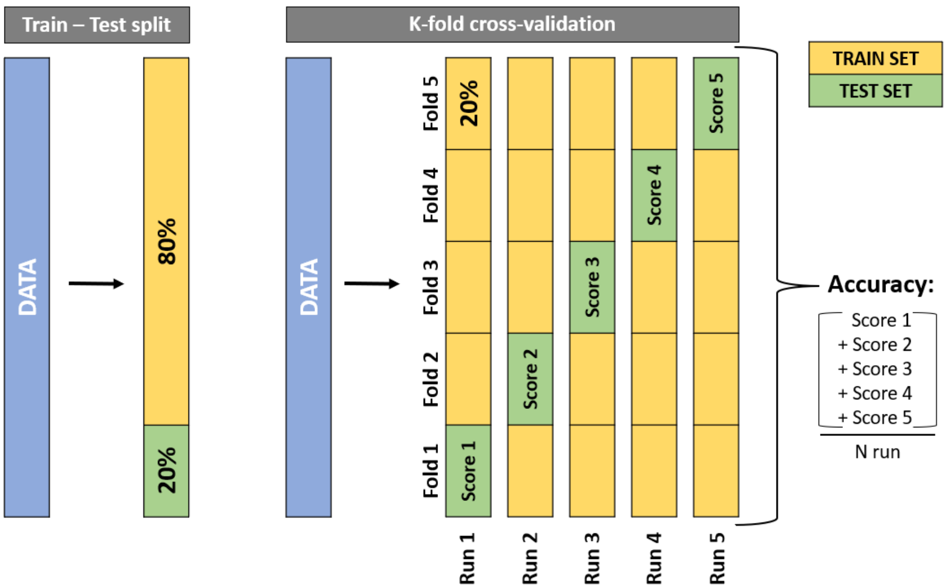
Step 2: Data separation

Once the data are processed, the next step is to separate the data into two independent samples, where one will be dedicated to fit a given model, and the other will remain unknown from the model (out of sample). In ML, the sample used to fit a model differs from the one used to assess its accuracy. This method reduces the risks of overfitting, meaning that the model is too specific to the data used for the fitting and thus not generalizable (Rosenbusch et al., 2021). For this purpose, two main methods, Train-Test split (or hold-out-method) and Cross-Validation, are used (Rosenbusch et al., 2021; Vabalas et al., 2019). A graphical representation and a description of these methods are depicted in **Figure 2**. In the

Train-Test split method, data are split into two samples, where around 60 to 80 % of the data are sampled in a train set dedicated to fit the model. The rest of the data are then placed in a sample named the test set. The test set is dedicated to assessing the accuracy of the fitted model and, thus, its generalization. Using the same procedure on the train set, a development set (also called validation set) can be created to tune the hyperparameters (Rosenbusch et al., 2021). Models can be adjusted (tuned) through parameters to optimize their predictions and increase accuracy. For that purpose, a chosen model can test a list of hyperparameter values using a grid search approach (Vabalas et al., 2019). In this approach, a certain number of possible values are reported in a list that will be used to train one model that will subsequently be evaluated on the development set. After all the possible values (or combinations of values) are applied and the related models evaluated, the model with the highest score on the development set is selected. This model is considered to have the best hyperparameter values and will be trained subsequently by using them. Regarding the cross-validation method, data are split into several folds (distinct parts). In this case, the concerned data can be the entire dataset or a dedicated train set. In cross-validation, several models equal to the number of folds are trained through several runs. The number of possible folds ranges from two to the total size of the data (N) in the case of a leave-one-out cross-validation, which involves considering each data sample as a fold. Each created fold will be used once as a test set in a specific run and part of the train set in the other runs. In doing so, each model is trained in a different training set and evaluated in a separate test set. Finally, cross-validation is a recommended method when tuning the hyperparameters of a ML model (Vabalas et al., 2019). Also, a cross-validation can take place inside an initial cross-validation in the case of a nested cross-validation to avoid any overfitting that might be due to hyperparameter tuning (Infanti et al., 2023, **Figure 3**).

Figure 2

Graphical representation of hold-out method (out-of-sample evaluation)

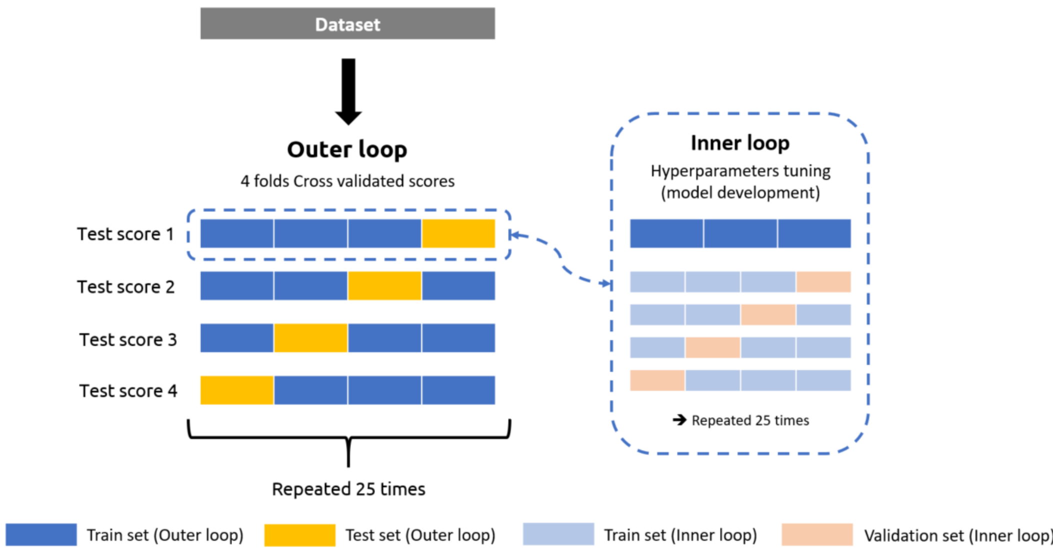


Train-Test split: Data are split into two samples; 80 % of the data are sampled in a *train set* (yellow block) dedicated to fit the model. The rest of the data (20%) are then placed in a sample named the *test set* (green block). The test set is dedicated to assessing the accuracy of the fitted model and, thus, its generalization.

K-fold cross-validation: Data are split into several folds. Then, several models equal to the number of folds are trained through several runs. Each created fold will be used once as a test set (green block) in a specific run and will be part of the train set in the other runs (yellow block).

Figure 3

Nested Cross Validation (Infanti, Starcevic, et al., 2023)

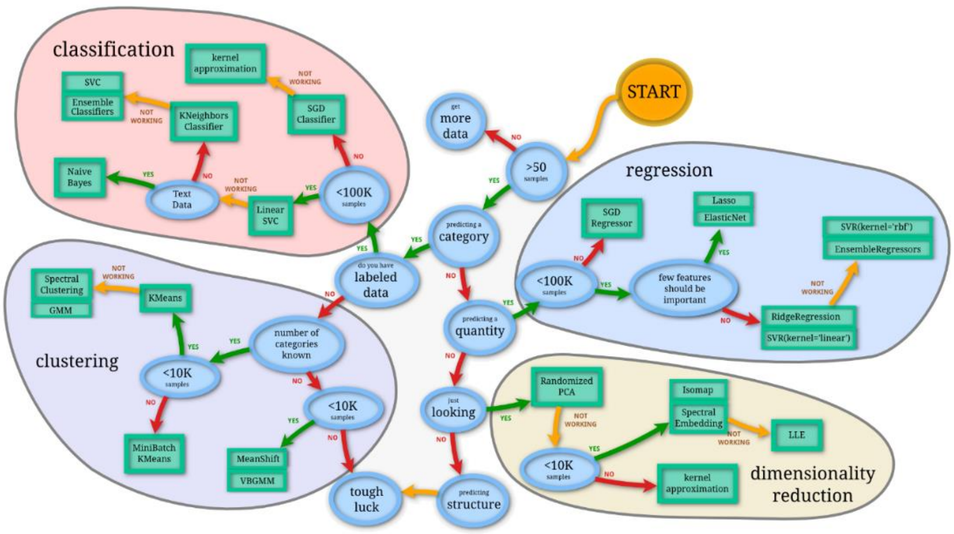


Step 3: Model's fitting

When the data are split, a third step consists in fitting the chosen model. As mentioned, tuning the model during the fitting phase results in obtaining better predictions and higher accuracies rates. Regarding the choice of the model (also called estimator), several pieces of information have to be considered. First, there is the possibility of following the flowchart, reported in **Figure 4**, proposed by the Python programming language library Scikit-Learn (Buitinck et al., 2013; Pedregosa et al., 2011; Varoquaux et al., 2015). Also, it is important to consider that the more complex the model is, the more difficult it will be to interpret despite generally presenting the highest accuracy (Orrù et al., 2020). This is the case for the ensemble methods, where a model is generated using several simple models (Orrù et al., 2020). For example, a Random Forest model is composed of 100 or more decision tree models. While the results of a decision tree model are easily interpretable, the presence of a high amount of them among a Random Forest ensemble model reduces its interpretability in a substantial way, even if the latest will present the highest accuracy (Orrù et al., 2020). Finally, the time dedicated to fit a model has also to be considered. Some models need a more prolonged period to fit depending on the number of features and data (Cho et al., 2019).

Figure 4

Flowchart proposed by the library Scikit-Learn (Varoquaux et al., 2015)



Step 4: Model evaluation

Once the chosen model is fitted, the final step is to evaluate the predictions made by the fitted model. In supervised machine learning, the metrics used for that purpose depend on the nature of the predicted variable. When predicting a categorical variable, several metrics can be derived from the confusion matrix (Tharwat, 2021). A confusion matrix is a contingency table were correct and false predictions are reported (**Table 2**). Several metrics, such as accuracy, recall (or sensitivity), specificity, F1 score, Area under the ROC Curve (AUC) score, and precision, can be computed from the confusion matrix (**Table 2**) (Rosenbusch et al., 2021; Sokolova & Lapalme, 2009). The accuracy assesses the global efficiency of the model. The recall (sensitivity) refers to the capacity of the model to identify the positive output, while the specificity is related to the identification of the negative output. On the other side, precision is the capacity of the model to avoid false positive prediction. The F1 score combines the recall and the precision scores. Thus, the higher the F1 score is, the higher the precision and recall scores would be. Finally, The AUC score represents the capacity of the model to avoid mistakes (Rosenbusch et al., 2021; Sokolova & Lapalme, 2009).

Table 2

Confusion Matrix and its derived metrics

Confusion matrix

		Predictions made by the model	
		Negative	Positive
Expected values	Negative	True Negative (**TN**)	False Positive (**FP**) *Type I error*
	Positive	False Negative (**FN**) *Type II error*	True Positive (**TP**)

Accuracy

$$\frac{TP + TN}{TP + FN + FP + TN}$$

Precision

$$\frac{TP}{TP + FP}$$

F1 score

$$\frac{2\,TP}{2\,TP + FN + FP}$$

Specificity

$$\frac{TN}{FP + TN}$$

AUC

$$\frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right)$$

Sensitivity (recall)

$$\frac{TP}{TP + FN}$$

Note. AUC = Area under the ROC Curve

In the context of a regression model, the R^2, the mean absolute error (MAE), and the root mean square error (RMSE) metrics can be reported (Rosenbusch et al., 2021). The R^2 represents the proportion for variance explained by the model. The best value of R^2 is 1, meaning that the model explains 100% of the variance of the target variable. It is not the case for the MAE and the RMSE where the best value is 0 (Chicco et al., 2021). These metrics refers to the distance, on average, between the predicted and the real values. The RMSE being more sensitive to outliers because it give more importance to substantial errors (Chicco et al., 2021; Rosenbusch et al., 2021).

In unsupervised ML, more specifically in clustering analyses, the model can be evaluated using internal validation which is based on the clustering structure (Palacio-Niño & Berzal, 2019). There are two different internal validation metrics, cohesion and separation. Cohesion is computed inside a cluster (i.e., how well they present homogeneity), while separation is computed across clusters (i.e., how well they differ). Two metrics, the silhouette and the Calinski-Harabasz (CH, also named variance ratio criterion), aim to quantify separation and cohesion into a single metric (Palacio-Niño & Berzal, 2019). The silhouette coefficient ranges between 1 and -1. A negative value represents an overlap between the clusters, while a positive value indicates a good differentiation between the clusters. Calinski-Harabasz is a measure that reports the dispersion inside and between the clusters. For both metrics, a higher value represents well defined clusters (Palacio-Niño & Berzal, 2019).

1.3.2. The use of machine learning in psychological research

As mentioned previously, several researchers recommend the use of ML analyses in addition to traditional statistics (Dehghan et al., 2022; Orrù et al., 2020; Rajula et al., 2020; Rosenbusch et al., 2021). It is thus important to tackle its advantages and pitfalls for the researchers that would like to implement these analyses in their research. It is also important to “demystify” the use of ML by mentioning its use and results in psychological research.

Strengths

There is a significant advantage of ML models over traditional statistical models due to their flexibility in handling any type of data with limited underlying assumptions (Rajula et al., 2020; Vélez, 2021). Unlike traditional statistical models, ML models are not bound by statistical assumptions, making them more applicable to real-world scenarios (Rajula et al., 2020; Sheetal et al., 2023). The use of ML also presents an opportunity for psychological research to become a more predictive science (Rosenbusch et al., 2021), offering personal-level predictions (Orrù et al., 2020), and increasing the possibility of the development of personalized care in clinical psychology (Vélez, 2021). Moreover, ML methods are advantageous due to their reliability and generalization since fitted models are evaluated on unseen data. This makes them more realistic and thus can help overcome the lack of replication in psychological research due to the unreliability of the p-value or p-hacking practices (Orrù et al., 2020).

Limitations

Even if ML presents several advantages compared to traditional frequentist or Bayesian analyses, it is worth noting that the limitations of ML are often similar to those of classic statistics (Fardouly et al., 2022). Even though ML would lead to more generalizable and realistic results, some practices, such as tuning without cross-validation or the avoidance of cross-validation, can lead to over-fitting or over-optimistic results (Orrù et al., 2020; Vabalas et al., 2019). Also, one of the downsides of ML is that interpreting the results of complex ML models, which provide the best results, can be challenging or impossible (Orrù et al., 2020; Rajula et al., 2020; Rosenbusch et al., 2021). Another limitation of ML is that it directly depends on the quality of the data used to fit the model. For example, in the case of supervised ML, a model that aims to predict the presence of a specific disorder will be, at best, as accurate as the screening or diagnostic tool used to assess the disorder (Fardouly et al., 2022). In that sense, unbalanced data can also be challenging for a ML model, which tends to struggle to predict the minority class, i.e., the less encountered case (Orrù et al., 2020). For example, if the prevalence of a specific disorder is around 2% in the population (and so, in the data used), the ML model could choose to achieve an accuracy of 98% just by systematically predicting the absence of the disorder (Rosenbusch et al., 2021). Thus, it is worth noting that, in the case of unbalanced data, the accuracy of a model is impacted by the probability of finding the disorder in the population (Orrù et al., 2020). Finally, it must be kept in mind that both expertise in the field and machine learning are necessary to avoid any misinterpretation or overstatement (Vélez, 2021).

The use of machine learning in psychological research and Internet-related disorder

Shatte, Hutchinson, and Teague (2019) published a scoping review of the use of ML in psychological research. These authors noticed four types of applications of ML. The first is the goal of most studies in the field and consists of identifying risks or early warning signs and applying a diagnosis. The second type of application of ML focuses on prognosis, treatment, and matching of support groups. The primary use of machine learning in this context is to predict long-term outcomes such as drug response, suicidal ideation, psychiatric symptoms, and abstinence from substance use (e.g., drug, tobacco). The third type of application concerns public health and the application of ML to estimate psychological wellbeing in populations, create risk models for health system improvement and monitor the impact of events or disasters on psychological wellbeing. Finally, the last type of application focuses on research and clinical administration. The purpose being to detect high-cost patients and potential participants for studies to facilitate the recruitment process or to improve the process of prioritizing and creating personalized treatment plans (Shatte et al., 2019).

When conducting research on Scopus using the following algorithm "*("cluster analysis" OR "machine learning") AND (online OR Internet) AND (problematic OR addiction OR risk) AND (behavioral OR behavior)"* and applying a filter that focuses on medicine and Psychology fields manuscripts written in English, 347 scientific articles were found (search completed on 25/03/2024). After reviewing each manuscript and selecting those that used ML in the context of Internet-related disorders, 27 manuscripts met the following criteria (**Table 3**): (a) use a PUI form as a dependent or independent variable, (b) use a psychometric evaluation of PUI form, (c) do not use mainly biological data, or data retrieved on a platform (e.g., gambling), and (d) is not a meta-analysis, or a systematic/scoping review of the literature. Two-step clustering and latent class clustering methods were not considered because they rely on a probabilistic approach and thus cannot be considered as ML methods. Among the selected manuscripts, 13 use unsupervised ML (clustering), 13 employ supervised ML through regression task (n = 4) or classification task (n = 9), and one paper uses both supervised and unsupervised ML (clustering and regression task). While the pathological use of Internet is the most represented topic (n = 11), the most addressed PUI forms are gambling (n = 5) and gaming (n = 9) disorders. In contrast, there is only one manuscript each for binge watching and cyberchondria topics, making them the least represented topics. Only three manuscripts did not involve traditional statistics. Overall, the manuscripts support the effectiveness of ML in psychological research and, therefore, support the notion that ML has the potential to accurately identify user-profiles and critical predictors of PUI forms, making it an invaluable analysis tool for psychological research through its capacity to be either person-centered or variable-centered.

Table 3

Manuscripts using ML in the context of PUI forms (summary)

Authors (years)	Country (population)	PUI form	N	Use traditional statistics	Type of ML	Model(s)	Test size	Tuning	N Features	Dependent variable	Results
Stavropoulos et al. (2023)	not defined (adults)	Gaming disorder	T1: 565; T2: 276	Yes	Classification task	LASSO, K-NN, SVM-Kernel, XGB, RF, NB, LR	20%	Yes	5	Gaming disorder risk	ROC_AUC (T1) = [.704 - .981] ROC_AUC (T2) = [.720 - .959]
Jiang et al. (2023)	Canada (university students)	Internet addiction; gambling	3096	Yes	Classification task	LR	20%	No	7	Problematic sexual behavior	RO_AUC = .739
Murch et al. (2023)	Canada (adults)	Gambling	9145	Yes	Classification task	LR, DT, K-NN, SVM, NN, RF	20%	Yes	10	moderate-to-high-risk gambling PGSI 5+); high-risk gambling (PGSI 8+)	ROC_AUC (PGSI 5+) = .843 ROC_AUC (PGSI 8+) = .825
Kairouz et al. (2023)	France (adults)	Gambling	9306	No	Classification task	SVM, DT, K-NN, LR	30%	No	64	moderate-to-high-risk gambling (PGSI 5+); high-risk gambling (PGSI 8+)	[SVM] ROC_AUC (PGSI 5+) = .832 ROC_AUC (PGSI 8+) = .877
Infanti, Valls-Serra et al. (2023)	Spain (adults)	Gaming disorder	845	Yes	Clustering; regression task	Hierarchical clustering, K-mean clustering, EN (CV)	33%	Yes	Clustering: 2 EN (CV): 6	Regression task: Harmonious passion; Obsessive passion	3 clusters: (a) engaged gamers, (b) risky gamers, (c) casual gamers Harmonious passion : R^2=.192 Obsessive passion : R^2=.190
Ioannidis et al. (2023)	South Africa, USA, UK (adults)	Internet use disorder	SA = 3275, USA-UK = 943	Yes	Clustering	Hierarchical clustering (separately for SA and USA-UK samples)	-	-	activities component of ISAAQ	-	2 clusters: (a) High PUI, (b) Low PUI

Hassan et al. (2023)	English speakers (adults)	Gaming disorder	500	Yes	Classification task	NN	30%	-	4	time spent playing PUBG (3 levels)	ROC_AUC: low (less than 2h) = .684; medium (2-4h) = .676; high (4+h) = .628
Infanti, Starcevic, et al. (2023)	French speaking: Switzerland, France, Belgium (adults)	Cyberchondria	725	Yes	Regression task	EN	nested cross validation (4 folds)	Yes	Model 1: 3; Model 2: 2	Model 1 : Distress (cyberchondria dimension); Model 2 : Compulsion (cyberchondria dimension)	Model 1: R^2= .344 (SD = .059) Model 2: R^2=.152 (SD = .046)
Vera Cruz et al. (2024)	English speakers (adults)	Dating app	1387	Yes	Regression task	RF	30%	No	29 variables	Level of problematic Tinder use	R^2 = .58
Bradt et al. (2024)	Belgium (adolescents)	Gaming disorder	1651	Yes	Clustering	Hierarchical, k-means clustering	-	-	3	-	4 clusters: (a) exclusively controlling, (b) autonomy-supportive, (c) perceived mix of both communication styles, (d) overall perceived lack of restrictive mediation
Seo et al. (2020)	Korea (adolescents)	Gambling	5045	Yes	Classification task	RF, SVM, extra trees, ridge regression	30%	Yes	10	Gambling Problem Severity Scale classification (<2 and 2+)	Best model = Extra Trees ROC_AUC = 0.755
Perrot et al. (2022)	France (adults)	Gambling	two datasets: ARJEL = 7359; FDJ = 5079	No	Classification task	RF, SVM, LR, NN	20%	Yes	ARJEL dataset: 22; FDJ dataset: 15	several binary classifications: PGSI8+/-; PGSI5+/-; PGSI1+/0. Later: 4 classifications (problem, moderate-risk, low-risk, non-problem)	ROC_AUC (skill-based games) = [.72 - .82]; ROC_AUC (pure chance games) = [.63 - .76] The classification of the four PGSI categories was very poor (ROC_AUC not reported)
Masi et al. (2021)	Italy (adolescents)	Internet use disorder	101	Yes	Clustering	hierarchical, non-hierarchical (no specification)	-	-	5	-	4 clusters: (a) low levels of both internalizing and externalizing dimensions, (b) high levels of internalizing dimensions, (c) high

											levels of both internalizing and externalizing dimensions, (d) high levels of the externalizing dimension.
Cabeza-Ramírez et al. (2021)	Spain (adolescents, young adults)	gaming disorder	580	Yes	Clustering	non-hierarchical (no specification)	-	-	15	-	4 Clusters: (a) sporadic-casual audience, (b) social audience, (c) hobby audience, (d) problematic audience
Marengo et al. (2022)	Italy (adults)	Problematic social media use	1094	Yes	Regression task	stacking ensemble: EN + RF	10% (repeated 10 times)	Yes	26 (supposed)	BSMAS score (social media addiction)	R^2 = .102, MAE= 3.41, RMSE= 4.23
Amendola et al. (2020)	Italy (adolescents)	problematic Internet use; gaming disorder	408	Yes	Clustering	Hierarchical, k-means clustering	-	-	3	-	4 clusters: (a) above average Internet and mobile-phone use, (b) below average technology use, (c) above average videogame use, (d) problematic technology use
Ioannidis et al. (2018)	USA, South Africa (adults)	Problematic Internet use; general surfing; gaming; online shopping; online auction; social network; online pornography	1749 (USA = 686; South Africa = 1063)	Yes	Regression task	LR, Ridge, EN, Lasso, RF	10-fold CV	Yes	51 (not clear)	Problematic use of Internet (IAT)	Best model = Lasso. RMSE median = 8.01 (SD=.281) (Obtained in supplementary material)
Vaillancourt-Morel et al. (2017)	USA (adults)	online pornography	830	Yes	Clustering	Hierarchical clustering	-	-	3	-	3 clusters: (a) recreational, (b) highly stressed non compulsive, (c) compulsive.

González-Bueso et al. (2020)	Spain (adolescents, males)	Gaming disorder	66	Yes	Clustering	Gaussian Mixture Model	-	-	12	-	2 clusters: (a) higher comorbid symptoms, (b) lower comorbid symptoms
Hsieh et al. (2019)	Taiwan (adults)	Problematic Internet use	217	No	Classification task	ensemble classifier (SVM, Bayesian Network Classifier, decision tree, K-NN) with Case Base Reasoning (CBR)	33% (repeated 10 times)	No	3	Internet use disorder classification (IAT: mild, moderate, severe)	Average accuracy = 89.9%. Accuracy for: Mild condition = 86.3%, Moderate condition = 84.9%, Severe condition = 98.6%
Claes et al. (2018)	Germany, Switzerland (adults)	Buying disorder, problematic Internet use	80 (39 patients and 41 healthy controls)	Yes	Clustering	Hierarchical, K-means clustering	-	-	5	-	4 clusters: (a) Moratorium, (b) Diffusion, (c) Foreclosure, (d) Achievement
Flayelle et al. (2019)	French speaking (adults)	Binge-watching, problematic Internet use	4039	Yes	Clustering	Hierarchical, k-means clustering	-	-	10	-	4 clusters: (a) recreational TV series viewers, (b) regulated binge-watchers, (c) avid binge-watchers, (d) unregulated binge-watchers
Gómez et al. (2017)	Spain (adolescents)	problematic Internet use	39993	Yes	Clustering	Hierarchical, k-means clustering	-	-	5	-	5 clusters: (a) occasional users, (b) moderate users with parental control, (c) moderate users without parental control, (d) habitual users with parent-child conflict, (e) intensive users
Ioannidis et al. (2016)	USA, South Africa (adults)	Problematic Internet use	2006	Yes	Classification task	LR, RF, NB	25% (cross-validation repeated 50 times)	Yes	20	Problematic Internet use (Yes / No)	Roc-AUC score: RF = .84 (SD=.03); NB = .83 (SD = .03)
Rochat et al. (2019)	English speaking (adults)	cybersex, mobile app dating	1159	Yes	Clustering	Hierarchical clustering, K-	-	-	9	-	4 clusters: (a) regulated, (b) regulated/low desire,

						mean clustering					(c) unregulated/motivated (d) unregulated/avoiders
Billieux, Thorens, et al. (2015)	France, Switzerland, Belgium, Other (adults)	Gaming disorder	1057	Yes	Clustering	Hierarchical clustering, K-mean clustering	-	-	9	-	5 clusters: (a) unregulated achievers, (b) regulated social role players, (c) unregulated escapers, (d) hard core gamers, (e) regulated recreational gamers.
Rial et al. (2015)	Spain (adolescents)	Problematic Internet use	1996	Yes	Clustering	Hierarchical clustering, K-mean clustering	-	-	12	-	4 clusters: (a) first steppers, (b) trainees, (c) sensible users, (d) heavy users.

Note. LASSO: Least Absolute Shrinkage Selection Operator; K-NN: k-Nearest Neighbors; SVM: Support Vector Machine; XGB: X Gradient Boosting; RF: Random Forests; NB: Naïve Bayes; LR: Logistic Regression; DT: Decision Tree; NN: Neural Network; EN: Elastic Net; CV: Cross-Validation; AUC: area under the curve

1.4. Aims and research overview

With the increasing significance of the Internet in our daily lives, the issue of Internet-related disorders has become a relevant public health issue on a global scale (Fineberg et al., 2022). Leading organizations such as the APA and the WHO have raised concerns about the potential negative effects of excessive Internet use on mental health (WHO, 2019). These concerns were further strengthened by the inclusion of gaming disorder as a condition for further study in the DSM-5, and later by its recognition and inclusion as a mental condition in ICD-11 by the WHO. The present PhD thesis aims to address two key research priorities in the field of PUI, formulated by the European Network for PUI (Fineberg et al., 2018), related to: (a) contributing to their conceptualization and (b) improving their assessment. In this regard, we deployed four different studies targeting gaming disorder (*Study 2- 4*) and cyberchondria (*Study 1*). This thesis centrally focuses on using ML, in addition to traditional statistics, to reach these objectives. The studies, their aims, and the ML methods used are summarized in **Table 4**.

Table 4

Overview of the studies included in the PhD thesis

Study 1	**PUI form**	Cyberchondria
	Title	Predictors of Cyberchondria During the COVID-19 Pandemic: Cross-sectional Study Using Supervised Machine Learning
	Aims	(a) Investigate levels of cyberchondria during the pandemic and comparing them with the retrospectively assessed pre-pandemic levels of cyberchondria. (b) Identify the psychological factors that predicted cyberchondria during the pandemic
	ML Method	Regression task: Elastic Net (nested cross-validation)
Study 2	**PUI form**	Gaming disorder
	Title	Gaming passion contributes to the definition and identification of problematic gaming
	Aims	(a) Identify different gamer groups (i.e., clusters) based on their profiles of passion towards gaming

		(b) How gaming disorder symptoms, assessed within the substance use disorder and gambling frameworks (e.g., tolerance, withdrawal, preoccupation, mood modification), are linked to harmonious and/or an obsessive passion for gaming.
	ML Method	(a) Clustering (b) Regression task: Elastic Net (cross-validation + train/test split)
Study 3	**PUI form**	Gaming disorder
	Title	Playing with well-being: How problematic video game use is related to emotional health in Spanish adolescents
	Aims	(a) Using gaming disorder criteria to predict depression and wellbeing levels (b) Identifying predictors of the gaming disorder level and their importance when predicting each criterion
	ML Method	(a) Regression task: Elastic Net (nested cross-validation) (b) Regression task: Random Forest (train/test split)
Study 4	**PUI form**	Gaming disorder
	Title	User-Avatar Bond as Diagnostic Indicator for Gaming Disorder: A Word on the Side of Caution Commentary on: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning (Stavropoulos et al., 2023)
	Aims	Warning against the presence of algorithm-generated data inside the test set, and the negative impact that it can have on the conceptualization and assessment of gaming disorder.
	ML Method	Classification task

From an institutional and contextual perspective, this thesis is part of the Doctoral Training Unit (DTU) on Data-Driven computational modelling and applications (DRIVEN) funded by the Luxembourg National Research Fund under the PRIDE programme (PRIDE17/12252781). The global goals of DRIVEN is to enable researchers to: (a) "*gather an overview and understanding of the different classes of data-driven and machine learning approaches*", (b) "*become familiar with the most promising ones for each research field"*, and (c) "*develop one or more approaches in the most useful and computationally efficient manner for each specific field*" (https://driven.uni.lu/objectives).

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2. Predictors of Cyberchondria During the COVID-19 Pandemic: Cross-sectional Study Using Supervised Machine Learning (*Study 1*)

Infanti, A., Starcevic, V., Schimmenti, A., Khazaal, Y., Karila, L., Giardina, A., Flayelle, M., Hedayatzadeh Razavi, S. B., Baggio, S., Vögele, C., & Billieux, J. (2023). Predictors of Cyberchondria During the COVID-19 Pandemic: Cross-sectional Study Using Supervised Machine Learning. *JMIR formative research*, *7*, e42206. https://doi.org/10.2196/42206

Abstract

Background: Cyberchondria is characterized by repeated and compulsive online searches for health information, resulting in increased health anxiety and distress. It has been conceptualized as a multidimensional construct fueled by both anxiety and compulsivity-related factors and described as a "transdiagnostic compulsive behavioral syndrome," which is associated with health anxiety, problematic Internet use, and obsessive-compulsive symptoms. Cyberchondria is not included in the International Classification of Diseases 11th Revision or the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, and its defining features, etiological mechanisms, and assessment continue to be debated. **Objective:** This study aims to investigate changes in the severity of cyberchondria during the COVID-19 pandemic and identify the predictors of cyberchondria at this time. **Methods:** Data collection started on May 4, 2020, and ended on June 10, 2020, which corresponds to the first wave of the COVID-19 pandemic in Europe. At the time the study took place, French-speaking countries in Europe (France, Switzerland, Belgium, and Luxembourg) all implemented lockdown or semilockdown measures. The survey consisted of a questionnaire collecting demographic information (sex, age, education level, and country of residence) and information about socioeconomic circumstances during the first lockdown (e.g., economic situation, housing, and employment status) and was followed by several instruments assessing various psychological and health-related constructs. Inclusion criteria for the study were being at least 18 years of age and having a good understanding of French. Self-report data were collected from 725 participants aged 18-77 (mean 33.29, SD 12.88) years, with females constituting the majority (416/725, 57.4%). **Results:** The results showed that the COVID-19 pandemic affected various facets of cyberchondria: cyberchondria-related distress and compulsion increased (distress $z=-3.651$, $P<.001$; compulsion $z=-5.697$, $P<.001$), whereas the reassurance facet of cyberchondria decreased ($z=-6.680$, $P<.001$). In addition, COVID-19-related fears and health anxiety emerged as the strongest predictors of cyberchondria-related distress and interference with functioning during the pandemic. **Conclusions:** These findings provide evidence of the impact of the COVID-19 pandemic on cyberchondria and identify factors that should be considered in efforts to prevent and manage cyberchondria at times of public health crises. In addition, they are consistent with a theoretical model of cyberchondria during the COVID-19 pandemic proposed in 2020. These findings have implications for the conceptualization and future assessment of cyberchondria.

Keywords: COVID-19; cyberchondria; fear of COVID-19; health anxiety; machine learning; online health information.

2.1. Introduction

The COVID-19 pandemic and related mitigation measures have drastically changed our lives. Although political efforts have somewhat alleviated the economic and public health consequences of the pandemic, experts have warned that its long-term effects on mental health tend to be neglected (Brooks et al., 2020; Holmes et al., 2020; Pfefferbaum & North, 2020). Research conducted since the initial outbreak of the COVID-19 pandemic in China showed an increase in general stress (Wang et al., 2020) and a substantial increase in psychopathological symptoms that are frequently encountered in clinically relevant mood and/or anxiety disorders (Fiorillo & Gorwood, 2020; Pierce et al., 2020). Preliminary evidence also suggests that survivors of COVID-19 appear to be at increased risk for mental health problems (Taquet et al., 2021).

Worries and fear are centrally involved in COVID-19-related psychopathologies and problematic behaviors (Albery et al., 2021; Hoffart et al., 2021; Schimmenti, Starcevic, et al., 2020; Taylor et al., 2020). Schimmenti, Billieux, and Starcevic (2020) proposed a model to account for fear experiences during the COVID-19 pandemic. This model posits that several domains of fear (bodily, relational/interpersonal, cognitive and behavioral) interact and contribute to the onset and perpetuation of COVID-19-related psychological distress through maladaptive, repetitive and functionally impairing behaviors. One such behavior used to gain control over fear during the COVID-19 pandemic concerns compulsive searches for online health information or “cyberchondria” (Schimmenti, Billieux, et al., 2020; Starcevic et al., 2021; Varma et al., 2021).

Cyberchondria is defined as a poorly controlled pattern of searching for health-related information online, resulting in heightened health anxiety and other negative consequences (e.g., interference with work or relationships and psychological distress), which can be functionally impairing and are associated with abnormal healthcare utilization (Starcevic, 2017; Starcevic, Berle, & Arnáez, 2020). Cyberchondria has been conceptualized as a multi-dimensional construct fueled by both anxiety and compulsivity-related factors (McElroy & Shevlin, 2014) and described as a “transdiagnostic compulsive behavioral syndrome” (Vismara et al., 2020) which is associated with health anxiety, problematic Internet use and obsessive-compulsive symptoms (Arsenakis et al., 2021; Starcevic et al., 2019). Cyberchondria is not included in the ICD-11 or the DSM-5, and its defining features, etiological mechanisms and assessment continue to be debated. The upshot of this situation is that reliable data on the prevalence of cyberchondria in the general population are not available (Akhtar & Fatima, 2019; Vismara et al., 2020). Nevertheless, preliminary data suggests that cyberchondria might be commonly encountered (White & Horvitz, 2009) and that it might be more frequent in patients with various medical conditions (Blackburn et al., 2019; Wijesinghe et al., 2019). With regard to its psychological correlates, previous research has shown that cyberchondria is associated with low self-esteem, dysfunctional meta-cognitive beliefs, heightened anxiety sensitivity and intolerance of uncertainty, as well as a tendency towards pain catastrophizing (see (Vismara et al., 2020 for a review).

According to Starcevic and colleagues (Starcevic et al., 2021), the COVID-19 context is likely to have contributed to the occurrence of cyberchondria or exacerbated it for several reasons: (a) there is a heightened perception of threat and the accompanying fear due to a recently identified and poorly understood disease; (b) uncertainty concerning the pandemic and the effectiveness of various mitigating measures (e.g., lockdowns and vaccination) undermines attempts to cope with the situation; (c) paucity of authoritative, trustworthy and evidence-based health information further thwarts coping efforts; (d) abundance of confusing, conflicting, unverified and constantly updated information amplifies bewilderment; and (e) engaging in excessive online health information seeking cannot provide the necessary information and reassurance. These factors have been posited to increase fear and distress, thereby also increasing the perception of threat, further reducing effective coping with uncertainty and perpetuating online health searches. It is worth noting that the psychological model of cyberchondria during the COVID-19 described here (Starcevic et al., 2021) was developed at a time (March 2020 – May 2020) when the uncertainties surrounding the pandemic were at their maximum level and when the data for the present research were collected.

In addition to this theoretical account, there is a growing number of empirical, mainly cross-sectional research reports focusing on various aspects of cyberchondria during the COVID-19 pandemic. Several important findings, in line with the psychological model proposed by Starcevic and colleagues (Starcevic et al., 2021), have emerged from these studies. First, a strong relationship was found between cyberchondria and the fear of COVID-19 (Jungmann & Witthöft, 2020; Oniszczenko, 2021; Seyed Hashemi et al., 2020; Wu et al., 2021), with some studies reporting that cyberchondria predicts fear of COVID-19 (Seyed Hashemi et al., 2020), other studies suggesting that the reverse might be true, i.e. that fear of COVID-19 predicts cyberchondria (Wu et al., 2021) and yet other research reporting that both cyberchondria and health anxiety are risk factors for fear of COVID-19 (Jungmann & Witthöft, 2020). Second, several reports have confirmed the important role of intolerance of uncertainty during the pandemic, although the precise nature of its relationship with cyberchondria differed between studies (Al Dameery et al., 2020; Bottesi et al., 2021; Wu et al., 2021). Third, information overload was found to predict cyberchondria during the pandemic (Laato et al., 2020), whereas excessive and misleading information usually obtained through social media resulted in both cyberchondria and information overload (Bala et al., 2021). Employing a two-wave longitudinal design during the initial outbreak of the pandemic in Europe, Jokic-Begic and colleagues (Jokic-Begic et al., 2020) showed that cyberchondria played a moderating role in the increase in the fear of COVID-19 between time 1 (when the first COVID-19 patients were diagnosed) and time 2 (when lockdown was introduced). Although these studies have improved our understanding of cyberchondria during the COVID-19 pandemic, much remains unknown about the psychological factors that contribute to the development of cyberchondria in the COVID-19 context.

2.1.1. Aims of the study

In line with the assumption that cyberchondria is an important public health issue in the COVID-19 context (Starcevic et al., 2021; Varma et al., 2021), the objectives of the present study were twofold. First, we investigated levels of cyberchondria during the pandemic and compared them with the retrospectively assessed pre-pandemic levels of cyberchondria. Second, we aimed to identify the psychological factors that predicted cyberchondria during the pandemic. The selection of predictor variables was based on the psychological model of cyberchondria during COVID-19 (Starcevic et al., 2021)[1], including intolerance of uncertainty, COVID-19-related fears, health anxiety, and somatic symptoms. In addition, we assessed impulsivity traits and attachment styles as predictor variables, because these psychological dimensions are potentially of relevance for behavioral patterns such as cyberchondria, which are characterized by diminished control and interpersonal difficulties (Vismara et al., 2020). To build a robust predictive model, the current study used supervised machine learning-based regression models (Elastic Net regression).

2.2. Method

2.2.1. Procedure

Participants for this study were recruited using an online survey (created with *Qualtrics*), which was disseminated via social media (i.e., Twitter, LinkedIn, Facebook, Twitter, and Instagram). The study was also disseminated via the research networks of the authors and the scientific societies they are affiliated with. Data collection started on May 4, 2020 and ended on June 10, 2020, which corresponds to the first

[1] At the time the present study was designed and conducted, the psychological model by Starcevic et al. (2021) was not yet published. Yet, some of the authors of the current study were involved in its development and were thus able to capitalize on it for the selection of variables to be included in the present study.

wave of the COVID-19 pandemic in Europe. At the time the present study took place, French-speaking countries in Europe (France, Switzerland, Belgium and Luxembourg) all implemented lockdown or semi-lockdown measures. The survey consisted of a questionnaire collecting demographic information (sex, age, education level and country of residence) and information on socioeconomic circumstances during the first lockdown (e.g., economic situation, housing and employment status), and was followed by several instruments assessing various psychological and health-related constructs. The entire survey was administered in French. The survey software was set up in a way that participants could not skip any question and, therefore, we had no missing or incomplete responses in the final dataset.

Participation was anonymous and voluntary. No compensation for completing the survey was provided. Participants were informed about the aims of the survey before signing an electronic informed consent. The study received approval from the institutional review board for psychological research of the Kore University of Enna (UKE), in the framework of a joint Italian and Swiss research program on cyberchondria and COVID-19-related fears (code: UKE-IRBPSY- 04.20.04).

Some of the independent Italian data related to this project have been published elsewhere (Schimmenti, Starcevic, et al., 2020). A list of all measures used in the online survey (including measures not considered here) is available from the Open Science Framework (OSF)[2]. All data, codes and materials are available from the OSF link provided.

2.2.2. Participants

Inclusion criteria for the study were being at least 18 years of age and having a good understanding of French. No specific exclusion criteria were used. Sociodemographic characteristics of the participants are reported in **Table 5**. The sample consisted of 725 participants aged 18 to 77 years (M = 33.29, SD =

[2] https://osf.io/swfmd/

12.88), with females constituting the majority (n = 416; 57.4%). Regarding a pandemic-related living situation, 5% (n = 36) reported to live with flat mates during the lockdown, 20.4% (n = 148) lived alone, 26.8% (n = 194) lived with their children, 27.6% (n = 200) lived with their parents and 43.3% (n = 314) lived as a couple. Most of the sample (n = 626; 86.3%) assessed their housing situation as adequate during the lockdown. With regard to their financial situation, the majority of the sample (n = 451; 62.2%) reported that they experienced no changes during the lockdown.

Table 5

Sociodemographic characteristics of the study sample

		n (%)
Gender		
	Male	302 (41.7%)
	Female	416 (57.4%)
	Non-Binary	7 (1%)
Education		
	Lower secondary	23 (3.2%)
	Upper secondary	102 (14.1%)
	Bachelor's Degree	308 (42.5%)
	Master's Degree	236 (32.6%)
	Doctoral Degree	56 (7.7%)
Profession		
	Employed	385 (53.1%)
	Unemployed	64 (8.8%)
	Retired	16 (2.2%)
	Full-time students	223 (30.8%)
	Other	37 (5.1%)
Country of residence		
	Switzerland	64 (8.8%)
	France	479 (66.1%)
	Belgium	45 (6.2%)
	Other	137 (18.9%)
Living situation		
	Live with flat mate(s)	36 (5%)
	Live alone	148 (20.4%)
	Live with children	194 (26.8%)
	Live with parents	200 (27.6%)
	Live with partner	314 (43.3%)

	Other	87 (12%)
Quality of housing situation during the pandemic		
	Adequate	626 (86.3%)
	Inadequate	99 (13.7%)
Economic situation during the pandemic		
	Worse than before	194 (26.8%)
	No changes	451 (62.2%)
	Better than before	80 (11%)

2.2.3. Measures

Cyberchondria Severity Scale – Short Form (CSS-12)

The CSS-12 (McElroy et al., 2019) is a short 12-item version of the original 33-item CSS (McElroy & Shevlin, 2014), which assesses the severity of cyberchondria. Items are rated on a 5-point Likert scale from 1 (never) to 5 (always). The global severity of cyberchondria is reported by using the total score derived from the 12 items. The psychometric properties of the CSS-12 were reported by previous studies and its factor structure was established by a combination of exploratory and confirmatory factor analyses (McElroy et al., 2019; Starcevic, Berle, Arnáez, et al., 2020). The CSS-12 was shown to measure four different dimensions of cyberchondria including *Excessiveness* (e.g., "*I enter the same symptoms into a web search on more than one occasion*"), *Distress* (e.g., "*I feel more anxious or distressed after researching symptoms or perceived medical conditions online*"), *Reassurance* (e.g., "*Researching symptoms or perceived medical conditions online leads me to consult with my GP*"), and *Compulsion* (e.g., "*Researching symptoms or perceived medical conditions online interrupts my offline social activities*"). In the current study, participants were asked to provide two different responses for each CSS-12 item: one response related to a general or "normal" context (i.e., before the COVID-19 pandemic), while the other related specifically to the COVID-19 context. As we adapted the response format without changing any item wording, we verified separately the factorial structure of the data obtained from each response format.

Confirmatory factor analyses showed that the previously established four-factor structure (excessiveness, distress, reassurance, and compulsion) fitted well our data obtained from both response formats (i.e., "before COVID-19" and "during COVID-19"). Confirmatory factor analyses conducted on our adapted CSS-12 are available from the Open Science Framework (OSF).

Multidimensional Assessment of COVID-19-Related Fears (MAC-RF)

The MAC-RF (Schimmenti, Starcevic, et al., 2020) consists of 8 items that assess various domains of COVID-19-related fears. Items are rated on a 5-point Likert scale from 0 (Very Unlike me) to 4 (Very like me). The fear domains assessed include: the bodily domain (fear for the body and fear of the body, e.g., "*I am frightened about my body being in contact with objects contaminated by the coronavirus*"), the interpersonal domain (fear for significant others and fear of significant others, e.g., "*I am frightened about my family members or close friends being in contact with other people and becoming infected with the coronavirus*"), the cognitive domain (fear of knowing and fear of not knowing, e.g., "*I do not want to be exposed to information about the coronavirus infection because it makes me feel upset and anxious*") and the behavioral domain (fear of taking action and fear of inaction, e.g., "*During the coronavirus pandemic I feel paralyzed by indecisiveness or fear of doing something wrong*"). The psychometric properties of the scale have been established via item-response theory and relationships with convergent psychological constructs (Schimmenti, Starcevic, et al., 2020). In the current study, a total score of COVID-19-related fears was used.

Intolerance of Uncertainty Scale-Short Form (IUS-SH)

The IUS-SH (Carleton et al., 2007) is a 12-item version of the original 27-item IUS (Freeston et al., 1994), which measures intolerance of uncertainty. Items are rated on a 5-point Likert scale from 1 (Not representative at all) to 5 (Completely representative). Higher scores signal higher intolerance of uncertainty. The scale provides a total score and scores on two dimensions of intolerance of uncertainty: inhibitory (e.g., "*When I am uncertain I can't function very well*") and prospective (e.g., "*It frustrates me* *not having all the information I need*"). Following the approach of a previous study relating intolerance of uncertainty to cyberchondria (Khazaal et al., 2021) and the recommendation by Carleton and colleagues (Carleton et al., 2007), a total score on the IUS-SH was used to evaluate intolerance of uncertainty.

Patient Health Questionnaire (PHQ-15)

The PHQ-15 (Kroenke et al., 2002) measures the severity of common somatic symptoms (abdominal pain, headache, nausea, and others) experienced during the previous month. The PHQ-15 is often used as a measure of somatic symptom proneness (e.g., (Heshmati et al., 2021)) and it has been shown to be useful in identifying somatic symptom disorder (Toussaint et al., 2020). Each item assesses the degree to which individuals experienced a specific somatic symptom rated on a scale from 0 ("*not bothered at all*") to 2 ("*bothered a lot*"), with higher scores indicating greater severity of somatic symptoms. One item pertains to menstrual pain, but this item was kept for the entire sample to ensure that male transgender participants could rate this item when appropriate. Scores on the PHQ-15 correlated with the severity of disability and functional impairment related to somatic problems (Kroenke et al., 2002).

Short Health Anxiety Inventory (SHAI)

The SHAI is a short form version of the original 64-item HAI (Abramowitz et al., 2007; Salkovskis et al., 2002). The questionnaire is composed of 18 items that evaluate the degree of individuals' worries about their own health adapted for non-treatment-seeking individuals. Each item is scored between 0 to 3, depending on the response provided (e.g., item 1 is rated as follows: 0 = "I do not worry about my health"; 1 = "I occasionally worry about my health"; 2 = "I spend much of my time worrying about my health"; 3 = "I spend most of my time worrying about my health"). Scores range between 0 and 54, with higher scores indicating a greater severity of health anxiety. The SHAI demonstrated good convergent and discriminant validity (Abramowitz et al., 2007). In this study, the total score of the measure was used.

Relationship Questionnaires (RQ)

The RQ (Bartholomew & Horowitz, 1991) is a four-item scale investigating four prototypical adult attachment styles: secure, dismissing, preoccupied and fearful. Each attachment style is evaluated through a first-person statement. Participants are asked to evaluate the correspondence of each statement with their relationship attitudes on a 7-point Likert scale (from 1 = "*strongly disagree*" to 7 = "*strongly agree*"). Example of an item (dismissing style) is: "*I am comfortable without close emotional relationships. It is very important to me to feel independent and self-sufficient, and I prefer not to depend on others or have others depend on me".* The RQ has been shown to possess good test-retest reliability and discriminant validity (Griffin & Bartholomew, 1994; Scharfe & Bartholomew, 1994) and has been successfully used in research focusing on Internet-mediated problematic behaviors (Costanzo et al., 2021).

Short UPPS-P Impulsive Behavior Scale (s-UPPS-P)

The s-UPPS-P (Billieux et al., 2012) is a short 20-item version of the original 59-item UPPS-P Impulsive Behavior Scale (Cyders et al., 2007; Whiteside & Lynam, 2001). Items are rated on a 4-point Likert scale from 1 (I agree strongly) to 5 (I disagree strongly). The s-UPPS-P measures 5 different impulsivity dimensions (4 items per dimension), namely negative urgency (e.g., "*When I am upset I often act without thinking*"), positive urgency (e.g., "*When I am really excited, I tend not to think on the consequences of my actions*"), lack of premeditation (e.g., "*Before making up my mind, I consider all the advantages and disadvantages*" – reverse-scored item), lack of perseverance (e.g., "*I finish what I start*" – reverse-scored item), and sensation seeking (e.g., "*sometimes I like doing things that are a bit frightening*"). The psychometric properties of the s-UPPS-P (e.g., factor structure, item-based network structure, test-retest reliability, association with convergent constructs) have been established in previous studies (Billieux et al., 2012, 2021a). In the current study, a global score of "general urgency" was used, as recent research showed that positive and negative urgency formed a single coherent construct (Billieux et al., 2021a).

2.2.4. Statistical Analyses

Our first aim was to test whether levels of cyberchondria increased during the pandemic in comparison with a retrospectively assessed cyberchondria, based on the CSS-12. As the CSS-12 scores in both response formats did not follow a normal distribution, we relied on non-parametric tests and computed Wilcoxon signed ranks test for dependent samples. We also report on the effects of gender, age, and education on the CSS-12 scores during COVID-19. The effect of gender was tested using the Mann-Whitney U test (non-binary participants were not considered in this analysis due to their low number) and the effects of age and education were tested using Kruskal-Wallis tests (see **Table 6** for more details).

Our second aim was to determine the factors that predict cyberchondria during the pandemic, based on the psychological model elaborated by Starcevic and colleagues (Starcevic et al., 2021). Our predictive models focused on the CSS-12 subscales, which were most impacted by the COVID-19 pandemic, i.e., those whose scores differed significantly from before the pandemic. Potential predictors for each model computed were selected based on their correlations with the dependent variable (i.e., the CSS-12 subscales most impacted by the pandemic). Because we planned to apply a regression model, we did use Spearman's correlations to select our predictors. Correlations can be used to quantify the dependence between our potential predictors and our dependent variable. Thus, all candidate predictor variables whose correlations with the dependent variable were ≥.30 (which corresponds to a moderate effect size [Cohen, 1988; Maher et al., 2013]) were retained and included in our predictive models. A series of predictive regression models were then computed based on a supervised machine learning approach.

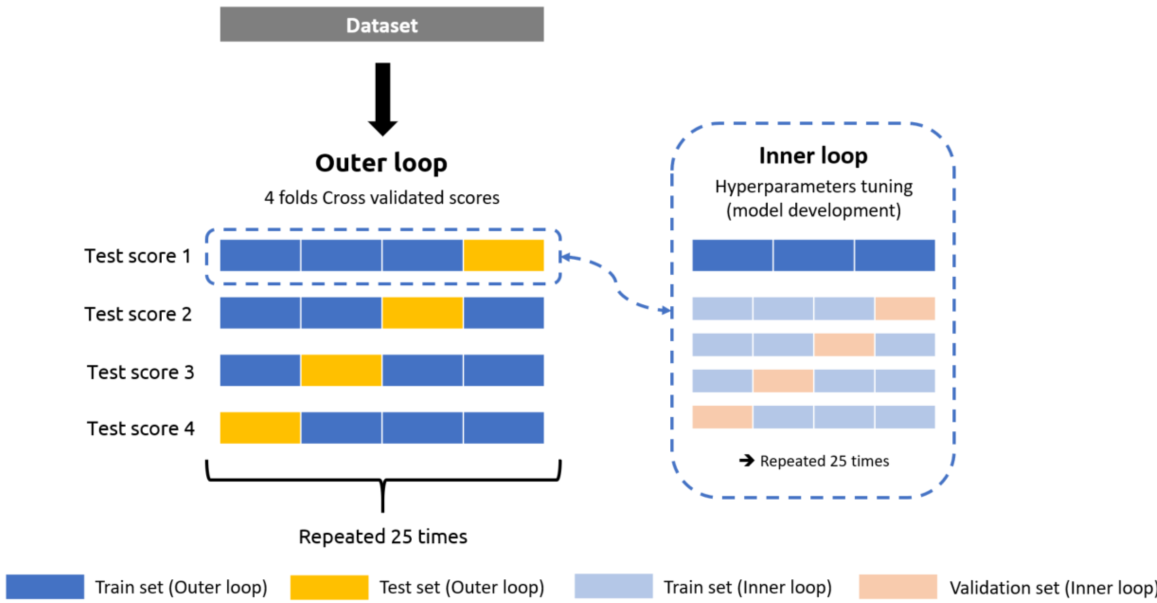
Supervised machine learning approaches are generally defined as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data"

(Murphy, 2012). Traditional multiple linear regression models are limited in the sense that they rely on the entire sample to fit a model and test their accuracy. These models are also susceptible to bias and may be “over-optimistic” in terms of variance explained or generalization to other independent samples. In contrast, the basic principle of supervised machine learning approach is to shuffle the data (using a “seed” which is a value set as a reference point to generate the randomization of the data) and then split them into two independent sub-samples: one sub-sample is used to fit the model (train set, 60% to 80% of the data), while the other is used to test the model’s accuracy (test set, 20% to 40% of the data). Compared to the traditional regression approach, this method is generally considered to be more reliable and to produce more robust findings as the accuracy of the computed predictive model is derived from a new and independent sample with unknown variance (Rosenbusch et al., 2019; Vabalas et al., 2019). Yet, such an approach needs a large sample to produce reliable findings, and another data splitting strategy has been proposed in the context of supervised machine learning if the sample size is limited. This strategy is called cross-validation and involves a series of runs whereby the entire dataset is split into several folds which are all used as train and test sets (Berrar, 2019). In each run, a unique fold is used to determine the accuracy of the model computed while the other folds are used to fit the model. Finally, each fold is used as a test set in one run and as a part of the train set in the other runs. The cross-validated score is obtained by computing a mean accuracy score based on the runs launched. This method is often used within the train set to “tune” the hyperparameters (a value that can be specified by the researcher) of a machine learning model. The fold used to compute cross-validation accuracy is called the validation set. Tuning a model consists of finding the hyperparameters that produce the best possible score on the validation set. When the hyperparameters are identified, the model is then re-fitted on the entire train set and its accuracy is evaluated by using the test set. Nevertheless, this method has been criticized for promoting “overfitting”, in the sense that the model and its hyperparameters are too specific to the train set, thus potentially limiting its reproducibility (Vabalas et al., 2019).

An alternative method called nested cross-validation is depicted in **Figure 5**. This method bypasses the limitations of the classical cross-validation approach (Vabalas et al., 2019). In the nested cross-validation, an "outer loop" cross-validation is applied to split the dataset into several folds to compute overall accuracy. In each run, an "inner loop" cross-validation is performed to tune and validate the model by means of the folds used to fit the model (train set) in the outer loop. When the inner loop cross-validation is performed, the model is re-fitted based on the best hyperparameters identified on the folds used as train sets, and its accuracy is obtained from the fold used as test set. In the current study, we used the nested cross-validation method with hyperparameters tuning, and we repeated the procedure 25 times to achieve the most robust results possible, following guidelines provided by Vabalas et al. (Vabalas et al., 2019) and Krstajic et al. (Krstajic et al., 2014). To select our machine learning model, we followed the flowchart provided by the Scikit-learn's documentation and concluded that the Elastic Net regression is suited to our aim, taking into account our sample size and number of variables used (sample N < 100K and few features are used). Thus, the linear regression model Elastic Net, which combines ridge and lasso penalties, was used for our analyses (Zou & Hastie, 2005). A seed value of 1 was set for replicable results. In the Results section, we report a mean R^2 for each model computed as we obtained one R^2 per run (4 x 25 runs were computed, see **Figure 5**). We then computed adjusted R^2 based on the formula $\bar{R}^2 = 1 - \frac{N-1}{N-p-1} * (1 - R^2)$, where *p* is equal to the number of independent variables used in the model (Yin & Fan, 2001). Finally, we did compare the adjusted R^2 of models using an independent t-test.

Figure 5

Illustration of the nested cross-validation method



Traditional statistics (Mann-Whitney U test, Spearman's correlations, Kruskal-Wallis test, Wilcoxon signed ranks test, and multiple linear regression) were computed using R (version 4.0.3), and machine learning analyses (Elastic Net regression) were computed using Scikit-learn (version 0.24) Python module (Varoquaux et al., 2015). As most study variables did not follow a normal distribution, preliminary analyses were conducted to support the use of a linear supervised machine learning-based Elastic Net regression. We thus computed a traditional multiple linear regression and two generalized linear models (negative binomial and quasi-Poisson regressions). These three models all presented a significant *P*-value (<.001) and showed similar results. Additional preliminary analyses are available from the OSF. Internal consistency (Cronbach's α) for all questionnaires used in the study were computed using Spearman's correlations.

2.3. Results

2.3.1. Objective 1: Comparison of cyberchondria scores before and during COVID-19

As shown in **Table 6**, a series of Wilcoxon signed ranks tests showed significantly higher scores during the pandemic on two facets of the CSS-12 (the *Compulsion* and *Distress* subscales) than before the pandemic. **Table 6** also shows significantly lower scores on the *Reassurance* subscale of the CSS-12 during the pandemic and no significant differences before and during COVID-19 pandemic on the *Excessiveness* subscale of the CSS-12 and the total CSS-12 score. Gender, age and education effects on the CSS-12 scores during COVID-19 are reported in **Table 7**. There were no gender differences with regard to the CSS-12 subscale and total scores. Age and education had some effect on the CSS-12 subscale and total scores, as shown in **Table 7**.

Table 6

Cyberchondria Severity Scale (CSS) scores before and during COVID-19

	Mean (SD) score before COVID-19	Mean (SD) score during COVID-19	Median score before COVID-19	Median score during COVID-19	Z	*P* value	Effect size
Total CSS scores	26.68 (8.04)	26.64 (8.88)	26	26	-.150	.880	0.006
CSS Excessiveness subscale scores	9.36 (2.85)	9.26 (3.06)	9	9	-.763	.446	0.028
CSS Distress subscale scores	6.67 (2.88)	6.83 (3.12)	6	6	-3.651	<.001	0.136
CSS Reassurance subscale scores	5.90 (2.32)	5.54 (2.48)	6	5	-6.680	<.001	0.248
CSS Compulsion subscale scores	4.75 (2.24)	5.00 (2.51)	5	4	-5.697	<.001	0.212

Note. CSS = Cyberchondria Severity Scale.

Table 7

Gender, age and education effects on the CSS-12 scores during COVID-19

	Test	Groups	N	CSS-12 total scores		CSS-12 Excessiveness subscale scores		CSS-12 Distress subscale scores		CSS-12 Reassurance subscale scores		CSS-12 Compulsion subscale scores	
				Mdn	Test result	Mdn	Test result	Mdn	Test result	Mdn	Test result	Mdn	Test result
Gender	Mann-Whitney U	Female	416	26	Z = -.413 *P* = .680	9	Z = -.013 *P* = .989	7	Z = -1.362 *P* = .173	5	Z = -1.075 *P* = .282	4	Z = -1.567 *P* = .117
		Male	302	26		9		6		5		4	
Age	Kruskal-Wallis H	15-24	248	28	$H(4)$ = 22.941 *P* < .001	10	$H(4)$ = 31.993 *P* < .001	7	$H(4)$ = 20.168 *P* <.001	5	$H(4)$ = 7.001 *P* = .136	4	$H(4)$ = 6.768 *P* = .149
		25-34	204	26		10		6.5		5		4	
		35-44	117	26		9		6		5		4	
		45-54	91	22		8		6		4		3	
		55 and +	65	25		9		6		5		3	
Education	Kruskal-Wallis H	Lower sec.	23	25	$H(4)$ = 10.825 *P* = .029	8	$H(4)$ = 11.838 *P* = .019	6	$H(4)$ = 15.115 *P* = .004	4	$H(4)$ = 12.366 *P* = .015	4	$H(4)$ = 2.597 *P* = .627
		Upper sec.	102	25		9		6		5		4	
		Bachelor	308	26		9		7		5		4	
		Master	236	26		10		7		5		4	
		PhD	56	22		8		5		4		4	

Note. CSS = Cyberchondria Severity Scale.

2.3.2. Objective 2: Psychological factors predicting cyberchondria during COVID-19

The three facets of the CSS-12 which proved to be affected by the COVID-19 context (*Distress, Compulsion, Reassurance*) were considered in relation to our second objective, which was to identify the best predictors of pandemic-related cyberchondria. To select the variables to be included in the computed supervised machine learning-based models, the correlations with the three retained CSS-12 subscales were considered (the entire correlation matrix is reported in **Table 8**). As no correlation reached the threshold of $r_s \geq .30$ (Cohen, 1988; Maher et al., 2013) for the *Reassurance* subscale, this facet was not considered in further analysis. In contrast, potential predictor variables were identified for the *Distress* and the *Compulsion* subscales.

A first supervised machine-based Elastic Net regression was computed for the *Distress* subscale of the CSS-12. The following predictors were considered in the analysis: COVID-19-related fears (MAC-RF; r_s =.515, P <.001); health anxiety (SHAI; r_s =.491, P <.001) and intolerance of uncertainty (IUS-SH; r_s =.315, P <.001). As displayed in **Table 9**, the Elastic Net regression computed a mean R^2 of 0.344 (SD=0.059), and we obtained an adjusted R^2 mean of 0.333 (SD=0.06, 95% CI [0.321, 0.345]). Therefore, the most important predictors of the cyberchondria-related *Distress* facet during the pandemic were COVID-19-related fears, health anxiety and intolerance of uncertainty.

A second supervised machine-based Elastic Net regression was computed for the *Compulsion* subscale of the CSS-12. The following predictors were considered in the analysis: COVID-19-related fears (MAC-RF; r_s =.348, P <.001) and health anxiety (SHAI; r_s =.355, P <.001). Both predictors included in the model (COVID-19-related fears and health anxiety) contributed similarly to the cyberchondria-related Compulsion facet during the pandemic. As shown in **Table 9**, the Elastic Net regression computed a mean R^2 of 0.152 (SD=0.046) and we obtained an adjusted R^2 mean of 0.143 (SD=0.047, 95% CI [0.133, 0.152]), which is significantly lower than the one obtained for the model predicting the Distress facet during

COVID-19 ($t(198)=24.954$, $P < .001$, 95% CI [0.175, 0.205]) . The *Distress* model contained 3 predictors whereas the *Compulsion* model contained only 2 predictors, which at least partly explains the lower explained variance for *Compulsion*. It is however worth noting that the reported adjusted R^2 take into account the number of predictors entered in the model.

Table 8

Internal reliability coefficients (Cronbach α) and Spearman correlations between the variables

	α	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. CSS-12 – Total score cyberchondria	.89	—																
2. CSS-12 – Excessiveness	.75	.807**	—															
3. CSS-12 - Distress	.85	.832**	.546**	—														
4. CSS-12 - Reassurance	.78	.733**	.454**	.487**	—													
5. CSS-12 - Compulsion	.82	.766**	.491**	.564**	.500**	—												
6. RQ – Secure attachment	N/A	.022	.048	-.016	.033	.017	—											
7. RQ – Preoccupied attachment	N/A	.161**	.187**	.175**	.035	.084*	-.059	—										
8. RQ – Fearful attachment	N/A	.230**	.179**	.221**	.169**	.157**	-.003	.244**	—									
9. RQ – Avoidant attachment	N/A	.044	.083*	-.018	.040	.037	.047	.225**	-.017	—								
10. s-UPPS-P – Lack of premeditation	.82	-.087*	-.098**	-.058	-.037	-.042	-.027	-.036	-.017	.007	—							
11. s-UPPS-P – Lack of perseverance	.88	.066	.064	.050	.060	.049	-.052	.045	.073*	.011	.420**	—						
12. s-UPPS-P – Sensation seeking	.83	.066	.076*	.010	.066	.057	.075*	-.040	.076*	.062	.143**	-.005	—					
13. s-UPPS-P – Global urgency	.82	.109**	.104**	.100**	.082*	.066	.018	.086*	.088*	.043	.361**	.187**	.177**	—				
14. Age	N/A	-.174**	-.194**	-.174**	-.074*	-.078*	.061	-.149**	-.237**	-.063	-.025	-.177**	-.171**	-.075*	—			
15. PHQ-15 (somatic symptoms)	.79	.184**	.147**	.220**	.079*	.124**	-.045	.184**	.106**	-.014	-.055	.009	-.039	.045	-.001	—		
16. MAC-RF (COVID-19-related fears)	.79	.439**	.279**	.515**	.237**	.348**	.007	.185**	.158**	-.003	-.102**	-.016	-.031	.049	-.061	.309**	—	
17. SHAI (health anxiety)	.87	.472**	.363**	.491**	.266**	.355**	-.038	.210**	.228**	-.029	-.045	.048	-.068	.039	-.020	.372**	.477**	—
18. IUS-SH (intolerance of uncertainty)	.92	.324**	.311**	.315**	.169**	.187**	-.084*	.379**	.288**	.090*	-.175**	.078*	-.116**	.095*	-.201**	.197**	.406**	.424**

** Correlation is significant at the 0.01 level (2-tailed) * Correlation is significant at the 0.05 level (2-tailed)
Note. Internal reliability coefficients are based on Spearman's correlations and not reported for RQ questionnaire as each attachment dimension is defined by a unique item. CSS: Cyberchondria Severity Scale; RQ: Relationship Questionnaires; s-UPPS-P: Short UPPS-P Impulsive Behavior Scale; PHQ: Patient Health Questionnaire; MAC-RF: Multidimensional Assessment of COVID-19-Related Fears; SHAI: Short Health Anxiety Inventory; IUS-SH: Intolerance of Uncertainty Scale-Short Form

Table 9

Repeated nested cross-validation using Elastic Net regression

Dependent variable	R^2 (SD)	Adjusted R^2 (SD) [95% CI]	RMSE (SD)	MAE (SD)	COVID-19-related fears coef. (SD)	Health anxiety coef. (SD)	Intolerance of uncertainty coef. (SD)
CSS-12 Distress subscale	0.344 (0.059)	0.333 (0.06) [0.321, 0.345]	2.512 (0.109)	2.003 (0.09)	1.018 (0.073)	0.938 (0.075)	0.158 (0.088)
CSS-12 Compulsion subscale	0.152 (0.046)	0.143 (0.047) [0.133, 0.152]	2.294 (0.14)	1.776 (0.092)	0.609 (0.054)	0.505 (0.055)	Variable not incorporated in the predictive model

Note. CSS: Cyberchondria Severity Scale.

2.4. Discussion

The present study aimed to determine whether levels of cyberchondria changed during the COVID-19 pandemic and identify psychological predictors of cyberchondria during the pandemic. The results suggest that the facets of cyberchondria were affected during the COVID-19 pandemic following distinguishable patterns: while levels of cyberchondria-related *Distress* and *Compulsion* increased, levels of *Reassurance* decreased. Using a supervised machine learning approach, we found that COVID-19-related fears (as assessed by the MAC-RF) and health anxiety (as assessed by the SHAI) were strong predictors of cyberchondria-related Distress and Compulsion during the pandemic.

An increase in the scores on the *Distress* and *Compulsion* subscales of the CSS-12 during the pandemic indicates higher levels of distress and greater interference with functioning resulting from repeated online health searches. Scores on the *Reassurance* subscale of the CSS-12 decreased during the pandemic, which suggests that online health searches were less likely to be conducted for the purpose of looking for medical professionals' advice. This is possibly a consequence of either a sharply decreased availability of non-vital medical services during the first wave of the pandemic or avoidance of medical facilities due to fear of contracting COVID-19. Taken together, this pattern of results suggests that in the COVID-19 context, excessive online health searches do not provide reassurance, which may make these searches more distressing and cause impairment. Along the same lines, it is possible to speculate that inability to obtain reassurance or necessary information via online health searches is also likely to increase the perception of threat and the accompanying fear of COVID-19, which may drive further searches.

These findings are in agreement with the theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021). Furthermore, they accord with a suggestion that the "fear of not knowing” is a critical cognitive dimension of fear during the pandemic, which might increase distress and anxiety-related behaviors (Schimmenti, Billieux, et al., 2020; Starcevic, Schimmenti, et al., 2020).

The scores on the *Excessiveness* subscale of the CSS-12 did not show significant changes during the COVID-19 pandemic, which indicates that the general proneness to performing repeated online health searches does not necessarily change in the pandemic context. Likewise, total CSS-12 scores did not change during the pandemic, suggesting that the use of total CSS-12 scores in research may not reflect relevant or meaningful alterations in the patterns of problematic online health searches. This has implications for future studies because most studies conducted so far in the pandemic context have relied on total scores either of the CSS-12 (Al Dameery et al., 2020; Seyed Hashemi et al., 2020; Wu et al., 2021) or the original CSS (Akgül & Atalan Ergin, 2021; Maftei & Holman, 2020), whereas various versions of the CSS are by far the most frequently used instrument for assessment of cyberchondria (Starcevic, Berle, Arnáez, et al., 2020; Vismara et al., 2020). Therefore, it is advisable for future research on cyberchondria to always scores on the CSS subscales in addition to total CSS scores. Furthermore, our findings raise concerns about the construct of cyberchondria as assessed by various versions of the CSS and support the notion that the issue of how best to assess cyberchondria needs to be revisited (Starcevic, Berle, Arnáez, et al., 2020).

In view of our findings about the total CSS scores and scores on the specific CSS subscales, we specifically examined predictors of the *Distress* and *Compulsion* facets of the construct of cyberchondria during the COVID-19 pandemic. The finding that COVID-19-related fears and health anxiety emerged as the strongest predictors of the *Distress* and *Compulsion* subscales of the CSS-12 supports the theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021), as this model stipulates that fear of COVID-19 is a key factor that drives online health searches in the pandemic context. A specific fear of COVID-19 and a more general propensity to be concerned about health and disease, as reflected in the construct of health anxiety, are likely to interact so that they mutually amplify one another. Our finding also confirms a significant relationship between health anxiety and cyberchondria that has been reported by numerous studies (Arsenakis et al., 2021; Fergus & Spada, 2018; McElroy et al., 2019; McMullan et al., 2019; Starcevic et al., 2019). Moreover, other research has found a significant relationship between COVID-19-related fears and cyberchondria (Jungmann & Witthöft, 2020; Oniszczenko, 2021; Seyed Hashemi et al., 2020; Wu et al., 2021).

Other variables that were investigated in the current study (somatic symptoms, intolerance of uncertainty, impulsivity traits and attachment styles) did not emerge as strong predictors of either the *Distress* or *Compulsion* facets of cyberchondria during the COVID-19 pandemic. Interestingly, intolerance of uncertainty was a strong predictor only of the *Distress* subscale of the CSS-12, but less so than COVID-19-related fears and health anxiety. Both previous research (Al Dameery et al., 2020; Bottesi et al., 2021; Fergus, 2013; Fergus & Spada, 2018; Wu et al., 2021) and the theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021) postulate a role for intolerance of uncertainty in cyberchondria, but this role needs to be further investigated and better understood, alongside the impact of fear of COVID-19 and health anxiety. With regards to impulsivity traits, their correlations with all subscales of the CSS-12 were the lowest, supporting the view that cyberchondria is better conceptualized as a behavior characterized by compulsivity and/or reassurance seeking (Starcevic, Berle, Arnáez, et al., 2020; Vismara et al., 2020) rather than impulsivity.

2.4.1. Limitations

Our study comes with some specific limitations. First, we could have included additional predictor variables in our analyses. For example, maladaptive metacognitive beliefs have been associated with cyberchondria, both outside the COVID-19 context (Fergus & Spada, 2018) and during the COVID-19 pandemic (Seyed Hashemi et al., 2020). Yet, we selected our candidate predictor variables largely on the basis of the theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021). Other limitations include (1) our reliance on self-report instruments that may be affected by response biases (e.g., social desirability, poor self-reflection abilities and recall bias), (2) the cross-sectional nature of the study which prevented us from investigating any causal relationships, (3) the self-selected nature of our sample, implying that it may not necessarily be representative of the general population (e.g., our sample was mostly composed of highly educated individuals, see **Table 5**) and (4) the retrospective assessment of pre-pandemic levels of cyberchondria.

2.4.2. Conclusion

The present study contributes to the literature on cyberchondria in general and cyberchondria in the context of the COVID-19 pandemic in several ways. First, the facets of cyberchondria that pertain to distress and interference with functioning as a result of problematic online health searches became more prominent during the COVID-19 pandemic and were strongly predicted by COVID-19-related fears and health anxiety, supporting the theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021). Second, this is the first study of cyberchondria to use a supervised machine learning approach. Third, we showed that both cyberchondria as a multidimensional construct and its assessment need to be re-examined.

The present study also confirms that cyberchondria is a public health issue of particular relevance during health crises such as pandemics (Starcevic et al., 2021; Varma et al., 2021). In such a context, it is very important to identify factors that foster cyberchondria, because targeting these factors will contribute to efforts to prevent cyberchondria and tailor interventions for individuals displaying problematic online health searches.

2.5. References

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3. Gaming passion contributes to the definition and identification of problematic gaming (*Study 2*)

Infanti, A., Valls-Serrano, C., Perales, J. C., Vögele, C., & Billieux, J. (2023). Gaming passion contributes to the definition and identification of problematic gaming. *Addictive Behaviors*, *147*, 107805. https://doi.org/10.1016/j.addbeh.2023.107805

Abstract

Even if for most people playing video games is a healthy leisure activity, a minority of vulnerable users present an excessive use associated to negative consequences (e.g., psychosocial maladjustment, sleep interference) and functional impairment. The current study first aims to identify psychological factors that contribute to discriminate highly involved (but healthy) gamers from problematic gamers. For that purpose, we used a cluster analysis approach to identify different groups of gamers based on their profiles of passion towards gaming (using the Dualistic Model of Passion). Another objective of the present study is to explore, using supervised machine-learning, how gaming disorder symptoms, assessed within the substance use disorder framework (e.g., tolerance, withdrawal), might be linked to harmonious and/or an obsessive passion for gaming. Three distinct clusters of gamers were identified based on their passion profiles, including risky gamers, engaged gamers, and casual gamers. Supervised machine-learning algorithms identified that specific gaming disorder symptoms (salience, mood modification, tolerance, low level of conflict) were predominantly related to harmonious passion, whereas others (withdrawal, high level of conflict, relapse) were more directly related to obsessive passion. Our results support the relevance of person-centered approaches to the treatment of problematic gaming.

Keywords: Gaming disorder; Gaming motivations; Harmonious passion; Impulsivity; Obsessive passion.

3.1. Introduction

3.1.1. Background

Video games are a leisure activity practiced by around 3.2 billion people worldwide (Newzoo, 2022). It is thus a widely spread activity that can take place on several platforms, from computers to smartphones. Even if for most people playing video games is a non-problematic leisure activity, a minority of users show excessive use associated with ill-health (e.g., addiction symptoms, psychosocial maladjustment, sleep interference, health issues) and functional impairment (Jo et al., 2019; Männikkö et al., 2020; Reed et al., 2022).

In 2013, for the first time Internet Gaming Disorder was considered as a potential emerging condition and included as a “condition for further study” in the fifth version of the Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association [APA], 2013). In the DSM-5, the criteria for a diagnosis of Internet Gaming Disorder include those of substance use disorder (e.g., withdrawal, tolerance, continue despite problems) and gambling criteria (e.g., deceiving, escape adverse mood) (Petry et al., 2014). At the same time, the risk of excessive pathologizing was tentatively addressed by suggesting a higher threshold than the one recommended by the DSM-5 (Lemmens et al., 2015). More recently, Gaming Disorder (GD) has been recognized as a psychiatric condition and has been listed as a “disorder due to addictive behaviors” in the 11th edition of the International Classification of Diseases (World Health Organization [WHO], 2019). Crucially, the WHO followed a more conservative approach and proposed that GD is characterized by three mandatory features (loss of control, increasing priority given to gaming, and continued used despite negative consequences) associated with clinically relevant functional impairment (Reed et al., 2022). In contrast, the most recent version of the DSM-5 (DSM-5 TR) neither includes an updated definition of GD nor recognizes it as a disorder (First et al., 2022).

Given the recency of the ICD-11 for GD, the largest part of problem gaming research of the last decade was based on DSM-5 criteria to assess GD. However, a growing body of literature shows that some substance use disorder or gambling disorder criteria – typically withdrawal and tolerance, preoccupation, mood regulation, or deception – are not necessarily relevant in the context of problematic gaming (Castro-Calvo, King, Stein, Brand, Carmi, Chamberlain, Demetrovics, Fineberg, Rumpf, Yücel, Achab, Ambekar, Bahar, Blaszczynski, Bowden-Jones, Carbonell, Chan, Ko, Timary, et al., 2021; Deleuze et al., 2017, 2018; Ko et al., 2014; Müller et al., 2019; Peeters et al., 2019; Rehbein et al., 2015). They largely fail to discriminate between intensive but non-problematic and pathological involvement in video games (Billieux et al., 2019; Charlton & Danforth, 2007), thus promoting the pathologizing of gaming behavior (Kardefelt-Winther et al., 2017). In this context, it is important to elucidate the mechanisms involved in high – but non-problematic – involvement versus problematic involvement in video games, to eventually contribute to refine and improve the diagnosis, assessment, and treatment of GD. Ultimately, acknowledging the difference between problematic and non-problematic intense involvement in video gaming would contribute to reduce the stigma around the concept of GD.

3.1.2. The Dualistic Model of Passion

The Dualistic Model of Passion proposed by Vallerand (2010, 2015) is a sound framework to investigate the distinction between high – but non-problematic – involvement and problematic involvement in video games. Vallerand’s framework posits a distinction between so-called “harmonious” and “obsessive” passions. Harmonious passion is the result of an autonomous internalization of a given activity into one’s identity. People with harmonious passion have a strong connection with an activity, but this does not interfere with other aspects of their lives. Harmonious passion is associated with mindful engagement instead of unregulated urges. In harmonious passion, the activity is performed with a secure sense of self-esteem, openness, and flexibility. In contrast, obsessive passion refers to controlled internalization of a given activity into the person's identity. This type of internalization is due to some intra- and/or interpersonal forces because of contingencies related to the activity (feelings of social acceptance, self-esteem), or because the excitement produced by the activity becomes uncontrollable. Obsessive passions are central in the life of individuals and are associated with a passive attitude; they "enslave" people who become controlled by their passion and cannot regulate their engagement. In this case, the activity typically conflicts with various areas of life (e.g., professional, social). As a result, people exhibiting obsessive passions present an uncontrolled and inflexible persistence, which ultimately promotes negative consequences and, in extreme cases, functional impairment. There is evidence that obsessive passion for video games is associated with negative outcomes (Bertran & Chamarro, 2016; Mills et al., 2018) and problematic and deregulated usage patterns (Lafrenière et al., 2009; Wang & Chu, 2007). Also, gamers with an obsessive passion report high levels of loneliness, reduced well-being (Mandryk et al., 2020), and tend to play to escape daily problems (Bertran & Chamarro, 2016). In contrast, harmonious passion operates as a protective factor against gaming-related negative consequences. Harmonious passion was associated with better life satisfaction, post play energy, and higher game enjoyment (Przybylski et al., 2009). Also, harmonious passion was associated with lower levels of loneliness and higher well-being (Mandryk et al., 2020). Nevertheless, both types of passions also have commonalities. For example, Lafrenière et al. (2009) showed in a sample of gamers that both harmonious and obsessive passions are associated with a positive experience toward gaming. Along the same lines, time spent on gaming is positively associated with both types of passion (Lafrenière et al., 2009; Mills et al., 2018; Przybylski et al., 2009), reinforcing the view that time spent gaming is not a good indicator of problematic gaming (Király et al., 2017; Skripkauskaite et al., 2022). Furthermore, playing for immersion purposes and obsessive passion constitute important predictors of problem gaming symptoms, which is not the case for self-reported gaming time (Kneer & Rieger, 2015). These findings were confirmed by a recent longitudinal study using objective playtime indicators (behavioral tracking) showing that (1) actual time spent gaming did not correlate with problem gaming symptoms and quality of life and (2) self-reported gaming time was on average 10h per week longer compared to objective gaming time (Larrieu et al., 2023). Taken together, these results suggest that (self-reported) time spent gaming is not a valid indicator (or even a proxy) of problematic gaming.

3.1.3. Present study

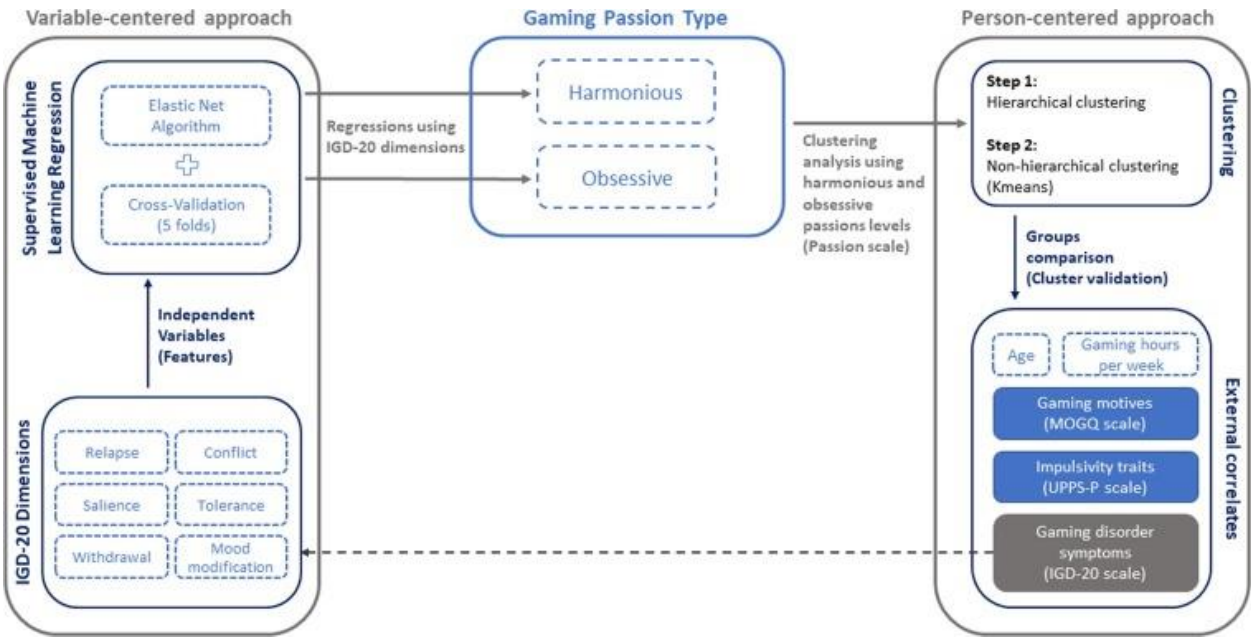
Against this background, the current study combines a person-centered and a variable-centered approach to pursue two main objectives (**Figure 6**). The person-centered approach (first objective) was designed to identify the psychological factors that discriminate highly involved (but healthy, i.e., non-problematic) gamers from problematic gamers. These results may provide useful information for the design of new treatment or prevention interventions, by focusing on specific psychological factors. The variable-centered approach (second objective) was used for the evaluation of GD criteria. The aim here was to identify the most discriminative criteria for the detection of a potential GD.

The first objective was implemented by using a cluster analysis approach to identify different gamer groups (i.e., clusters) based on their profiles of passion towards gaming (using the theoretical framework of Vallerand described previously). The purpose in choosing these two variables for the cluster generation was to identify different passion profiles among gamers, and to compare them in terms of relevant external criteria. Such person-centered approach was used as it allowed us to consider how both types of passion co-exist or not in the same person, and how this affects the function or dysfunctional nature of gaming behaviors. Based on previous research on problematic gaming, the external criteria considered included GD symptoms, gaming motives, and impulsivity traits. We focused on gaming motives and impulsivity as these two psychological dimensions have been extensively explored in the context of problematic gaming (Király et al., 2022; Şalvarlı & Griffiths, 2022). Gaming motives such as escapism (e.g., the desire to evade everyday worries), coping (e.g., playing to cope with adverse moods), fantasy (e.g. the interest in stepping out of the own identity and creating a new one far from reality), competition (e.g. achievement purposes), or skills (e.g. playing to improve abilities like coordination) have been related to problematic gaming (Bäcklund et al., 2022; Ballabio et al., 2017; Bányai et al., 2019; Biolcati et al., 2021; Columb et al., 2020; Laconi et al., 2017; Melodia et al., 2022; Rafiemanesh et al., 2022; Šporčić and Glavak-Tkalić, 2018; Wu et al., 2017). Regarding impulsivity, several studies have found that impulsivity traits positively correlate with the severity of problematic gaming symptoms (Ding et al., 2014; Ryu et al., 2018). Some authors also argued that impulsivity could be a risk factor regarding the transition from recreational to problematic gaming (Raybould et al., 2022). Moreover, the negative urgency impulsivity trait has been identified as a predictor of comorbidity between ADHD and GD in a sample of outpatients diagnosed *a postiori* using the new ICD-11 criteria (Cabelguen et al., 2021).

The second objective of this study was variable-oriented. We explored how gaming disorder symptoms, assessed within the substance use disorder and gambling frameworks (e.g., tolerance, withdrawal, preoccupation, mood modification), are linked to harmonious and/or an obsessive passion for gaming. For the second objective we used supervised machine learning to identify which GD criteria/symptom predict either a harmonious or an obsessive passion.

Figure 6

Methodological approach



3.2. Method

3.2.1. Participants

Participants were recruited from four Spanish universities (the Catholic University of Murcia, the University of Granada, the University of Extremadura, and the University of the Basque Country). The study consisted of an online survey and potential participants were invited by email. Confidentiality was guaranteed and participants were requested to give their online consent to participate after being informed about the aims of the study. Participants were required to report playing video games at least two hours per week and to be at least 18 years of age to be included in the study. Five gift cards of 15€ were raffled at the end of the study as an incentive for participation. A total of 1130 participants started the completion of the online survey. Participants were excluded if they had at least one missing data point on one of the study's variables (n = 133), did not met the inclusion criteria (n = 48), or if they provided invalid information such as playing more than seven days per week or more than 24 hours per day (n = 104). The final sample consisted of 845 participants. Participants were aged between 18 and 50 years (M = 23.5, SD = 5.03). Gender distribution and gaming preferences are reported in **Table 10**. In the final sample, 11 participants were identified as disordered gamers according to the IGD-20 (cut-off score of 71) (Pontes et al., 2014). The study was conducted in accordance with ethics for human research in the Declaration of Helsinki and was approved by the Ethics Committee of the Catholic University of Murcia (CE031905).

Table 10

Demographic variables (N= 845)

		Mean (*SD*)	**N (*%*)**
Age		23.51 (5.03)	
Hours of gaming per day		2.02 (1.79)	
IGD-20		36.76 (11.86)	
Gender	Male		426 (50.41)
	Female		417 (49.35)
	Other		2 (0.24)
Educational level	Primary education		4 (0.47)
	Secondary education		15 (1.78)
	Vocational Education and Training		13 (1.54)
	Certificate of Higher Education		58 (6.86)
	Bachelor's Degree		157 (18.58)
	University degree		439 (51.95)
	Master's Degree		139 (16.45)
	Doctorate		20 (2.37)
Loot boxes consumption	Yes		194 (22.96)
	No		651 (77.04)
Playing on PC	Male		182
	Female		87
	Other		1
	Total		270 (31.95)
Playing on Console	Male		159
	Female		61
	Other		0

	Total	220 (26.04)
Playing on portable / tablet	Male	85
	Female	269
	Other	1
	Total	355 (42.01)
Online	Yes	666 (78.82)
	No	179 (21.18)

Note. IGD-20 = Internet Gaming Disorder Test.

3.2.2. Measures

The Passion Scale (Marsh et al., 2013) was of central importance for the current study as we used it to generate groups of gamers through a cluster analytical approach (see data analytic strategy section). This scale is composed of 12 items answered on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). Among the 12 items, six assess harmonious passion, and six assess obsessive passion. Participants are asked to think about their gaming activity. Harmonious passion is evaluated using items such as *"This activity is in harmony with the other activities in my life"*, or *"This activity allows me to live a variety of experiences"*. In contrast, obsessive passion is evaluated with items such as "*I have almost an obsessive feeling for this activity"*, or *"This activity is the only thing that really turns me on*". For the present study, we used the validated Spanish version of the passion scale (Chamarro et al., 2015) which presents good internal consistency. In the current sample, Cronbach's alpha was equal to .89 for obsessive passion and .87 for harmonious passion. Spearman's rank correlation between harmonious and obsessive passions was .37 ($p < .001$). This positive correlation can be explained by the fact that harmonious and obsessive passion are sharing some aspects related to the definition of passion such as seeing the activity as a passion, giving some value to it, its integration into the self, and dedicating time and energy to it (Vallerand et al., 2003). However, even if harmonious and obsessive passions belong to the same scale and are sharing common aspects related to passion, such correlation does not involve collinearity issues between these two variables which can be considered as distinct constructs for the cluster analysis.

The Motives for Online Gaming Questionnaire (MOGQ) (Demetrovics et al., 2011) is composed of 27 items assessing seven motives. Respondents are requested to use a 5-point Likert scale (1 = never; 5 = almost always/always). Gaming motives assessed include social (e.g., *"I play online games because I can get to know new people*"), escape (e.g.*, "I play online games because gaming helps me to forget about daily hassles"*), competition (e.g., "*I play online games because I enjoy competing with others*"), skill development (e.g., "*I play online games because gaming sharpens my senses*"), coping (e.g., "*I play online games because it reduces tension*"), fantasy (e.g., "*I play online games to feel as if I was somebody else*"), and recreation (e.g., "*I play online games because I enjoy gaming*"). The psychometric properties of the Spanish MOGQ will be described in another research report based on the same dataset. Confirmatory factor analysis for the Spanish MOPGQ can be obtained from the following Open Science Framework link (OSF, https://osf.io/jk94v/?view_only=118f5cee309a4d9aa48fdf1dde1392e4). In the Spanish MOGQ, escape and coping motives are regrouped in a single motivation dimension. Cronbach's alphas for the other dimensions in the present sample were .93 for general motivation, .79 for social, .91 for escape/coping, .85 for competition, .92 for skill, .84 for fantasy, and .82 for recreation.

The Internet Gaming Disorder Test (IGD-20) (Pontes et al., 2014) assesses GD symptoms based on the DSM-5 and the "Components Model" of addiction (Griffiths, 2005). Each item is scored on a 5-points Likert scale (1 = strongly disagree; 5 = strongly agree). This questionnaire thus assesses GD symptoms within a substance-use based framework, through the following dimensions: salience (e.g., "*I usually think about my next gaming session when I am not playing*"); mood modification (e.g., "*I play games to help me cope with any bad feelings I might have*"); tolerance (e.g., "*I need to spend increasing amounts of time engaged in playing games*"); withdrawal (e.g., "*I feel sad if I am not able to play games*"); conflict (e.g., "*I think my gaming has jeopardized the relationship with my partner*"); and relapse (e.g., "*I do not think I could stop gaming*"). For this study, the Spanish version by Fuster et al. (2016) was used. This version showed good psychometric properties (e.g., structural validity, internal reliability). In the current sample, Cronbach's alphas were .91 for the total score, .65 for the salience dimension, .63 for mood modification, .65 for tolerance, .76 for withdrawal, .71 for conflict, and .76 for relapse. Even if the scale is named "*Internet Gaming Disorder Test*", the items of the scale do not specifically refer to online gaming and can also refer to offline gaming.

The Short UPPS-P Impulsivity scale (Billieux et al., 2012) contains 20 items that assess five distinct impulsivity traits, including negative urgency (e.g., "*When I am upset I often act without thinking*"), lack of premeditation (e.g., "*My thinking is usually careful and purposeful*"), lack of perseverance (e.g., "*I finish what I start*"), sensation seeking (e.g., "*I quite enjoy taking risks*"), and positive urgency (e.g., "*I tend to act without thinking when I am really excited*"). Items are scored using a 4-point Likert scale (1 = strongly agree; 4 = strongly disagree). The strength of the UPPS-P model of impulsivity is that it allows for a comprehensive assessment of the multi-faceted nature of impulsivity (Whiteside & Lynam, 2001). For this study, the Spanish version was used (Cándido et al., 2012). This version has good psychometric properties (structural and construct validity, internal reliability). In the current sample, Cronbach's alphas were .82 for negative urgency, .76 for lack of premeditation, .79 for lack of perseverance, .81 for sensation seeking, and .66 for positive urgency. Here we decided to group the negative and positive traits into a single urgency dimension, since it has recently been demonstrated that these two traits actually form a single coherent construct (Billieux et al., 2021a). Cronbach's alpha for urgency was .81.

3.2.3. Data analysis

Following the recommendations by Hair et al. (2010), we performed cluster analysis by combining hierarchical and non-hierarchical approaches. Using both hierarchical and non-hierarchical methods allows for compensating weaknesses of each method by capitalizing on the advantages of the other (Hair et al., 2010). As explained earlier, the variables used to create the clusters were the obsessive and harmonious passions scores. Before performing the cluster analysis, we first ensured that there was no collinearity between the two variables composing the passion scale. We then scaled and centered the variables used for the generation of clusters. This was followed by hierarchical clustering using the Ward method with squared Euclidian distances to identify the optimal number of clusters to be used in the following non-hierarchical clustering. The NbClust R package (Charrad et al., 2014) was used to evaluate the best number of clusters to retain. This package uses the majority rule which is a simple method for selecting the optimal number of clusters based on the number of times a particular value of k is chosen as the best clustering solution by different clustering indices (kl, ch, hartigan, ccc, scott, marriot, trcovw, tracew, friedman, rubin, cindex, db, silhouette, duda, pseudot2, beale, ratkowsky, ball, ptbiserial, frey, mcclain, dunn, hubert, sdindex, dindex, sdbw). The majority rule selects the k value best clustering solution the largest number of clustering indices. Once the optimal number of clusters was identified thanks to the majority rule, a non-hierarchical K-means cluster analysis was computed (iter max = 250, nstart = 50). Obtained clusters were then retrieved and compared according to our external correlates. Variables used as external correlates were gaming motives (MOGQ), GD symptoms (IGD-20), and impulsivity traits (UPPS-P). Clusters were also compared in terms of age and the number of hours spent daily on video gaming. These analyses were carried out using R (v4.2.0). The dataset and the code are available on the OSF link provided.

Our second research objective was approached by using supervised machine learning to identify which GD symptoms constitute robust predictors of harmonious versus obsessive passion for video games. By using unknown data to evaluate the fitted model, supervised machine learning brings more robust results than traditional approaches where the model is fitted and evaluated on the same data. Two models (elastic Net regressions) were computed (one for each type of passion), with the various dimension of IGD-20 assessing GD symptoms used as predictors. These analyses were computed using the ElasticNetCV model, which is a cross-validated (n fold = 5, random state = 42, max iter = 2500) Elastic Net model that finds the best regularization term (L1 ratio) value for the Elastic Net regression. The aim of the regularization term is to prevent overfitting of the model. This model has been chosen following the flowchart provided by the Scikit-learn Library documentation. We also used a pipeline (a tool that allows you to chain multiple data preprocessing and modeling steps together into a single object) that scales the data (standard scaler) and fits the model. Based on the supervised machine learning principle, one-third of the data (33%) were set aside to form a test set to ascertain the model’s accuracy. Lastly, we retrieved the coefficients, and the permutation importance values for each predictor. Permutation importance (not related to the coefficients) was computed by shuffling the scores of one predictor and observing the impact of this shuffling on the R^2 score. The purpose of this shuffling is to break the potential relationship between the predictor and the outcome variable (here, harmonious or obsessive passion). The more the fitted model depends on the predictor, the more the shuffling decreases the model’s R^2. This procedure was used for all the predictors in separate runs to compute the permutation importance for each of them. The entire process was repeated 250 times to control the potential effect of a specific shuffling, thus we report the mean and the standard deviation of the permutation importance of each predictor. A permutation importance value of zero means that the shuffled variable had no impact on the predictions done by the fitted model. Supervised machine learning analyses were run using Scikit-Learn V1.0 library in Python (Varoquaux et al., 2015).

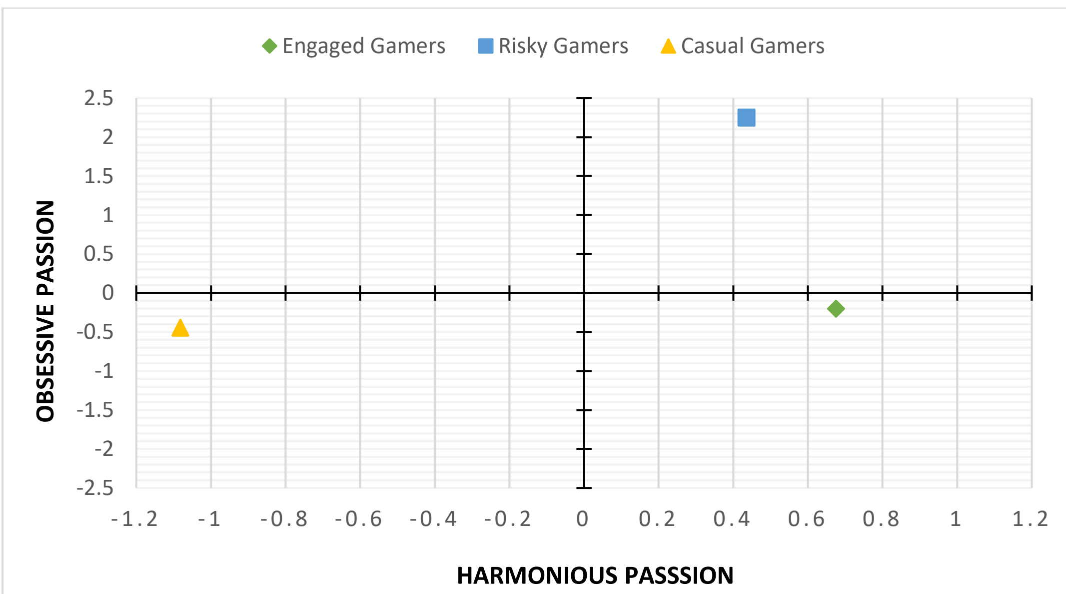
3.3. Results

3.3.1. Cluster generation

Hierarchical clustering suggested to retain three clusters according to the majority rule. The three clusters’ profiles were then generated using the non-hierarchical K-means cluster analysis. Cluster one was labelled "*engaged gamers*" *(n = 434)* characterized by high harmonious passion (Z_{Score} = 0.675) and low obsessive passion (Z_{Score} = -0.201). Cluster two was labelled "*risky gamers*" *(n = 100)* with grouped gamers being characterized by a combination of elevated obsessive passion (Z_{Score} = 2.251) and moderately high harmonious passion (Z_{Score} = 0.435). Finally, the third cluster was labeled "*casual gamers*" *(n = 311)* containing those with low harmonious (Z_{Score} = -1.082) and low obsessive passion (Z_{Score} = -0.443) (**Figure 7**). These clusters significantly differed in terms of harmonious (X^2 (2) = 565.87, p < .001) and obsessive (X^2 (2) = 224.49, p < .001) passion scores.

Figure 7

Clusters generation using harmonious and obsessive passion (Z-scores)



3.3.2. Cluster validity

Because the Shapiro-Wilk and Kolmogorov-Smirnov normality tests showed non-normal distributions across our data, we used non-parametric tests to examine differences between the clusters in terms of the study variables (variables used to create the clusters and external correlates). To this end, a Kruskal-Wallis rank sum test (X^2) and a post-hoc pairwise Wilcoxon rank sum test with Bonferroni correction were conducted and are reported in **Table 11** (also, **Figure 8**). All clusters differed significantly from each other regarding harmonious passion (X^2 (2) = 565.87, p < .001), obsessive passion (X^2 (2) = 334.49, p < .001), and the IGD-20 subscales (Relapse : X^2 (2) = 117.34, p < .001 ; Conflict : X^2 (2) = 89.751, p < .001 ; Withdrawal : X^2 (2) = 103.66, p < .001 ; Salience : X^2 (2) = 158.17, p < .001 ; Tolerance : X^2 (2) = 109.19, p < .001 ; Mood modification : X^2 (2) = 56.974, p < .001). Differences between clusters were also significant for gaming motives. All gamer groups differed on escape/coping (X^2 (2) = 88.997, p < .001), competition (X^2 (2) = 51.951, p < .001), skill (X^2 (2) = 90.32, p < .001), and fantasy (X^2 (2) = 76.996, p < .001) motives, where the risky gamers group showed the highest scores, and the casual gamers group the lowest. Also, potentially problematic and engaged gamers differed from casual gamers on recreation (X^2 (2) = 95.211, p < .001) and social (X^2 (2) = 56.848, p < .001) motives. There were no other significant group differences in gaming motives. For the impulsivity traits, potentially problematic and casual gamers differed from engaged gamers on urgency (X^2 (2) = 25.761, p < .001) and lack of premeditation (X^2 (2) = 16.221, p < .001), with lower scores for engaged gamers. Engaged and casual gamers differed from risky gamers on lack of perseverance (X^2 (2) = 15.509, p <.001). For the sensation seeking impulsivity trait, only engaged and risky gamers differed significantly (p < .001). No other significant differences were observed regarding impulsivity traits. There were no differences between clusters in age (X^2 (2) = 5.41, p = .067). Finally, the number of hours of gaming per day was lower in casual gamers (Mdn = 1) than in both the engaged (Mdn = 2, p <.001) and risky gamers (Mdn = 2, p <.001), with no difference between the latter two (p = 0.21).

Table 11

Clusters means and differences on age, daily hours of gaming, IGD-20, UPPS-P, and MOGQ (N = 845)

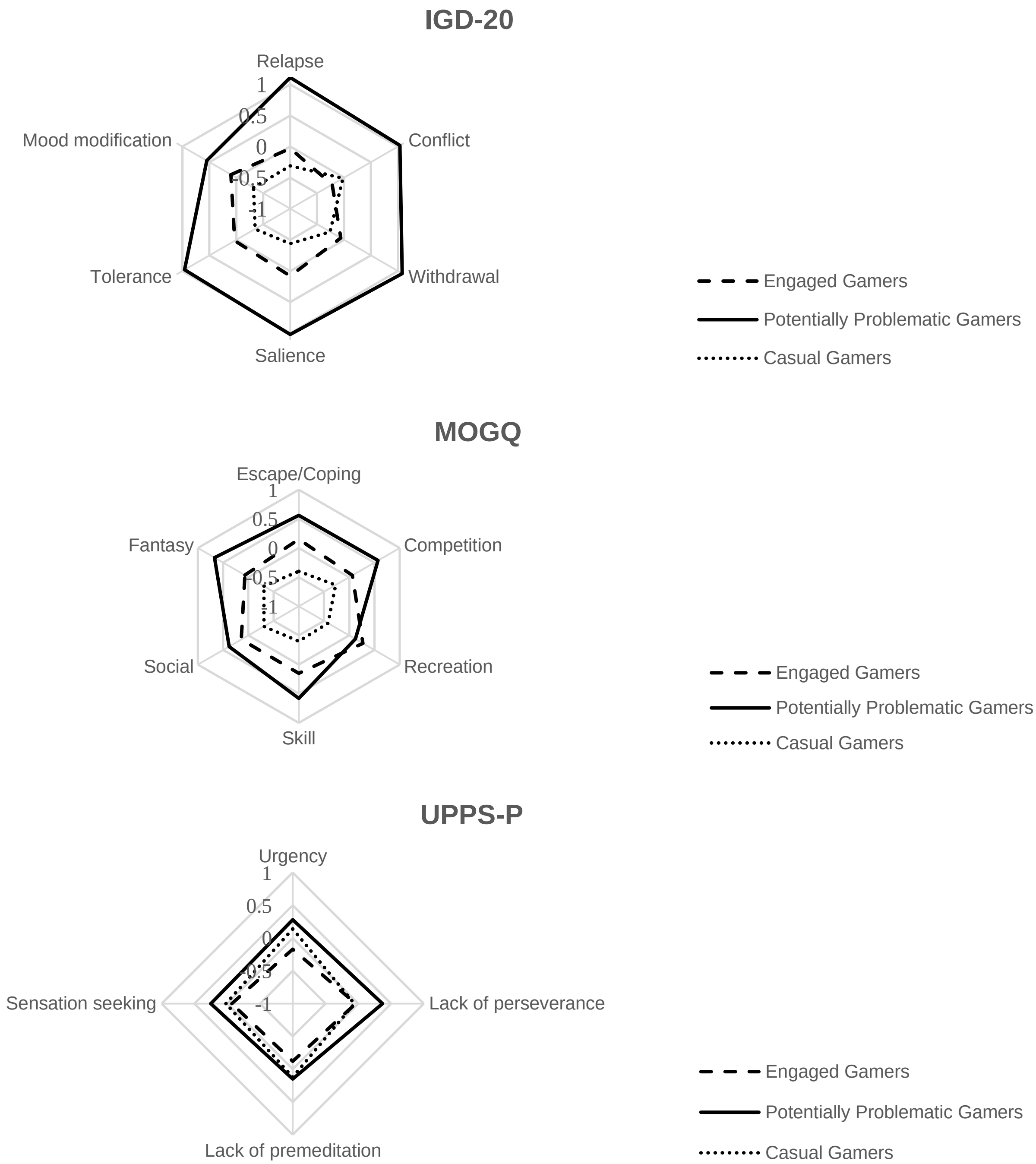
Scale	Factor	Range	Dataset Mean (SD)	Engaged Gamers n = 434		Potentially Problematic Gamers n = 100		Casual Gamers n = 311		Kruskal-Wallis test		
				Z-score (SD)	Median	Z-score (SD)	Median	Z-score (SD)	Median	X^2	df	p
Passion	**Obsessional**	6 - 42	10.89 (7.17)	-0.2 (0.48)	$9^{b**, c**}$	2.25 (1.03)	24.5^{c**}	-0.44 (0.43)	6	334.49	2	<.001
	Harmonious	6 – 42	23.93 (9.77)	0.67 (0.52)	$30^{b*, c**}$	0.43 (0.79)	30^{c**}	-1.08 (0.53)	13	565.87	2	<.001
IGD-20	**Relapse**	3 – 15	5.05 (2.47)	-0.03 (0.88)	$4^{b**, c**}$	1.11 (1.27)	8^{c**}	-0.31 (0.79)	3	117.34	2	< .001
	Conflict	5 – 24	8.63 (3.35)	-0.22 (0.8)	$7^{b**, c*}$	1.04 (1.26)	12^{c**}	-0.02 (0.94)	9	89.751	2	<.001
	Withdrawal	3 – 15	4.39 (1.99)	-0.06 (0.84)	$4^{b**, c**}$	1.08 (1.43)	6^{c**}	-0.26 (0.79)	3	103.66	2	<.001
	Salience	3 – 15	5.7 (2.57)	0.08 (0.85)	$6^{b**, c**}$	1.02 (1.24)	8.5^{c**}	-0.44 (0.82)	4	158.17	2	<.001
	Tolerance	3 – 15	5.3 (2.33)	0.03 (0.89)	$5^{b**, c**}$	0.96 (1.27)	7^{c**}	-0.35 (0.82)	4	109.19	2	<.001
	Mood modification	3 – 15	7.69 (2.91)	0.1 (0.99)	$8^{b*, c**}$	0.55 (1.12)	9^{c**}	-0.32 (0.86)	7	56.974	2	<.001
	Total score	20 – 90	36.76 (11.86)	-0.03 (0.78)	$36^{b*, c**}$	1.25 (1.27)	52.5^{c**}	-0.36 (0.85)	29	144.46	2	< .001
MOGQ	**Escape / coping**	7 – 35	17.31 (7.41)	0.15 (0.96)	$18^{b*, c**}$	0.56 (1.11)	22.5^{c**}	-0.4 (0.87)	13	88.997	2	< .001
	Competition	4 – 20	9.55 (4.25)	0.06 (1)	$9^{b**, c**}$	0.57 (1.07)	11^{c**}	-0.27 (0.89)	8	51.951	2	< .001
	Recreation	3 – 15	11.66 (3.2)	0.27 (0.89)	13^{c**}	0.12 (0.86)	12^{c**}	-0.42 (1.05)	11	95.211	2	< .001
	Skill	4 – 20	9.53 (4.66)	0.15 (1.02)	$10^{b**, c**}$	0.58 (1.01)	12^{c**}	-0.4 (0.8)	7	90.32	2	< .001
	Social	3 – 15	5.7 (2.84)	0.14 (1.05)	5^{c**}	0.38 (1.12)	6^{c**}	-0.31 (0.78)	4	56.848	2	< .001
	Fantasy	3 – 15	5.37 (3.09)	0.07 (1.01)	$4^{b**, c**}$	0.67 (1.21)	7^{c**}	-0.31 (0.76)	3	76.996	2	< .001
	General motivation	24 – 110	59.12 (18.55)	0.19 (0.92)	$63^{b**, c**}$	0.69 (1.1)	77^{c**}	-0.49 (0.84)	47	137.46	2	< .001

UPPS-P	**Urgency**	8 – 32	18.63 (4.95)	-0.17 (0.94)	$18^{b**, c**}$	0.28 (0.91)	20	0.14 (1.06)	19	25.761	2	<.001
	Lack of Perseverance	4 – 16	7.49 (2.64)	-0.04 (1)	7^{b**}	0.37 (1.07)	9^{c**}	-0.06 (0.96)	7	15.509	2	<.001
	Lack of premeditation	4 – 16	7.13 (2.36)	-0.12 (0.99)	$7^{b*, c**}$	0.15 (0.98)	7	0.12 (1)	7	16.221	2	<.001
	Sensation Seeking	4 – 16	9.96 (3.02)	-0.07 (0.98)	10^{b**}	0.25 (0.96)	11	0.02 (1.03)	10	9.7982	2	<.05 (=.0075)
Age		18 – 50	23.51 (5.03)	0.04 (0.98)	23	0 (0.94)	22	-0.06 (1.05)	22	5.41	2	**.067**
Daily hours		0 – 16	2.02 (1.79)	0.16 (1.02)	2^{c**}	0.48 (1.45)	2^{c**}	-0.38 (0.59)	1	114.51	2	< .001

Note. IGD-20 = Internet Gaming Disorder Test; MOGQ = Motives for Online Gaming Questionnaire; UPPS-P = Urgency (negative), Premeditation (lack of), Perseverance (lack of), Sensation Seeking, Urgency (positive), Impulsive Behavior Scale. Wilcoxon rank sum test (p-value adjustment method: Bonferroni): b = Different from cluster 2; c = Different from cluster 3; * = Significant at p <.05; ** Significant at p <.001.

Figure 8

Clusters profiles on IGD-20, UPPS-P, and MOGQ (Z-scores)



Note. IGD-20 = Internet Gaming Disorder Test; MOGQ = Motives for Online Gaming Questionnaire; UPPS-P = Urgency (negative), Premeditation (lack of), Perseverance (lack of), Sensation Seeking, Urgency (positive), Impulsive Behavior Scale.

3.3.3. Supervised machine learning analysis (elastic net regression models)

Two models were computed to identify which types of GD symptoms (measured by the IGD-20) predicted either harmonious or obsessive passion for gaming (see **Table 12**, for details). Both Elastic net regression models were trained using a train sample composed of 566 participants and tested on a test sample of 279 participants (33% of the dataset).

The first model aimed to predict the harmonious passion level ($R^2 = 0.192$). The salience dimension showed the highest positive coefficient ($\beta = 2.91$), followed by mood modification ($\beta = 1.86$), tolerance ($\beta = 1.59$), and relapse ($\beta = 0.35$). The conflict dimension showed a high but negative coefficient (β) of -3.35. A negative coefficient was also found for the withdrawal dimension ($\beta = -0.10$). When examining permutation importance (PI), the conflict (PI = 0.22) and salience (PI = 0.18) dimensions were associated with the largest reduction in R^2 when their scores were shuffled.

The second model aimed to predict the obsessive passion level ($R^2 = 0.190$). Four GD symptoms were found to contribute almost equally to explaining obsessive passion for gaming. These include withdrawal ($\beta = 1.04$), conflict ($\beta = 1.03$), salience ($\beta = 1.00$), and relapse ($\beta = 0.91$). The tolerance ($\beta = 0.70$) and mood modification ($\beta = 0.47$) dimensions obtained the lowest coefficients. Regarding permutation importance, the conflict (PI = 0.03) and relapse (PI = 0.02) dimensions were related to the largest reduction in R^2 when their scores were shuffled.

Table 12

Cross-Validated (5 folds) Elastic Net regression analyses (supervised machine learning)

Predictors	Harmonious passion ($R^2 = 0.192$)		Obsessive passion ($R^2 = 0.190$)	
	Coeff	Permutation Importance (SD)	Coeff	Permutation Importance (SD)
Salience	2.913	0.180 (0.032)	1.000	0.009 (0.013)
Mood modification	1.858	0.077 (0.024)	0.470	-0.002 (0.007)
Tolerance	1.585	0.044 (0.018)	0.703	-0.001 (0.009)
Withdrawal	-0.102	0.000 (0.001)	1.039	0.012 (0.015)
Conflict	-3.350	0.219 (0.039)	1.028	0.028 (0.014)
Relapse	0.352	0.005 (0.004)	0.913	0.021 (0.013)

3.4. Discussion

This study aimed to identify different profiles of gamers based on passion types, but also to determine which GD-related symptoms and constructs predict either harmonious or obsessive passion. Three distinct clusters of gamers were identified based on their passion profiles, including risky gamers, engaged gamers, and casual gamers. Supervised machine-learning algorithms identified specific GD symptoms (salience, mood modification, tolerance, low level of conflict) to predominantly predict harmonious passion, whereas a different subset of them (withdrawal, high level of conflict, relapse) were more strongly related to obsessive passion.

3.4.1. Cluster analysis (person centered approach)

Risky gamers comprised 12% of our final sample and were characterized by a combination of high levels of obsessive passion and moderately high harmonious passion. Previous research using a variable-centered approach found, on the one hand, that obsessive passion is linked to excessive gaming and negative consequences (Bertran & Chamarro, 2016; Lafrenière et al., 2009); on the other hand, harmonious passion was found to potentially protect from such negative consequences (Bertran & Chamarro, 2016). Our study, which endorses a person-centered approach shows for a subgroup of gamers, that obsessive features overcome harmonious features and promote problematic and uncontrolled engagement in gaming (as reflected by higher GD symptoms) despite the presence of moderately high harmonious passion. In terms of gaming motives, risky gamers showed higher levels of escape/coping, competition, skill, and fantasy motivations than the other groups, but also the highest general motivation. This is in line with previous variable-centered research, which found that obsessive passion is associated with maladaptive motives such as fantasy, escape, competition, and coping (Orosz et al., 2018). It is worth noting that such motives have also been related to problematic gaming (Ballabio et al., 2017; Bányai et al., 2019; Biolcati et al., 2021; Columb et al., 2020; Laconi et al., 2017; Melodia et al., 2022; Moudiab & Spada, 2019; Rafiemanesh et al., 2022; Šporčić & Glavak-Tkalić, 2018; Wu et al., 2017). In terms of impulsivity traits, we found that risky gamers are especially characterized by a lack of perseverance, which is defined as the "*difficulty to remain focused on potentially boring and/or demanding tasks*" and is closely linked to the conscientiousness trait of the Big Five model of personality (Whiteside & Lynam, 2001). This result is consistent with the results of a previous variable-centered study, which reported a positive relationship between the lack of perseverance dimension of impulsivity and obsessive passion (Orosz et al. 2016). Yet, and more interestingly, our results echo previous person-centered research results, which identified a group of "unregulated escapers" characterized by elevated lack of perseverance and coping motives (Billieux, Thorens, et al., 2015), or a group of "escapers" characterized by low conscientiousness and coping motives (Larrieu et al., 2022). It is worth noting that while urgency is particularly relevant in substance use disorders (Hildebrandt et al., 2021), this impulsivity trait did not differ between potentially problematic and casual gamers in our study. Risky gamers seem to display a combination of dysfunctional traits and motivational profile, calling for individualized treatment approaches aiming at reducing impulsivity and implementing more adaptive coping and/or emotion regulation strategies. Such interventions could help these gamers to reduce their obsessive gaming involvement and help them gaming in a way that is integrated into their daily life instead of interfering with it.

Engaged gamers comprised more than half of the participants (51%). They are characterized by a very high level of harmonious passion and a low level of obsessive passion. This cluster was named after the seminal work of Charlton and Danforth (2007) suggesting the need to discriminate between two types of intensive involvement in gaming, namely high but non-problematic engagement versus high and dysfunctional engagement. Crucially, despite not being different from risky gamers in terms of reported time spent gaming, they showed the lowest level of conflict (i.e., gaming-related negative consequences), providing further evidence to Vallerand's notion that harmonious passions are well integrated into one's life, allowing for needs to be fulfilled without interfering with important areas of functioning (e.g., social, professional). Our results are also in line with previous studies showing that gaming time (or screen time) is not a good indicator of problematic gaming (Billieux et al., 2013; Charlton & Danforth, 2007; Demetrovics & Király, 2016; Király et al., 2017). Engaged gamers present a balanced motivational background, with the highest level of recreational motives and low to medium impulsivity. They are also characterized by the lowest scores in urgency and lack of premeditation, and report higher perseverance than the potentially problematic gamer group, which probably contributes to their regulated and non-problematic involvement in gaming.

The casual gamer group corresponds to 37% of the sample. These gamers are characterized by a low level of both harmonious and obsessive passions. They show lower involvement in video games (e.g., self-reported lower time spent gaming) and fewer GD symptoms than the other two groups. An analysis of their gaming motives also revealed that - in general - they report less pronounced gaming motives, whatever their type. This profile aligns well with the recreational gamers subtype identified previously by Billieux, Thorens, et al. (2015) and Larrieu et al. (2022). In fact, it is likely that these gamers fulfill their basic needs through non-gaming activities and thus cannot be considered as passionate gamers in the sense of Vallerand (2010; 2015). In terms of impulsivity, they are generally more impulsive than engaged gamers but less impulsive than problematic ones. Given this profile, it is worth noting that it cannot be excluded that the most impulsive members of this group would display deregulated involvement in other rewarding activities not assessed in the present study. Some studies have highlighted the positive impact that video games can have, thanks to some aspects of the game such as socializing, and on well-being and mental health if they are practiced in a balanced way (Barr & Copeland-Stewart, 2021; Giardina et al., 2021; Halbrook et al., 2019). It is conceivable that casual gamers do not benefit from these positive effects, while engaged gamers do.

3.4.2. Supervised machine learning analyses (variable centered approach)

The second objective of the study aimed to identify the GD symptoms predicting either harmonious or obsessive passion. The supervised machine learning analyses conducted revealed some important findings, which align well with previous findings from the gaming literature. Regarding harmonious passion, the trained model showed a strong and negative relationship with conflict and positive relationships with salience, mood modification, and tolerance. In contrast, for obsessive passion, the trained model showed positive associations with conflict, relapse, and withdrawal. Taken together, these results are well aligned with previous research showing that substance use disorder criteria, when applied to gaming, mix “central” features indicative of a problem (i.e., conflict, relapse, withdrawal) and “peripheral” features, which rather reflect non necessary problematic involvement (i.e., salience, tolerance, mood modification) (Billieux et al., 2019; Brunborg et al., 2013; Charlton & Danforth, 2007; Deleuze et al., 2018). Interestingly, these results also align well with a recent international Delphi consensus study about the clinical validity, clinical utility, and prognosis value of GD diagnostic criteria included in the DSM-5 and ICD-11 (Castro-Calvo et al., 2021). In detail, the expert panel recruited in this Delphi study agreed that criteria such as tolerance or mood modification, which were more related to harmonious passion in the present study, are not clinically useful as they cannot discriminate between problematic and non-problematic gaming patterns. In contrast, the DSM-5 or ICD-11 criteria such as loss of control (reflected by the relapse items in the IGD-20) or continued use despite negative consequences (reflected by the conflict items in the IGD-20) were judged by the Delphi panel as clinically useful and able to identify pathological gaming patterns, thus aligning with our results regarding obsessive passion. Moreover, it is interesting to note that this pattern is almost identical with the very definition of compulsivity (Muela et al., 2022). Thus, our results are also in line with the work of Muela et al. (2022) who operationalize compulsivity as the main factor driving dysregulated or excessive behavior.

Overall, our pattern of results further suggests that recycling substance use disorder or gambling criteria, in the context of gaming behavior, is susceptible to conflate problematic and non-problematic usage and thus pathologize non-problematic behavior (Billieux et al., 2019; Kardefelt-Winther et al., 2017).

3.4.3. Limitations

This study has several limitations. First, the cross-sectional nature of the study does not allow for causality assumptions. Further longitudinal studies would bring more insight into the dynamic regarding passions, motivations, and impulsivity traits. Longitudinal studies are also required to determine whether the clusters identified are stable over time. Second, we used self-reported measures that can be influenced by response bias (Dunning et al., 2004). Third, while 21.18% of our sample reported being offline gamers, one of the scales used in this study refers to online gaming motives (MOGQ). Although some motives might be perceived as less relevant for offline gaming (e.g., social or competition motives), most remain relevant in the context of online gaming (e.g., escape/coping, recreation, skill, or fantasy motives). It is worth noting that the MOGQ was not used to create the clusters, and only served as an external correlate to compare clusters. Fourth, our sample is composed of a majority of highly educated participants. Nevertheless, the sample size (N=845) and the fact that we had a very good balance with regards to gender can be considered as a clear strength of this study. Finally, even if we were able to identify several key risk factors for GD in the present study, other factors such as self-esteem (Billieux, Thorens, et al., 2015), childhood trauma (Shi et al., 2020), or mood disturbance (Ostinelli et al., 2021) could also have been considered.

3.4.4. Conclusion

By combining person-centered and variable-centered approaches, the present study contributes to models of and clinical approaches to the treatment of GD. Regarding the theoretical models, our results emphasize the importance of considering not only symptomatic or diagnostic features, but also underlying psychological processes and mechanisms (Brand, Rumpf, King, et al., 2020). The present results also further emphasize the risk of “recycling” substance use disorder criteria to assess and diagnose GD (Castro-Calvo et al., 2021; Kardefelt-Winther et al., 2017) and potentially other types of excessive behaviors (Billieux et al., 2022; Flayelle et al., 2022). On the clinical aspect, our results support the relevance of person-centered approaches to the treatment of problematic gaming (Billieux, Schimmenti, et al., 2015; Park et al., 2021). Further research should thus be conducted to investigate how process-based and person-centered treatment approaches could be developed and validated to address problem gaming issues. It remains an empirical question under which circumstances obsessive involvement in video games changes to a harmonious one, and whether psychological interventions can facilitate this transition, assuming a “controlled use” paradigm rather than an “abstinence-based” paradigm.

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4. Playing with well-being: How problematic video game use affects emotional health and life satisfaction in Spanish adolescents (*Study 3*)

Nogueira-López, A.*, Alexandre Infanti, A*., Rial-Boubeta, A., Vögele, C., and Billieux, B. Playing with well-being: How problematic video game use affects emotional health and life satisfaction in Spanish adolescents. *Manuscript in preparation*

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Abstract

In recent years, there has been a proliferation of studies focusing on the relationship between problematic video game use and wellbeing in adolescents. Despite the amount of data available, it remains unclear whether video games serve as a coping strategy against psychological symptoms such as depression, or on in contrast, if their use is responsible for the deterioration of young people's emotional well-being. The use of adapted screening tools might contribute to answer these unresolved questions and discriminate between various co-occurring conditions. The goal of this study was to predict depression and well-being levels among adolescents using the criteria for gaming disorder, which is measured by the Gaming Addiction Score for Adolescents (GASA). The study also aimed to identify the predictors of gaming disorder level and observe how relevant each predictor is when predicting GASA's criteria individually. For that purpose, a large sample of Spanish adolescents (N = 33.364) aged from 12 to 16 years old were recruited. Item-based analyses showed that salience, tolerance, and relapse criteria were associated with well-being, while withdrawal, conflict, problems, and mood modification criteria were associated with higher levels of depression. Regarding the predictors of gaming disorder level (GASA total score), the selected predictors were gender, depression, video game frequency, and money spent in/on video games. While video game frequency was the most important predictor of gaming disorder level, but also salience, tolerance, and relapse criteria, its importance decreased when it came to the prediction of mood modification, withdrawal, conflict, and problems criteria. Interestingly, when the importance of game frequency decreased, depression gained importance, becoming even more important than video game frequency when it came to the prediction of the problems criterion. Finally, the model's accuracy (R^2) was higher when predicting peripheral criteria of gaming disorder (i.e., salience, tolerance, mood modification) and lower when predicting core criteria of gaming disorder (i.e., conflict, problems, relapse, withdrawal). Results suggest that the appropriateness of GASA to assess video gaming disorder needs to be further questioned to avoid over-pathologizing intensive but non-problematic gaming.

Keywords: Online gaming, adolescence, well-being, life satisfaction, video game disorder.

4.1. Introduction

Online video games have become one of the most popular and attractive activities for humans, especially among teenagers (13-17 years old) were, in 2018, 97% of boys and 83% of girls declared to play video games in the US (Statista, 2018). Advances in the field of technology mean that, in addition to entertainment, the controlled practice of video games is a powerful educational tool and an important source of benefits for the personal development of young people (Coyne et al., 2015; Granic et al., 2014; Männikkö et al., 2020).

Online video games can positively impact short-term well-being through factors such as emotional and social reinforcement, or their ability to satisfy basic psychological needs like competence, relatedness, and autonomy (Giardina et al., 2023; Monley et al., 2023; Przybylski et al., 2010). Among others, these factors can make online video games appealing to young people and could, therefore, encourage the emergence of excessive gaming use (Abbasi et al., 2023). For example, lower need satisfaction predicts obsessive passion for gaming (Przybylski, Rigby, and Ryan, 2010), while this type of passion has been associated with problematic gaming (Infanti et al., 2023). However, this does not mean that video games *per se* are an activity that causes addictive behaviour (Markey & Ferguson, 2017), but rather that it is some of their structural characteristics that favour the emergence of problematic gaming patterns in the most vulnerable populations (Király et al., 2023).

Adolescence is a time where we are constantly seeking new stimuli and experiences to develop our personalities and prepare us for the next stages of life (Coyne-Beasley & Halpern-Felsher, 2020). Moreover, this stage is also characterized by the difficulty to control desires, the eagerness to have fun and to act without thinking about the possible negative consequences, which makes it more difficult to self-regulate, reduce or even temporarily stop our online gaming behaviour (King & Potenza, 2019).

The World Health Organisation (WHO, 1946) defines health as a state of complete physical, social and mental (spiritual and intellectual) well-being. While life satisfaction refers to the degree to which a person positively evaluates his or her own life as a whole, based on individual perceptions of achievement, happiness and sense of purpose (Diener et al., 1985). With this in mind, some studies (Coyne-Beasley & Halpern-Felsher, 2020; Cudo et al., 2020; González-Bueso et al., 2018; Machimbarrena et al., 2022; Männikkö et al., 2020; Wartberg et al., 2022) have begun to examine the possible negative consequences for physical health and psychological well-being, in particular a significant deterioration in young people's overall quality of life associated with problematic video game use. While these studies found a possible association between problem gaming and adolescents' psychosocial and psychological well-being, the direction of causality remained unclear.

In this sense, depression is one of the most commonly used and reliable indicators to assess the psychosocial well-being and life satisfaction (González-Bueso et al., 2018; Hrafnkelsdottir et al., 2018; Myrseth et al., 2017; Tsui & Cheng, 2021), as that they seem to share symptoms such as anhedonia, social withdrawal, poor performance, fatigue or sleep problems (Ostinelli et al., 2021). However, in relation to video game use, it is not yet clear what its role is, whether it is a cause (i.e., gaming as an escape or coping strategy) or a consequence (i.e., gaming may be a trigger for the onset of depressive behaviour).

As mentioned above, this is a topic surrounded by doubts, as the number of studies analysing the relationship between gaming, psychological well-being, and life satisfaction is relatively small. Moreover, the results do not allow to determine with complete certainty whether problematic video game use is a risk factor, a coping strategy, or even both, depending on the specific context being analysed (Ballou & Van Rooij, 2021; Király et al., 2023; Lemmens et al., 2011; Marinaci et al., 2021; Pagani et al., 2022; Slack et al., 2022). However, it seems that functional impact analysis, life satisfaction and well-being may become necessary registries to provide more robust information to identify cases or profiles of problem gaming (Larrieu et al., 2022), particularly in online gaming, where the risk of developing a problematic behaviour pattern with significant functional impairment appears to be highest (Flayelle et al., 2023).

In this context, instruments to assess excessive gaming behaviour are key to discrimination and screening. While it is essential to develop tools that are as reliable as possible to minimize errors in the screening. These psychological assessment tools are often criticized for their accuracy and reliability. Reviews of their psychometric properties reveal inconsistencies and shortcomings in terms of establishing cut-off points, inconsistent symptom coverage, and inadequate data on the predictive validity and reliability of the scales. This puts these instruments under scrutiny as they are essential in accurately diagnosing and treating mental health conditions (King et al., 2020). Many of the tools used to assess problematic gaming have been developed based on criteria from other disorders or adapted from those originally developed to assess other addictive disorders, resulting in inconsistent and/or inadequate measurement (Groves et al., 2015). Therefore, it seems crucial to pay attention to the tools used in the context of problematic gaming and to question their appropriateness.

The present study was developed with the aim of exploring the relationship between problematic gaming criteria, depression, and psychological well-being. In addition, the study aims to identify the best predictors of gaming disorder level from a list of potential predictors, including gender, age, household, parental control, depression, well-being, video game frequency, and money spent on video games. Afterward, it assesses (a) the accuracy of a model composed of the best predictors of gaming disorder level when predicting its specific symptoms (i.e., salience, tolerance, mood modification, relapse, withdrawal, conflict, and problems), and (b) the relevance of each identified predictor when predicting the gaming disorder criteria (or symptoms) individually.

4.2. Methods

4.2.1. Participants and procedure

The sample of this study is a sub-sample of adolescents between 12 and 16 years of age, taken from a study conducted jointly by the University of Santiago de Compostela and UNICEF Spain, with the aim of providing a diagnosis of the use and impact of technology in adolescence, analyzing both Internet use habits, video game consumption and online gaming, as well as different risk practices such as sexting, contact with strangers and cyberbullying. The target population consisted of all students living in Spain and attending compulsory secondary education in Spain, aged between 11 and 18 years. A two-stage sampling methodology was used, integrating cluster and quota sampling (Cooksey & McDonald, 2019; Rada & Martín, 2014). Clusters were used to select the largest units in the country, namely the schools in each municipality. Quotas (city, province, gender, age, and school ownership) were also used to identify the smallest groups, that is, to select individual units, namely students.

Prior to the data collection, information letters were sent to the parents of the selected pupils to explain the purpose and procedure of the data collection, and to obtain their consent for their children to be included in the study. Between February and April 2021, the data collection was carried out, informing all adolescents of the purpose, and the confidential, voluntary and anonymous nature of their responses. The study was approved by the Bioethics Committee of the University of Santiago de Compostela with the registration number USC-35/2021/08/07. The final sample used in the present study consisted of 33.364 adolescents, 40.7% (n= 13589) female, 58.3% (n= 19454) male, and 1% (n=321) who did not specify their gender, aged between 12 and 16 years (M = 13.71; SD = 1.22). 76.3% of the participants live in a two-parent household. More than the half of the sample reported to playing video games almost every day

(38.8%) or every day (31.6%). A previous study using the same dataset has been published elsewhere (Nogueira-López et al., 2023).

4.2.2. Instruments

The study consists in an online questionnaire. In addition to demographic information, a series of psychometric questionnaires were used. In the context of the current study, only the gaming-related variables were taken into account. Data collection was carried out through a platform of the University of Santiago de Compostela (Galicia Supercomputing Centre), under the technical and legal supervision of the General Council of Professional Colleges of Computer Engineering of Spain.

Gaming habits and Demographic variables.

The variables collected to describe gaming habits consisted of gaming frequency and money spent on video games. For the demographic variables, gender, age, and living situation were collected and reported in **Table 13**.

Problematic Gaming

The Game Addiction Scale for Adolescents (GASA-Short version) (Lemmens et al., 2009; Lloret et al., 2018) was used to assess problematic gaming. This scale assesses problematic gaming from a substance use disorder framework (e.g., tolerance, withdrawal, etc.) and is composed of seven items preceded by the statement "*During the last six months, how often . . .*" and is scored with a 5-point Likert scale, ranging from 1 (never) to 5 (very often). All responses over 3 (sometimes) are given a score of 1, with a cut-off point of ≥4, which allows the creation of three categories: non-problematic use (0–3), problematic use (4–6) and possible gaming disorder (7). The scale shows high internal consistency (α = 0.87).

Emotional Wellness – Psychological Well-Being Scale

Subjective wellbeing was assessed with the Children's Worlds Survey (Rees et al., 2015). The Children's Worlds survey included a variety of different measures asking about overall well-being. These reflect different aspects of Diener's Tripartite Model of Subjective Well-Being: life satisfaction, positive affect and negative affect (Diener, 1984); and the six aspects of Ryff's Model of Psychological Well-Being: self-acceptance, environmental mastery, relations with others, autonomy, personal growth and purpose in life (Ryff, 1989a, 1989b; Ryff & Keyes, 1995). It consists of 6 Likert-type items (from 0 = "*strongly disagree*" to 10 = "*strongly agree*") showing acceptable internal consistency (α = 0.76). A high score in this scale reflects a good subjective well-being.

Depression

Depressive symptoms were assessed with the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001; Spitzer, 1999; Spanish version Miranda & Scoppetta, 2018). Recommended by the *American Academy of Pediatrics* to assess the emotional well-being and depression in children and adolescents according to DSM-IV criteria. It consists of rating the frequency with which 9 depressive symptoms (depressed mood; anhedonia; sleep problems; feelings of tiredness; changes in appetite or weight; feelings of guilt or worthlessness; difficulty concentrating; feelings of sluggishness or worry; and suicidal ideation) have occurred in the past 2 weeks using a Likert scale (0 = "*never*", 1 = "*some days*", 2 = "*more than half of the days*" and 3 = "*almost every day*"). To obtain the scores, the responses for each item were summed to obtain a score ranging from 0 to 27, with higher scores indicating more severe depressive symptoms. Depressive symptoms can be categorized according to their severity into five groups: minimal (scores 0 to 4), mild (5 to 9), moderate (10 to 14), moderately severe (15 to 19) and severe (20 to 27), as recommended by Kroenke et al. (2001). The scale shows a high internal consistency (α = 0.87).

Table 13

Demographic variables

		M (SD)	n (%)
Age		13.71 (1.22)	
Gender	Male		19454 (58.3)
	Female		13589 (40.7)
	Other		321 (1)
Video Games frequency	Once a month		5423 (16.3)
	Once a week		4477 (13.4)
	Almost everyday		12934 (38.8)
	Everyday		10530 (31.6)
Video Games money	Nothing		24457 (73.3)
	Less than 10€		4780 (14.3)
	11-30€		2377 (7.1)
	31-50€		726 (2.2)
	51-100€		406 (1.2)
	More than 100€		618 (1.9)
Live with	Neither of the parents		1063 (3.2)
	Mother or father		6841 (20.5)
	Both parents		25460 (76.3)
GASA		2.03 (2.04)	
PHQ-9		8.10 (5.86)	
Well-Being		7.66 (1.54)	

Note. PHQ-9 = Patient Health Questionnaire; GASA = Game Addiction Scale

4.2.3. Data analytic strategy

Data analysis was performed in five steps with additional exploratory analyses. Firstly, a descriptive analysis of the data and a frequency analysis were performed to summarize the socio-demographic data and gaming habits of the sample. Secondly, normality assumptions were tested using the Kolmogorov-Smirnov test (Lilliefors K-S), skewness, kurtosis and the graphical tests, Q-Q plot and histograms. Pearson correlations and Spearman's rho were then performed to indicate the strength of the association between the study variables. Thirdly, additional analyses have been made to explore the predictive power of the GASA items on depression (PHQ-9) and well-being. For that purpose, two nested cross-validated Elastic net regressions have been done. Nested cross-validation is a robust and effective technique used in ML for model evaluation, hyperparameter tuning, and generalization assessment. It consists of a nested structure with an outer loop and an inner loop, which collectively provide a thorough evaluation of the model's performance (for more details, see: Infanti et al., 2023; Vabalas et al., 2019). Fourth, from an exploratory perspective, ML analyses were used to select the best predictors of gaming disorder level among a list of eight predictors (i.e., gender, age, living situation, parental control, depression, well-being, video game frequency, and money spent in/on video games). The best predictors were selected using a sequential feature selection that add predictor step by step. At each step, a predictor is added to the model based on the cross-validation (n folds = 10) score obtained by a Random Forest regressor until half of the predictors present in the list are selected. Once the best predictors were selected, they were used in new Random Forest regressor models to predict each criterion of gaming disorder (i.e., salience, tolerance, mood modification, relapse, withdrawal, conflict, and problems). This led to seven regression models using the best predictors. To test the models' accuracy, 20% of the data were used, while the leftover data were used to train the models. The feature importance (importance that the trained model gives to a predictor) and the permutation importance (importance of a give predictor regarding the model’s efficacity while predicting unseen data) have then been reported for each predictor. Scikit-learn (V1.2) Python’s library has been used for ML analyses, and JASP have been used for traditional statistics.

4.3. Results

Significant and positive correlation was observed between GASA and depression ($r = .154$, $p < .001$), while significant and negative correlations were observed between GASA and well-being ($r = -.160$, $p <$

.001), and between depression and well-being (r = -.556, p <.001). All Pearson correlations and Spearman's rho are reported in **Table 14**.

Table 14

Correlational analysis between GASA, PHQ-9 and well-being and life satisfaction

	GASA Total score		**PHQ-9**	
	Pearson correlation	**Spearman's rho**	**Pearson correlation**	**Spearman's rho**
GASA Total score	/	/		
PHQ-9	.154 *p* <.001	.144 *p* <.001	/	/
Well-Being	-.160 *p* <.001	-.149 *p* <.001	-.556 *p* <.001	-.517 *p* <.001

Note. GASA: Game Addiction Scale; PHQ-9: Patient Health Questionnaire.

Regarding the Elastic Net regressions (ML) using the GASA items to predict PHQ-9 and well-being. The first nested cross-validated Elastic Net regression predicting depression showed an R-squared of .1 (SD = .01) and an adjusted R-squared of .1 (SD = .01), while the second that predicting well-being showed an R-squared of .069 (SD = .01) and an adjusted R-squared of .067 (SD = .01).

When predicting depression and well-being, the results are consistent with each other. While GASA's items 1, 2, and 4 have a negative coefficient for predicting depression scores (respectively: -.543; -.136; -.606), they are also the only ones to have a positive coefficient when it comes to predicting well-being (respectively: .068; .036; .074). In addition, criterion 3 and 7 both have the highest coefficient regarding depression (respectively: 1.513; .818) and well-being (respectively: -.245; -.241) predictions (see **Table 15**).

Table 15

Nested cross validated Elastic Net regression predicting Depression (PHQ-9) and Well-Being

		DV = Depression	DV = Well-being
		Mean (SD)	**Mean (SD)**
R^2		0.1 (0.01)	0.069 (0.01)
Adjusted R^2		0.1 (0.01)	0.067 (0.01)
RMSE		5.549 (0.07)	1.485 (0.02)
MAE		4.345 (0.05)	1.143 (0.01)
Items	**GASA 1 –** Salience	-0.543 (0.011)	0.068 (0.003)
Coefficients	**GASA 2 –** Tolerance	-0.136 (0.012)	0.036 (0.003)
	GASA 3 – Mood modification	1.513 (0.012)	-0.245 (0.003)
	GASA 4 – Relapse	-0.606 (0.011)	0.074 (0.003)
	GASA 5 – Withdrawal	0.24 (0.012)	-0.036 (0.004)
	GASA 6 – Conflict	0.178 (0.012)	-0.028 (0.003)
	GASA 7 – Problems	0.818 (0.012)	-0.241 (0.003)

Note. GASA = Game Addiction Scale; RMSE = Root mean squared error; MAE = Mean absolute error; DV = Dependent variable

For the last analyses, a sequential feature selector has been used to select the best predictors of gaming disorder level (i.e., GASA total score). Gender, depression (i.e., PHQ-9 total score), video game frequency, and money spent in/on video games were selected as predictors for the subsequent regressions using a Random Forest model. For each regression, 80% (n = 26.691) of the data were dedicated to fit the model and 20% (n = 6.673) to assess its performance. The first regression aimed to predict the gaming disorder level obtained an adjusted R^2 of 0.399, with video game frequency as the most important variable (feature importance = 0.65, permutation importance =0.39, see **Table 16**). The Random Forest regressions aimed at predicting gaming disorder criteria resulted in adjusted R^2 values of .417 for the salience criterion, .3 for the tolerance criterion, .296 for the mood modification criterion, .242 for the relapse criterion, .225 for the withdrawal criterion, .152 for the conflict criterion, and .17 for the problems criterion. For some of the criteria, the feature importance and premutation importance scores of the depression (predictor) become more important, this is the case for mood modification (*"Did you play games to forget about real life?"*), withdrawal ("*Have you felt bad when you were unable to play?*"), conflict ("*Did you have fights with others (e.g., family, friends) over your time spent on games?*"), and problems ("*Have you neglected other important activities (e.g., school, work, sports) to play games?*") criteria (see **Table 16** and **Figure 9**). Regarding the predictive power of the models, we found that the predictors combination (i.e., gender, depression, video game frequency, and money spent in/on video games) is more effective for predicting the salience criterion ("*Did you think about playing a game all day long?*", adjusted R^2 = .417), and less effective for the conflict criterion ("*Did you have fights with others (e.g., family, friends) over your time spent on games?*", adjusted R^2 = .152).

Table 16

Random Forest regressions of GASA total score and its criteria

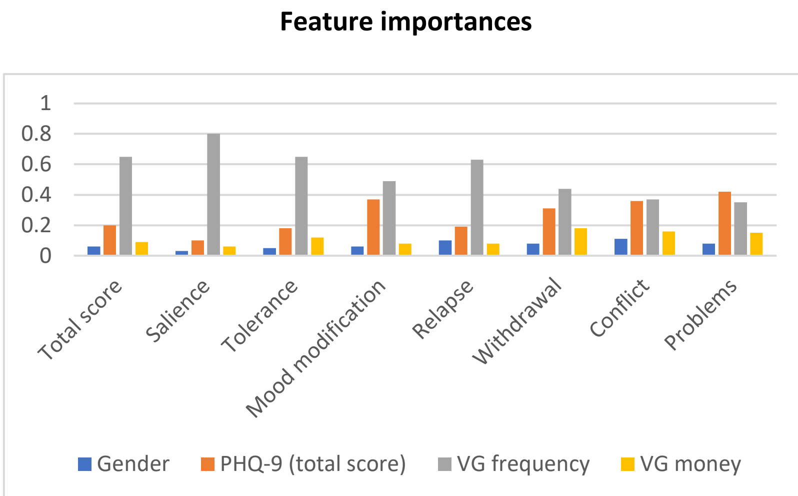
	Predictors	Feature Importance	Permutation Importance (SD)	R^2	Adjusted R^2
GASA – Total score	Gender	0.06	0.08 (0.01)	0.399	0.399
	PHQ-9 (total score)	0.20	0.15 (0)		
	VG frequency	0.65	0.39 (0.01)		
	VG money	0.09	0.09 (0)		
Item 1 – Salience	Gender	0.03	0.05 (0)	0.417	0.417
"Did you think about playing a game all day long?"	PHQ-9 (total score)	0.10	0.05 (0)		
	VG frequency	0.80	0.54 (0.01)		
	VG money	0.06	0.06 (0)		
Item 2 – Tolerance	Gender	0.05	0.05 (0)	0.301	0.3
"Did you spend increasing amounts of time on games?"	PHQ-9 (total score)	0.18	0.07 (0.01)		
	VG frequency	0.65	0.34 (0.01)		
	VG money	0.12	0.08 (0.01)		
Item 3 – Mood modification	Gender	0.06	0.05 (0)	0.296	0.296
"Did you play games to forget about real life?"	PHQ-9 (total score)	0.37	0.25 (0.01)		
	VG frequency	0.49	0.28 (0.01)		

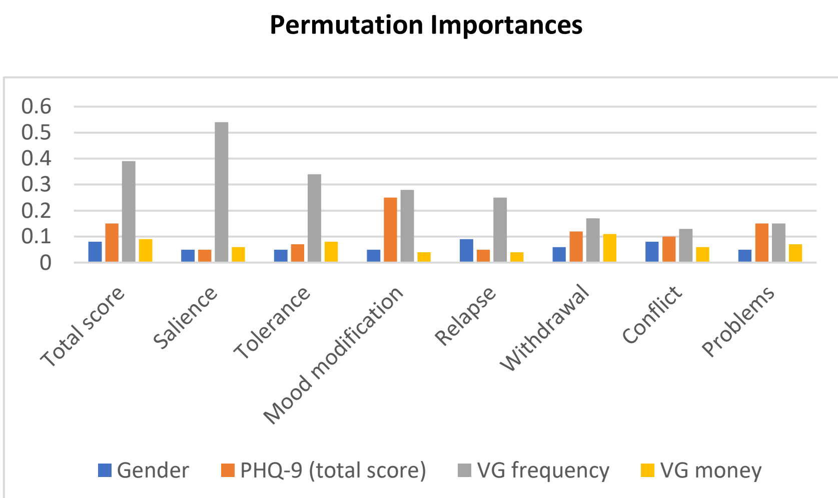
	VG money	0.08	0.04 (0)		
Item 4 – Relapse "Have others unsuccessfully tried to reduce your game use?"	Gender	0.10	0.09 (0.01)	0.242	0.242
	PHQ-9 (total score)	0.19	0.05 (0)		
	VG frequency	0.63	0.25 (0.01)		
	VG money	0.08	0.04 (0)		
Item 5 – Withdrawal "Have you felt bad when you were unable to play?"	Gender	0.08	0.06 (0)	0.225	0.225
	PHQ-9 (total score)	0.31	0.12 (0)		
	VG frequency	0.44	0.17 (0.01)		
	VG money	0.18	0.11 (0.01)		
Item 6 – Conflict "Did you have fights with others (e.g., family, friends) over your time spent on games?"	Gender	0.11	0.08 (0.01)	0.152	0.152
	PHQ-9 (total score)	0.36	0.10 (0.01)		
	VG frequency	0.37	0.13 (0.01)		
	VG money	0.16	0.06 (0)		
Item 7 – Problems "Have you neglected other important activities (e.g., school, work, sports) to play games?"	Gender	0.08	0.05 (0.01)	0.17	0.17
	PHQ-9 (total score)	0.42	0.15 (0.01)		
	VG frequency	0.35	0.15 (0.01)		
	VG money	0.15	0.07 (0)		

Note. VG = Video Game; PHQ-9 = Patient Health Questionnaire; GASA = Game Addiction Scale; N_{Train} = 26.691, 80%; N_{Test} = 6.673, 20%

Figure 9

Feature and Permutation importances of predictors for each criterion





Note. VG = video game

4.4. Discussion

Adolescence is a key period in the human development, and it is therefore essential that young people have the best possible psychological development and can cope with the demands of this context in the most effective way. The use of video games is one of the most common behavior at this developmental stage due to its high value as a highly beneficial leisure and entertainment activity, although excessive involvement is known to affect young people's psychological and psychosocial well-being (Kelly & Leung, 2021; Männikkö et al., 2020; van den Eijnden et al., 2018), life satisfaction and quality of life (Cudo et al., 2020; Lehenbauer-Baum & Fohringer, 2015; Lim et al., 2016; Tang et al., 2021).

Our results show that adolescents with a higher risk of potential addiction are also those with higher levels of depression and lower levels of well-being which is consistent with most of the literature on this topic (Fazeli et al., 2020; Lim et al., 2016; Wartberg et al., 2022). This suggests that there is evidence of possible emotional consequences among problem gamers (Tang et al., 2021). However, this low predictive value leads us to believe that problem gaming does not appear to be the main cause of emotional problems in this sample, but that there are other variables or factors that better explain the rates of depression and well-being in this population. Furthermore, this also leaves open the possibility that the adolescents in this study are using video games as a coping strategy for the emotional problems they are experiencing, leading to a decrease in emotional well-being (Jeong et al., 2019; Marinaci et al., 2021; Tang et al., 2021). For González-Bueso et al. (2018) and Richard et al. (2020), a possible explanation for this complex relationship between emotional disorders and problematic behaviours with video games could be based on the fact that both behaviours share much of the symptomatology that defines them.

The analysis of individual items allowed us to obtain information about the impact of each item on levels of depression and well-being. Among the GASA items that refer to the DSM-5 (Griffiths, 2005; Lemmens et al., 2009), we can see that the relevance or importance attached to playing (salience), the increase in frequency and time spent playing (tolerance), and the tendency to return to playing despite attempts to reduce the behavior (relapse) appear to be associated with better mood (i.e., no depression) and well-being. While mood modification and problems could be used as possible criteria to identify depressive emotional states and low emotional well-being. These findings have been confirmed by the last analysis, where depression presented a higher importance in the model when predicting mood modification, withdrawal, conflict, and problems criteria. Interestingly, when the importance of game frequency decreased, depression gained importance, becoming even more important than video game frequency when it came to the prediction of the problems criterion. Moreover, the model's accuracy was higher when predicting peripheral criteria of gaming disorder (i.e., salience, tolerance, mood modification) and lower when predicting core criteria of gaming disorder (i.e., conflict, problems, relapse, withdrawal). Results suggest that the appropriateness of GASA to assess video gaming disorder needs to be further questioned to avoid over-pathologizing intensive but non-problematic gaming. The fact that all the items doesn't share a similar link with depression and gaming frequency raise the questions of their clinical utility (i.e., their capacity to make the difference problematic and normal behaviour). A recent Delphi study highlighted the inequality of the DSM-5 criteria regarding their clinical utility (Castro-Calvo et al., 2021). When considering the potential comorbidity and overlap between depression and problematic gaming (Ostinelli et al., 2021), this relation could also be used to assess the potential relevance of each criterion. We might thus expect a closer link between items that present a clinical utility and depression or wellbeing levels. Another interpretation might also be the fact that the comorbidity with depression is more prevalent with some specific symptoms of gaming disorder when video gaming is a coping strategy rather than the object of a unique disorder.

These results seem to support the idea that our sample may use video games as a coping strategy for their everyday problems, in line with Lemmens et al. (2011), who considered it more likely that poorer psychosocial well-being is a cause rather than a consequence of problem gaming, although they did not rule out the possibility that this activity could increase social isolation, making video game use a risk factor in itself. For their part, Fazeli et al. (2020) tried to explain this relationship, warning that in certain situations, what starts as a release strategy could end up being a source of psychological and emotional distress, given the high need to play and the reduction in social contact, which in turn could cause a clear interference with other activities in their daily lives. However, Sauter et al. (2021) added that those who play with friends they know from outside the gaming world may be more satisfied with life in general and therefore less prone to emotional problems such as anxiety.

For this reason, it is clear that both our findings and those mentioned here should be treated with caution, always trying to take into account as many personal and contextual variables as possible when analysing and explaining the relationship between problematic gaming and well-being. It should also be pointed out that the lack of consensus on the effectiveness of some of the criteria (e.g., salience or tolerance) for detecting the presence of problematic use of video games may be a factor that makes the understanding of this phenomenon more difficult.

4.4.1. Limitations

This study has a number of limitations: Firstly, one of the main strengths of this study is the large and representative sample used, but as it is only Spanish adolescents, it does not allow the results to be generalized to other populations. Therefore, it would be very useful to carry out similar studies in other populations in order to be able to compare the results across countries and cultures. Secondly, although the instruments used have good psychometric properties and have been widely used in samples such as the one in this study, they have some weaknesses, as in the case of the GASA, a tool that was developed taking into account some criteria that may not be relevant to its clinical utility. Thirdly, this was a cross-sectional study, which did not allow us to observe possible causal effects between well-being/life satisfaction and problematic use of videogames. Therefore, a longitudinal study could provide data that would help to analyse the trend of the relationship between video game use and emotional variables. Fourthly, although self-report measures have been shown to be reliable and even better than other methods for analysing certain behaviours such as substance use and addictive disorders (Babor et al., 1989; Winters et al., 1990), their use may affect adolescents' responses and the emergence of biases such as social desirability, underestimation or overestimation of the behaviours they perform and their possible consequences.

4.4.2. Conclusion

Our findings suggest a connection between problematic video game usage and depression. This highlights the importance and influence of external factors and variables in the child or adolescent's environment on the development of this kind of behaviour. Adolescence is a critical period of maturation that, together with other emotional conditions, seems to favour the development of risky behaviours. Therefore, it seems that studies are needed to understand whether problematic video game use is a coping mechanism or whether depression is caused by this pattern of problematic gaming. Furthermore, this study highlights the need to examine the suitability of instruments used to measure problematic gaming to prevent the misclassification of healthy gamers and develop accurate tools that precisely measure the behaviour in question. Additionally, alternative approaches may be considered, such as adjusting cut-off points for scales.

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5. User-Avatar Bond as Diagnostic Indicator for Gaming Disorder: A Word on the Side of Caution. Commentary on: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning (Stavropoulos et al., 2023) (*Study 4*)

Infanti, A., Giardina, A., Razum, J., King, D.L., Baggio, S., Snodgrass, J.G., Vowels, M., Schimmenti, A., Király, O., Rumpf, H-J., Vögele, C., l Billieux, J. User-Avatar Bond as Diagnostic Indicator for Gaming Disorder: A Word on the Side of Caution. Commentary on: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning (Stavropoulos et al., 2023). *Journal of Behavioral Addictions*, Accepted for publication.

Abstract

In their study, Stavropoulos et al. (2023) capitalized on supervised machine learning and a longitudinal design and reported that the User-Avatar Bond could be accurately employed to detect Gaming Disorder (GD) risk in a community sample of gamers. The authors suggested that the User-Avatar Bond is a "digital phenotype" that could be used as a diagnostic indicator for GD risk. In this commentary, our objectives are twofold: (1) to underscore the conceptual challenges of employing User-Avatar Bond for conceptualizing and diagnosing GD risk, and (2) to expound upon what we perceive as a misguided application of supervised machine learning techniques by the authors from a methodological standpoint.

Keywords: Gaming Disorder, Machine Learning, User-Avatar Bond

5.1. Introduction

We commend Stavropoulos et al. (2023) for their study which aimed to test whether Gaming Disorder (GD) risk cases could be accurately detected based on Machine Learning (ML) algorithms trained with, among other variables, information regarding the User-Avatar Bond (UAB) (Blinka, 2008). Using longitudinal data, they claimed that the UAB has the potential to detect GD risk with implications for treatment and assessment. Specifically, the authors concluded that capitalizing on their method would permit the use of the UAB as a potential diagnostic indicator of GD risk. This kind of study is particularly relevant at this time, given the limited number of longitudinal studies, and the need to refine and improve the assessment and screening of GD. However, given the novelty of this approach and its potential impact on the field, we believe that some of the claims made by the authors warrant caution, both at the theoretical and methodological level.

In line with the authors' proposal, we agree on the psychological relevance of the relationship with the avatar in the study of problematic gaming patterns (Lemenager et al., 2020; Razum & Huić, 2023). Observing such a relationship seems to be especially important in the presence of identity vulnerabilities such as poor self-esteem and self-concept clarity when Massively Multiplayer Online Role-Playing Games (MMORPGs) are played (Green et al., 2021; Király et al., 2023; Szolin et al., 2022). Certainly, in clinical contexts involving individuals exhibiting problematic gaming behaviors, the examination of avatar perception could be a valuable avenue for gaining insight into implicit identity processes that underlie prevalent themes, conflicts, and developmental issues during consultations (Lemenager et al., 2020). Nevertheless, we believe that the authors' claim that *"the UAB could operate as a diagnostic indicator of GD risk both at present and prospectively (six months later), when addressed using trained ML/AI procedures*" (Stavropoulos et al., 2023, p.13) is premature. Therefore, in this commentary, our objectives are twofold: (1) to underscore the conceptual challenges of employing UAB for conceptualizing and diagnosing GD risk, and (2) to expound upon what we perceive as a misguided application of supervised ML techniques by the authors from a methodological standpoint.

5.2. Conceptual criticism

The first reason for exercising caution is conceptual in nature. Although fascinating, Stavropoulos et al.'s (2023) idea that avatars might be considered as “digital phenotypes” (i.e., a digital/gamified footprint of an individual’s mental health) is challenging for several reasons. First, digital phenotyping should provide data that is superior to self-report, and can use digital markers (Montag & Rumpf, 2021). In this sense, the objective analysis of in-game activities may provide many clues about the risk of addictive behavior (Larrieu et al., 2023), while current measures and conceptualizations of the UAB lack sufficient discriminatory power to be considered objective digital markers. Second, the concept of avatars as “digital phenotypes'' requires that a relationship with the avatar exists. The existence of such a relationship may depend on two intertwined factors: 1) the type of videogame played and 2) the way avatars are experienced by the player. As for the first, in most MMORPGs the establishment of a meaningful relationship with an avatar is indeed possible and commonly documented, yet not intrinsically central (Mancini et al., 2019, 2024). However, for other types of games equally associated with GD and more popular nowadays, such as First Person Shooters (FPS), Real Time Strategy (RTS) games, Battle Royale (BR) games or Multiplayer Online Battles Arenas (MOBA), avatars are not central to game play and experience and can be customized only to a limited extent (Statista, 2023). Such constraints may diminish the likelihood of identification with or idealization of avatars, thus limiting players in fostering meaningful connections with these virtual representations and reducing their usefulness in understanding problematic gaming patterns (Király et al., 2023; Rehbein et al., 2021). In **Table 17**, we propose an approximate inter-genre classification of most popular online games’ genres based on the salience of avatars for the category[3], i.e., the possible degree of avatars' customization in the category and the relevance for the gameplay/player experience.

A few differences are summarized here. In MOBA games, players are required to select from a predetermined roster of "heroes," resulting in limited or absent avatar customization compared to MMORPGs. Nonetheless, the choice of a hero in MOBA games, each characterized by distinct attributes and backgrounds, significantly influences gameplay dynamics. Moreover, MOBA players often develop emotional attachments to specific heroes, sometimes prioritizing their selection over strategic considerations for individual matches. In FPS and BR games, there exists a degree of customization, such as altering weapon appearances or selecting the avatar from predefined "skins." However, the customizations in these genres tend not to confer competitive advantages in gameplay, and the bond between players and avatars tends to be more aesthetic-instrumental rather than emotionally driven. Lastly, in RTS and sports games (with certain exceptions depending on the sport), individual avatars are absent, with players instead choosing from groups represented as teams or factions.

Table 17

Game-play experience of avatars based on game genres

	Customization	Relevance	Score
MMORPGs	High	Medium	5
MOBA	Low	High	4
BR	Medium	Low	3
FPS	Medium	Low	3
RTS	Very low	Very low	0
Sport games	Very low	Very low	0

[3] We are aware that this classification represents a simplification of the huge variety of videogames (and avatars' settings) within the same genre. However, we believe it stays sufficiently true to the general features of each genre and to the inter-genre comparison.

Note: MMORPGs = Massively Multiplayer Role-Playing Games; MOBA = Multiplayer Online Battle Arenas; BR = Battle Royale; FPS = First Person Shooter; RTS = Real-Time Strategy; Very Low = 0; Low = 1; Medium = 2; High = 3; Relevance = Impact on the gameplay/emotional bond of players; Score = summarized score of the values in the Customization and Relevance columns

It is evident that the genre of the video game may impose certain important constraints on the avatar-player relationship. However, the mere classification of video game genres does not ensure a specific perception of the avatar. Embedded within the preference for a particular game genre is thus the players' individual experiences with avatars, which can vary in nature. Stavropoulos et al. (2023) base their proposal on the players' experience of avatars as *extensions of themselves* into the virtual world – thereby suggesting processes of identification with the avatar, idealization of the avatar, and/or utilization of the avatar within the game environment to compensate for personal and interpersonal deficiencies. Nevertheless, problematic gaming can also occur when avatars are experienced as mere tools to interact with the game or as friends and adventures' companions (Snodgrass et al., n.d; Green et al., 2021). For example, according to Banks (2015) the level of psychological differentiation of players from their avatars (i.e., the autonomy of avatars from players themselves) is only one of four factors determining the UAB. The others include the level of emotional investment, the ability to imagine avatars as something more than just digital tools or personalized entities (i.e., a suspension of disbelief) and the degree of perceived control over the avatar. Based on how these elements vary, Banks and Bowman (2016, 2021) propose that players can relate to the avatar: (a) as an *object*, where avatars are experienced in a non-social way, i.e., as mere tools to play the game; (b) as *me*, where a significant emotional bond sustains the identification with a non-idealized avatar; (c) as a *symbiote*, where there is an identification with an idealized avatar; or (d) as *other,* where avatars are perceived as separate being in a social and emotionally salient way, and thus are akin to friends or adventures' companions. According to this conceptual framework, the approach advocated by Stavropoulos et al. (2023) may effectively identify problematic gaming behaviors in instances where players exhibit strong emotional connections with their avatars, as seen in "me" or symbiote avatars. This approach, however, may fall short in detecting problematic gaming when there is a lack of emotional attachment between the players and their avatars, as observed in the "avatar as an object" category, or when the avatar is perceived as a socially significant entity distinct from the player, as exemplified in the avatar "as other" category (Snodgrass et al., n.d.). These considerations might also help explain Stavropoulos et al.'s (2023) finding that the immersion dimension of the UAB Questionnaire (UAB-Q; Blinka, 2008) was the best predictor of GD risk in their sample. One reason behind such a stronger association may be that the items of the current UAB-Q immersion dimension (1) mostly refer to thinking about the character or the game while not playing (recalling the "preoccupation" criterion of the DSM-5 Internet Gaming Disorder condition; American Psychiatric Association, 2013; Castro-Calvo et al., 2021), but also that (2) they assess a general emotional bond with the character (i.e., "sometimes I feel ashamed for/proud of my character"). Accordingly, these items do not necessarily refer to the experience of the avatar as an extension of the self (i.e., as "me" or as a symbiote) but they might also imply a perception of the avatar as a sort of "playmate" (i.e., the condition of avatar as "other"). In this respect, it is noteworthy that Blinka, Sirinkova & Stasek (2023) recently tested an updated version of the UAB-Q, the UAB 2.0, on 6391 adult gamers. In this revised version, the dimension which showed the highest correlation (ß = .32) with GD symptoms was the compensation of gamers' weaknesses through the avatars' superior characteristics. Furthermore, in the UAB 2.0 an Emotional Bond dimension was identified via factor analysis, which could be an important variable for examining other kinds of UABs in which avatars are perceived as "*other*" (Banks, 2015; Banks & Bowman, 2021).

In summary, scenarios exist in which avatars are perceived as extensions of the self-fostering identification, idealization, or compensation and contributing to GD symptoms, as it is sometimes observed in MMORPGs or MOBA players (Stavropoulos et al., 2023; Szolin et al., 2022). However, there could be also multiple scenarios in which problematic gamers have an avatar that is perceived as a separate companion (as in the "*other*" category proposed by Banks (2015), or even cases where no particular emotional bond is created between the player and the avatar, as it could happen with FPS or RTS games (Rehbein et al., 2021; Snodgrass et al., n.d.). From this perspective, the UAB as implemented by Stavropoulos et al. (2023) may hold clinical significance in instances where avatars are perceived as "me" or as a symbiote (e.g., within MMORPGs). Nevertheless, it seems premature to consider the UAB as an inherently reliable indicator for GD diagnosis universally. An indicator must provide a clear threshold which would be a fundamental step to be taken to go in this direction. Furthermore, additional research is warranted to investigate whether specific UABs correspond with various video game genres (Banks & Bowman, 2021).

5.3. Methodological criticism

The second point of caution we emphasize is of a methodological nature. The way ML algorithms are implemented in Stavropoulos et al. (2023), but also more recently in Brown et al. (2024) and Hein et al. (2024), is based on an elevated proportion of simulated (i.e., algorithm-generated) data. A crucial step in ML pertains to the splitting of the available database into two different sets: the *train set,* which is used to fit the model, and the *test set,* which is used to evaluate the fitted model on unseen data to estimate its performance (Rosenbusch et al., 2021). To obtain an equal proportion of No-GD risk and Yes-GD risk cases in their two sets, Stavropoulos et al. (2023) generated virtual data (i.e., simulated gamers profiles) using an algorithm called K-NN Synthetic Minority Oversampling Technique (SMOTE)[4]. This approach is particularly useful since it tackles a common problem in psychological research, where the clinical group

[4] This algorithm generates simulated data for the minority class (oversampling technique) while taking into account a number (K) of nearest neighbors (NN) when considering the Euclidean distance. This algorithm can also randomly remove/select some cases from the majority class (under-sampling) to balance the data. For more details about the algorithm please see Chawla, Bowyer, Hall, and Kegelmeyer (2002).

usually represents a minority of the population, leading to a considerable imbalance in databases. Under such circumstances, a specific ML classifier model would use the majority class (non-clinical population) for its predictions and give very limited importance to the minority class (clinical population; Chawla et al., 2004). Thus, by using the K-NN SMOTE algorithm, Stavropoulos et al. (2023) adopted a potentially sound approach to bypass this issue. Nevertheless, these authors implemented the algorithm *before* splitting their data to produce the train and test sets. By using K-NN SMOTE, the authors artificially inflate the number of cases in the minority group (Yes-GD risk). Surprisingly, the authors also artificially inflated, instead of under-sampling, the number of cases in the majority group (No-GD risk). After the use of the K-NN SMOTE algorithm, the final database used was composed of 1060 participants, where 424 Yes-GD risk cases (80% of this subsample) and 100 No-GD risk cases (18.87% of this subsample) were algorithm-generated data[5]. Crucially, these algorithm-generated data represent 49.43% of the final sample before the split is made to create the *train* and *test* sets. It is worth noting that the SMOTE algorithm has been criticized for its inability to generate reliable cases in the minority class (Kosolwattana et al., 2023). Moreover, a related problem is that algorithm-generated data are present in the *test* set used to establish the accuracy of the fitted model (i.e., the *test* set is composed of a mixture of real and simulated data). These decisions are questionable because the specific way in which the authors have augmented their dataset with synthetic data negatively impacts the generalizability of the model and significantly inflates its apparent performance. In our view, it would have been important that Stavropoulos et al. (2023) fully disclose that the methodology they implemented might be able to detect "mainly algorithm-generated data" and that further research is needed to establish the actual validity of this method as a potentially valid diagnostic indicator in the context of real cases.

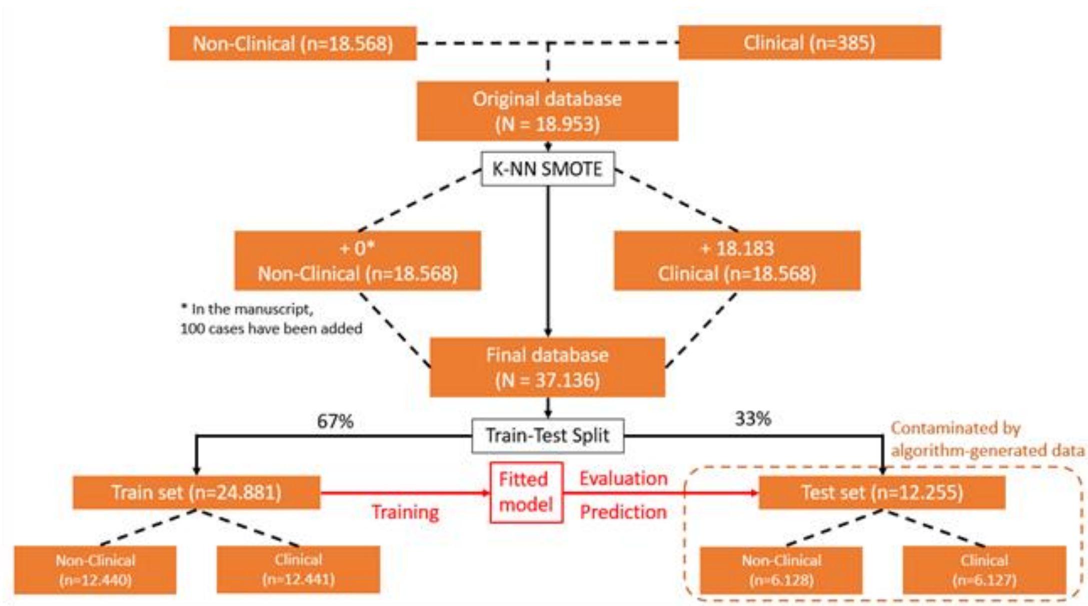
[5] The authors have acknowledged the oversampling of the Yes-GD risk cases. However, they did not mention the oversampling of the No-GD risk cases.

We argue that a sounder approach could be to implement the K-NN SMOTE algorithm *after* splitting the data and exclusively in the *train set*. This would render the *test set* realistic and implies that the model's accuracy is tested in a real condition (see **Figure 10** for a graphical explanation).

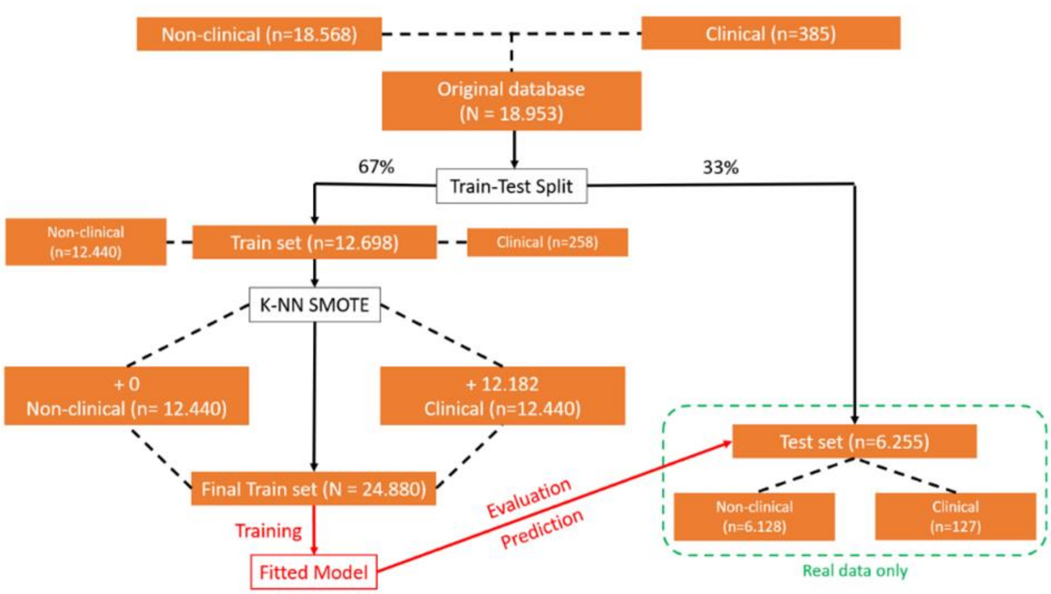
Figure 10

Difference between the two methods

Using SMOTE before split



Using SMOTE after split



As the database used by Stavropoulos et al. (2023) is not available in the online supplement, we used an available dataset to illustrate our proposal (**Table 18**). The database we used for this purpose is available from the open science framework: https://doi.org/10.17605/OSF.IO/2P6SX. Our proposal was thus operationalized using a large dataset in which participants with or without a mental health condition completed a self-reported scale measuring various impulsivity traits (the short French UPPS-P impulsive behavior scale, see Billieux et al., 2012 for the scale and Billieux et al., 2021 for more details on the sample). The database comprises 18.953 participants, and among them, 385 have a mental disorder (clinical cases). We compared the approach of Stavropoulos et al. (2023) and the alternative proposal in the present comment (i.e., implementing the K-NN SMOTE algorithm after the splitting of the data and on the *train* set exclusively) to predict the clinical status of the participants based on the UPPS-P questionnaire assessing impulsivity traits[6]. For the supervised ML analyses, we used the Random Forest ensemble model, which was the most accurate in the study by Stavropoulos et al. (2023), but without tuning. We aimed to demonstrate the potential impact of including algorithm-generated data inside the *test* set. Thus, our comparison is focused on this very point, which is methodological and not specific to a dataset.

The procedure is illustrated in **Figure 10. Table 18** compares the accuracy of the two approaches using real cases from an available database. Impulsivity traits (negative urgency, positive urgency, lack of premeditation, lack of perseverance, and sensation seeking) were used as predictors of the clinical status (non-clinical or clinical). The (diagnostic) accuracy, which represents the percentage of correct prediction, was 99% with the approach used by Stavropoulos et al. (2023) and 98% with the method we suggest in

[6] The supplementary material provided by Stavropoulos et al. (2023) does not include the bake recipe, folds train boot or VIP, which is susceptible to errors and compromises the reproducibility of the procedure. Also, several unclear manipulations (e.g., creating folds for the cross-validation without using them, or the use of another SMOTE algorithm in the recipe) have been found in the provided code. For this reason, and to guarantee the reproducibility of the present analyses and findings, we adapted the code and the procedure to illustrate our proposal. Our user-friendly data analytic code is available in supplementary material. The issues we encountered further highlights the importance of endorsing open science practice where well-documented and reproducible analytical code are available (Eben et al., 2023).

the present paper. The accuracy itself, however, is not sufficient to assess the quality of the model's predictions. For that reason, metrics such as precision (the model's ability to prevent false positive predictions) and recall (or sensitivity, the model's ability to identify positive results accurately) are also reported for a more nuanced evaluation of the models. In our comparison, we noticed that when simulated data was generated after the sample split, precision and recall scores dropped significantly for clinical sample predictions. Precision decreased from 99% to 28%, and recall decreased from 98% to 11%, leading to a very poor predictive model. Our result thus challenges the practical relevance and utility of the model proposed by Stavropoulos et al. (2023).

It would also have been beneficial for the authors to consider implementing a supervised ML regression analysis. The GDT-4 scale was primarily designed to assess the severity of disordered gaming by using a total score rather than providing a diagnosis (Pontes et al., 2021). This is even more relevant when considering the impact of the data quality on a supervised ML model's performance. The prediction of a supervised ML model is, in the best-case scenario, as accurate as the instrument output (Fardouly et al., 2022). Regarding this point, it is worth noting that, in Stavropoulos et al. (2023), the functional impairment criterion was not considered necessary to identify participants as Yes-GD risk cases[7]. This approach contrasts with the recommendation provided by Pontes et al. (2021), which consists of meeting all criteria (a criterion being endorsed when answering "Often" or "Very often") to identify disordered gamers, referring to the conservative approach to diagnosis defended in the ICD-11 (Billieux et al., 2017). Thus, the nature of the sample identified as GD risk gamers remains unclear, leading to potentially highly involved but healthy gamers being included in this sample (Billieux et al., 2019). For this reason, we believe that it would have been helpful if Stavropoulos et al. (2023) had strictly followed Pontes et al.'s (2021)

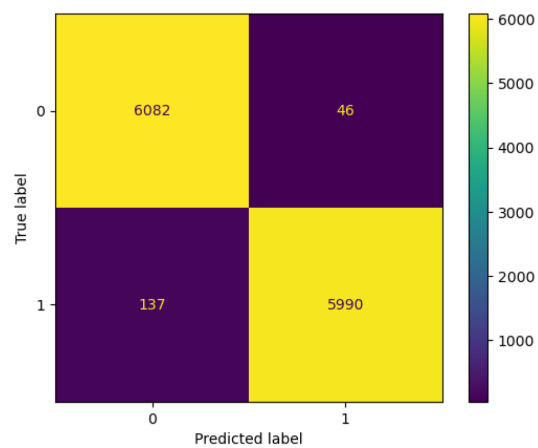
[7] The analytic code included in the online supplement does not match with what the authors say they have done. While the authors say in their article that a response modality of 4 ("often") or higher is the rule to consider a gaming disorder criterion as endorsed, their data analytic code considers a criterion endorsed when the response modality is 3 ("sometimes") or higher.

recommendations to strengthen diagnostic-related claims, especially when creating groups based on the GDT-4 (Pontes et al., 2021).

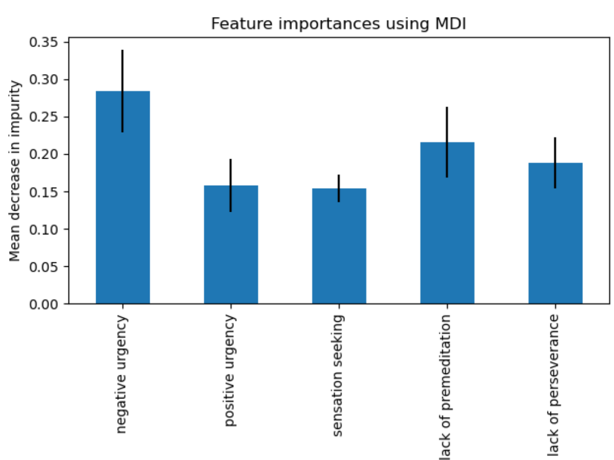
Table 18

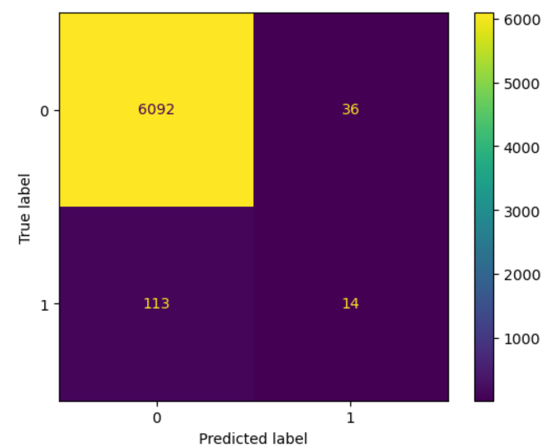
Comparison of the impact of data's split before or after the generation of data

Generating data **before** train-test split	Generating data **after** train-test split

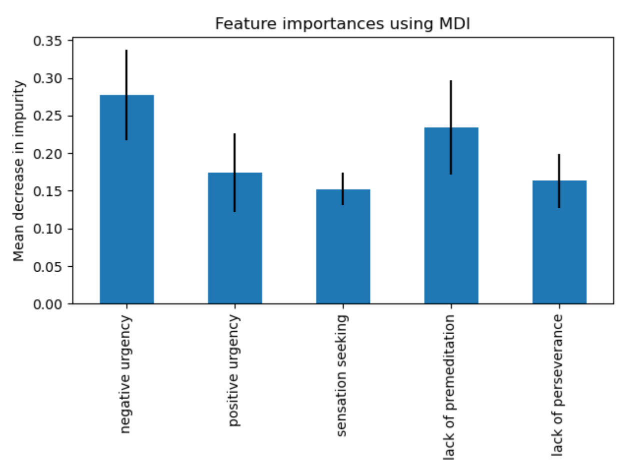


	precision	recall	f1-score	support
0	0.98	0.99	0.99	6128
1	0.99	0.98	0.98	6127
accuracy			0.99	12255





	precision	recall	f1-score	support
0	0.98	0.99	0.99	6128
1	0.28	0.11	0.16	127
accuracy			0.98	6255



5.4. Conclusion

The UAB may be an important element to explore and consider in the context of case formulation for people with problematic gaming behaviors. Nevertheless, we believe that there are often limits to the clinical relevance of the UAB. We are not convinced at this time that the UAB concept is appropriately supported by empirical evidence to be considered a clinical feature or diagnostic indicator of GD. Moreover, the results brought by the authors through their methodology do not provide sufficiently robust arguments to support the UAB for that purpose. We are also concerned about the generalization of the results based on how supervised ML was implemented in their study (see Brown et al., 2024 and Hein et al. (2024) for other recent studies using a similar methodology).

In conclusion, based on the current state of literature, the relevance of the UAB in GD can vary significantly depending on the interaction between the game genre and the way avatars are experienced by the player. Determining the relevance of UAB in any given case is unlikely to be a straightforward process. Furthermore, the results obtained by Stavropoulos et al. (2023) are limited to the identification of algorithm-generated – and thus simulated – data for the Yes-GD risk case, which hinders the generalization of the results to actual problematic gamers. When generating data after the sample split, we observed a significant decrease in the model's ability to detect clinical cases. Therefore, the model performance was greatly impacted when testing the model on a sample consisting solely of actual cases. Further case studies, research on clinical samples focusing on the relationship with the avatars in different game genres, and the evaluation of different methods to assess the relationship with avatars are, therefore, needed before exploring further the idea of the UAB as a “digital phenotype” or a potential indicator (or diagnostic feature) of GD.

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6. General discussion

The present PhD thesis had two objectives that were addressed through four different empirical studies (for an overview of the studies' aims and main findings, see **Table 19**). The studies focused on two distinct forms of PUI, namely, cyberchondria (*Study 1*) and gaming disorder (*Studies 2-4*). In line with the position statement formulated by the European Network for PUI (Fineberg et al., 2022), this PhD project addressed two key research priorities associated to PUI, namely (a) the need to approach a consensus on the conceptualization of PUI and its various forms, and (b) the improvement of their assessment. To this end, the present work capitalized on different types of supervised ML techniques, such as clustering, regression, and classification tasks.

Summary of main results

Study 1 aimed to investigate changes in the severity of cyberchondria during the COVID-19 pandemic and to identify predictors of cyberchondria during that period. For that purpose, data were collected from May 4, 2020 to June 10, 2020, which corresponds to the first wave of the COVID-19 pandemic in Europe. At the time *Study 1* took place, French-speaking countries in Europe (France, Switzerland, Belgium, and Luxembourg) all implemented lockdown or semi lockdown measures. The survey consisted of a questionnaire collecting demographic data and socioeconomic circumstances during the first lockdown and was followed by several instruments assessing various psychological and health-related constructs. The results showed that the COVID-19 pandemic affected various facets of cyberchondria: cyberchondria-related distress and compulsion increased, whereas the reassurance facet of cyberchondria decreased. In addition, COVID-19-related fears and health anxiety emerged as the strongest predictors of cyberchondria-related distress and interference with functioning during the pandemic. These findings provide evidence of the impact of the COVID-19 pandemic on cyberchondria and identified specific risk factors that should be targeted in efforts to prevent and manage cyberchondria at times of public health crises. In addition, the data collected were consistent with a theoretical model of cyberchondria during the COVID-19 pandemic (Starcevic et al., 2021, see section 1.1.2). The findings suggest a reexamination of the conceptualization of cyberchondria as a multidimensional construct, which has important implications in terms of its assessment and treatment.

Study 2 aimed to identify psychological factors that discriminate highly involved (but healthy) gamers from problematic gamers. For that purpose, a cluster analysis approach has been deployed to identify groups of gamers based on their profiles of passion towards gaming (relying on the Dualistic Model of Passion by Vallerand, 2015). Another objective of *Study 2* was to explore, using supervised ML, how gaming disorder symptoms, assessed within the substance use disorder framework (e.g., tolerance, withdrawal), might be linked to harmonious and/or an obsessive passion for gaming. Three distinct clusters of gamers were identified based on their passion profiles, including risky gamers, engaged gamers, and casual gamers. Supervised ML algorithms identified that specific gaming disorder symptoms (salience, mood modification, tolerance, low level of conflict) were predominantly related to harmonious passion, whereas others (withdrawal, high level of conflict, relapse) were more directly related to obsessive passion. The results support the relevance of person-centered approaches to tailor treatment of problematic gaming. They also call for caution regarding the use of so called "peripheral criteria" (such as tolerance or preoccupation) in the assessment of gaming disorder, which is susceptible to over-diagnosis and thus pathologize normal patterns of gaming. These findings further indicate that borrowing substance-abuse related criteria to define Internet-related disorders, such as gaming disorder, may not be clinically valid and conflate intensive and problematic patterns of involvement (Billieux et al., 2019, 2022; Castro-Calvo et al., 2021; Flayelle et al., 2022; Kardefelt-Winther et al., 2017).

The goal of *Study 3* was to predict depression and well-being levels among adolescents using the criteria for gaming disorder as assessed by the Gaming Addiction Score for Adolescents (GASA). *Study 3* aimed to identify the best predictors of gaming disorder level (i.e., GASA total score) from a list of potential predictors, including gender, age, household, parental control, depression, well-being, video game frequency, and money spent on video games. Afterward, it assessed (a) the accuracy of a model composed of the best predictors of gaming disorder level when predicting specific symptoms assessed by the GASA (i.e., salience, tolerance, mood modification, relapse, withdrawal, conflict, and problems), and (b) the relevance of each identified predictor when predicting GASA's criteria (or symptoms) individually. For that purpose, a large sample of Spanish adolescents (N = 33.364) aged from 12 to 16 years old were recruited. Item-based analyses showed that salience, tolerance, and relapse criteria were positively associated with well-being, while withdrawal, conflict, problems, and mood modification criteria were positively associated with higher levels of depression. Regarding gaming disorder level (GASA total score), the selected predictors included gender, depression, video game frequency, and money spent in/on video games. While video game frequency was the most important predictor of gaming disorder level (i.e., GASA total score), but also salience, tolerance, and relapse criteria, its importance decreased when it came to the prediction of mood modification, withdrawal, conflict, and problems criteria. Interestingly, when the importance of game frequency decreased, depression gained importance, becoming even more important than video game frequency when it came to the prediction of the problems criterion. Finally, the model's accuracy (R^2) was higher when predicting peripheral criteria of gaming disorder (i.e., salience, tolerance, mood modification) and lower when predicting core criteria of gaming disorder (i.e., conflict, problems, relapse, withdrawal). Results suggest that the appropriateness of GASA to assess video gaming disorder needs to be further questioned to avoid over-pathologizing intensive but non-problematic gaming. In that sense, *Study 3* arrived at the same conclusion as *Study 2*, cautioning against using substance-abuse-related criteria to define gaming disorder. Using these criteria (identified as peripheral criteria) may lead to identifying highly involved but healthy gamers as being gamers who present an intense and problematic involvement toward video games. (Billieux et al., 2019, 2022; Castro-Calvo et al., 2021; Flayelle et al., 2022; Kardefelt-Winther et al., 2017)

Finally, *Study 4* aimed to inform about the risks associated with misunderstanding supervised ML approaches and the consequences of problematic ML use regarding the research of PUI. For this purpose, *Study 4* consisted of a comment regarding a recent study in which Stavropoulos et al. (2023) capitalized on ML to support the use of user-avatar bond as a diagnostic indicator for gaming disorder. In their study, Stavropoulos et al. (2023) initially encountered an imbalanced dataset composed of a large majority of non-at-risk gamers. One issue with imbalanced datasets in ML is that a specific ML classifier model may heavily rely on the majority class (e.g., non-clinical population) for its predictions and give limited importance to the minority class (e.g., clinical population; Chawla et al., 2004). To address this issue, Stavropoulos et al. (2023) increased the number of at-risk gamers using an algorithm called K-NN Synthetic Minority Oversampling Technique (SMOTE). However, the authors implemented the SMOTE algorithm before splitting their dataset to create the so-called train and test sets. *Study 4* argues that using algorithm-generated data to inflate the number of at-risk gamers to create a balanced dataset before splitting it into a train and a test set raises questions about the methodological approach. This approach can negatively affect the generalizability of the model and lead to an inflated perception of the model's performance. *Study 4* demonstrated the negative impact of including algorithm-generated data in the test set by comparing the performances of a model with and without such data. Moreover, *Study 4* addressed concerns about the multiplication of misuse of ML in psychological research, since a second study (Brown et al., 2024) already employed a similar methodology to the one used by Stavropoulos et al. (2023). Thus, it was essential to highlight the risks associated with the improper use of ML, but also to warn against perpetuating such methodological errors that can lead authors to overestimate their results due to a misunderstanding of basic ML principles. This concern was further raised when even a third study (Hein et al., 2024) used the methodology by Stavropoulos et al. (2023), after the manuscript related to *Study 4* was accepted for publication.

Table 19

Presentation of the studies, the addressed PUI form, their aims, and the ML method used

Study 1	**PUI form**	Cyberchondria
	Title	Predictors of Cyberchondria During the COVID-19 Pandemic: Cross-sectional Study Using Supervised Machine Learning
	Sample	• N = 725 (57.4% women) • Aged between 18 and 77 years old (M = 33.29, SD 12.88) • 82.8% bachelor's degree or higher • French speakers (Switzerland, France, Belgium, Other)
	Results	***Aim 1: comparison of cyberchondria scores before and during COVID-19*** • Compulsion and distress cyberchondria dimensions increased during the pandemic • Reassurance cyberchondria dimension decreased during pandemic • No significant difference between pre and during the pandemic cyberchondria total scores ***Aim 2: Psychological factors predicting subscales cyberchondria during COVID-19*** • Distress (IV= COVID-19 related fear, health anxiety, intolerance of uncertainty): Adjusted R^2 = .333 (SD= .06); RMSE = 2.512 (SD=0.109); MAE = 2.003 (SD = 0.09). COVID-19 related fear and health anxiety are the two most important predictors. • Compulsion (IV = COVID-19 related fears and health anxiety): Adjusted R^2 = .143 (SD = 0.047); RMSE = 2.294 (SD= 0.14); MAE = 1.776 (0.092). COVID-19 related fear and health anxiety contributed similarly. • Adjusted R^2 of compulsion prediction is significantly lower than the one obtained for distress. • COVID-19 related fears and health anxiety are strong predictors of cyberchondria-related distress and compulsion during the pandemic ***Other:*** • No gender differences on cyberchondria (total score and subscales); No differences regarding age and education on compulsion subscale • Age and education effect: 15–24-year-old group scored the highest (total score, excessiveness, distress); Bachelor and Master degree presented the highest scores in total score and subscales (but no differences in compulsion subscale)
Study 2	**PUI form**	Gaming disorder
	Title	Gaming passion contributes to the definition and identification of problematic gaming
	Sample	• N = 845 (50.41% men) • Aged between 18 and 50 years old (M = 23.5, SD = 5.03) • 88.99% bachelor's degree or higher • Spanish speakers (Spain)
	Results	***Aim 1: Cluster generation (3 clusters)*** • Engaged gamers: High harmonious passion and low obsessive passion. • Risky gamers: combination of high obsessive passion and moderately high harmonious passion. Present significantly higher levels of IGD symptoms, motivations of gaming (with the exception of the recreation and social motivations), and lack of perseverance impulsivity trait. No significant difference with the engaged gamers on the daily hours of gaming • Casual gamers: low harmonious passion and low obsessive passion

Aim 2: prediction of Harmonious and obsessive passion using gaming disorder symptoms.
• Harmonious passion: $R^2 = 0.192$
The most important coefficients concern salience (β = 2.91), mood modification (β = 1.86), tolerance (β = 1.59), and conflict (β = − 3.35) dimensions.
• Obsessive passion: $R^2 = 0.190$
The most important coefficients concern withdrawal (β = 1.04), conflict (β = 1.03), salience (β = 1.00), and relapse (β = 0.91) dimensions.

Study 3

PUI form	Gaming disorder
Title	Playing with well-being: How problematic video game use is related to emotional health in Spanish adolescents
Sample	• N = 33.364 (58.31% of boys) • Aged between 12 and 16 years old (M = 13.71, SD = 1.22) • Spanish adolescent
Results	*Aim 1: Using gaming disorder criteria to predict depression and wellbeing levels* • Salience, tolerance, and relapse criteria are negatively related to depression (coefficients mean of -0.543, -0.136, and -0.606, respectively) level and positively related to wellbeing (coefficients mean of 0.68, 0.036, and 0.074, respectively) • Mood modification, withdrawal, conflict, and problems criteria are positively related to depression (coefficients mean of 1.513, 0.24, 0.178, and 0.818, respectively) and negatively related to Wellbeing (coefficients mean of -0.245, -0.036, 0.028, and -0.241, respectively) *Aim 2: Identifying predictors of the gaming disorder level and their importance when predicting each criterion* • Among 8 potential predictors (gender, age, household, parental control, depression, wellbeing, video game frequency, money spent in/on video games), 4 have been selected using a machine learning method to predict total score of GASA. The retained predictors were gender, depression (PHQ-9 total score), video game frequency, and money spent on video games. • The model predicting the total score of GASA obtained a R^2 of 0.399, with video game frequency as the most important variable. • The model's accuracy decreases when predicting a core criterion of gaming disorder (e.g., conflict, problems, relapse, withdrawal). Also, the importance given by the model to the PHQ-9 total score (depression) increases when predicting a core criterion.

Study 4

PUI form	Gaming disorder
Title	User-Avatar Bond as Diagnostic Indicator for Gaming Disorder: A Word on the Side of Caution Commentary on: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning (Stavropoulos et al., 2023)
Sample	*Non-clinical sample:* • N = 18,568 (60.9% women) • Mean age = 26.55 years old (SD = 10.88) *Clinical sample:* N = 385 participants (39.7% women) Mean age = 36.54 years old (SD = 15.86)
Results	*Aim: Warn against the misuse of ML to support the use of user-avatar bond as a diagnostic indicator for gaming disorder.*

		When predicting a test set without algorithm-generated data, the model's precision decreased from 99% to 28%, and the recall decreased from 98% to 11%, leading to a very poor predictive model despite an accuracy of 99%. This study demonstrates the danger of the misuse of ML in psychological research.

Note. PHQ-9 = Patient Health Questionnaire, IGD = Internet Gaming Disorder

6.1. Contributions of the thesis

The upcoming sections will discuss the contribution of the present PhD thesis to the conceptualization and evaluation of PUI. Additionally, the applicability of ML in psychological research using psychometric data will be discussed.

6.1.1. On the conceptualization of problematic use of the Internet and their assessment

The studies conducted in this PhD thesis emphasize the need to further identify the phenotypes, the psychological mechanisms, and the comorbidities involved in different forms of PUI. It is of utmost importance to assume the specificity of each form since the characteristics behind PUI forms such as gaming disorder and cyberchondria differ from each other.

In the case of gaming disorder, *Study 2* (see **Table 19**) emphasized the relationship between the user and their gaming activities. The results show that risky gamers present an obsessive passion for gaming that is predominant, which is related to negative consequences and functional impairment due to an uncontrolled and inflexible involvement in one activity (Vallerand, 2010, 2015). *Study 2* also suggests that gaming motives such as escape/coping, competition, skill development, and fantasy all play crucial roles in the risky gamers' profiles. Additionally, risky gamers frequently report high scores on the lack of perseverance dimension of impulsivity according to the UPPS-P model. *Study 3* (see **Table 19**) also highlights the importance of considering potential psychopathologies such as depression in explaining gaming disorders symptoms. Together, several factors, such as specific gaming motives (e.g., escape/coping, competition, skill development, and fantasy), impulsivity traits (e.g., lack of perseverance), and the presence of psychopathology (e.g., depression), can be argued to be risk factors for problematic gaming behavior. Moreover, in the long term, these risk factors could change the nature of the relationship that a gamer could have with the gaming activity. This could be represented by a transition from a harmonious to a more obsessive passion, which may then be related to uncontrolled gaming activity, negative consequences, and functional impairment. Overall, these findings contribute to a better understanding of gaming disorder and its manifestations.

Regarding cyberchondria, *Study 1* (see **Table 19**) found that intolerance of uncertainty, health anxiety, and fears related to a specific disease (COVID-19) are important factors in understanding its development and maintenance. These findings supported the theoretical model of cyberchondria during the COVID-19 pandemic proposed by Starcevic et al. (2021). This model emphasizes the importance of two factors: (a) the fear of COVID-19 and (b) the intolerance of uncertainty, which together motivate online searches about COVID-19. If not satisfactory, these online searches can become excessive and increase the fear and distress that will fuel the two factors previously mentioned, leading to a vicious circle. *Study 1* also suggest that cyberchondria is most likely characterized by compulsivity or reassurance-seeking behavior (Starcevic, Berle, Arnáez, et al., 2020; Vismara et al., 2020) rather than by impulsivity traits. The association between cyberchondria and impulsivity traits was found to be very low. Thus, impulsivity traits seem not to play a significant role in the development of cyberchondria, in contrast to gaming disorder, where a specific impulsivity trait (i.e., lack of perseverance) seems to be related to risky gaming. This difference is crucial since a distinction exists between impulsivity and compulsivity in the forces driving a given behavior. While impulsivity is fueled by the desire to experience pleasure, arousal, and gratification, compulsivity is fueled by the potential to relieve anxiety or discomfort (Hollander &

Rosen, 2000). Unlike gaming, which represents a pleasant activity, health-related online searches are taking place to relieve health anxiety and discomfort that might be triggered by a perception of threat and intolerance to uncertainty. This indicates that compulsivity is present at the very early stage of cyberchondria, which is not the case for gaming disorder, and thus seems to play an important role in its development. Furthermore, *Study 1* suggests that people who show health anxiety and intolerance to uncertainty often search for health-related information on the Internet to alleviate their concerns. These searches, however, may not always provide the desired reassurance. In fact, they may even contribute to increased distress and prompt more searches, leading to an overwhelming amount of online health information that may be inconsistent or even contradictory (Starcevic, 2023). This vicious cycle can then become uncontrollable, leading to cyberchondria manifestations that might engender functional impairment.

Taken together, the results of these studies support the idea that the variables mentioned above might be linked with a person's predisposition towards PUI. Even if the classification of cyberchondria still needs to be determined, some authors proposed that frameworks such as the Interaction of Person-Affect-Cognition-Execution (I-PACE) model, which is a valuable model for understanding addictive disorders, might be applicable to cyberchondria (Mestre-Bach & Potenza, 2023). According to the I-PACE model (Brand et al., 2016, 2019), a person's core characteristics can lead to a predisposition towards a specific PUI. It argued that while an online behavior is initially gratifying, in the later stages, it may lead to compensation that is then associated with less control and negative consequences in day-to-day living. When focusing on these person's core characteristics, the authors proposed two types of predisposing variables: general variables (e.g., genetic factors, psychopathology, general coping styles, temperamental features) and behavior-specific variables (e.g., specific needs, motives, values). In this regard, the identified risk factors (*Studies 1-3)* can be assigned to general predisposing variables and behavior-specific predisposing variables according to the I-PACE model (see **Table 20**). What speaks against the application of the I-PACE model to cyberchondria is that the latest does not seem to be characterized by impulsivity but compulsivity. The I-PACE model suggests that a combination of predisposing variables and an impulsive coping strategy increases the probability of engaging in specific online behavior reinforced by gratification (Brand et al., 2016, 2019).

Brandtner et al. (2021) made the interesting proposition of integrating desire thinking, defined as "*a conscious and voluntary cognitive process orienting to prefigure images, information and memories about positive target-related experience*" (Caselli & Spada, 2015), into the I-PACE model. The authors suggest that the perception of external and internal triggers, which is dependent on the person's core characteristics according to the I-PACE model (Brand et al., 2016, 2019), may lead to two different entering pathways into desire thinking which is then integrated into the affective and cognitive responses (Brandtner et al., 2021). While one pathway is pleasure-oriented and refers to a gratification expectation, the other is relief-oriented and refers to a compensating expectation. Furthermore, since desire thinking may provoke craving, the authors suggest that both pathways might get dysfunctional (Brandtner et al., 2021). In another study, Demetrovics et al. (2022) observed that in the most substantial cases of behavioral addiction, compulsivity surpasses impulsivity. They thus argued that this might be due to a transition from a reward-driven behavior (characterized by positive reinforcement) to a relief-driven behavior (characterized by negative reinforcement) (Demetrovics et al., 2022). When considering the work of Brandtner et al. (2021) and Demetrovics et al. (2022) in the context of the I-PACE model, the limitation highlighted previously regarding its application to potential addictive behavior characterized by compulsivity instead of impulsivity becomes less harmful. On the one hand, the updated version of the I-PACE model proposed a distinction between the early stages of the development of addictive behavior and the later stages that participate in the maintenance of addictive behaviors (Brand et al., 2019). In the early stages, affective and cognitive responses to triggers induce a decision to engage in the activity that leads to a higher experience of gratification. For the later stages, affective and cognitive responses to triggers are replaced by cue-reactivity and craving, which induce habitual behavior that leads to a higher experience of compensation. On the other hand, the integration proposed by Brandtner et al. (2021) of desire thinking in the I-PACE model is an interesting path to understanding how a potentially addictive behavior characterized by compulsivity can be understood using the I-PACE model. The relief-oriented pathways could already occur in the early stages and promote craving, which would, in the long-term, participate in the maintenance of the addictive behavior (later stages). By capitalizing on the relief-oriented pathway, addictive behaviors characterized by compulsivity (e.g., cyberchondria) could already present higher compensation in the early stages, which is not the case for those characterized by impulsivity (e.g., gaming disorder) (Brandtner et al., 2021). Nevertheless, when considering the work of Demetrovics et al. (2022), it seems that in the later stages and in the most substantial cases, both cyberchondria and gaming disorder are characterized by compulsivity surpassing impulsivity and higher levels of compensation.

When considering whether a behavior is relief-driven or reward-driven, the I-PACE model can help understand the development and maintenance of different forms of PUI. While the classification of cyberchondria is still unclear, its interpretation through the I-PACE model suggests its consideration as an online behavioral addiction. In a broader sense, the I-PACE model shows a flexibility that can be used to understand different forms of PUI. Yet, it is important to consider the particularities of different forms of PUI such as cyberchondria and gaming disorder. As shown, the variables associated with a person's core characteristics greatly differ between gaming disorder and cyberchondria, especially regarding their association with impulsivity and compulsivity. For this reason, the versatility presented by the I-PACE model might be a double-edged weapon. On the one hand, it may be a powerful framework to explore and understand potentially new forms of PUI regarding their development and maintenance on a general level. On the other hand, its complexity and flexibility come at the expense of being more precise regarding the etiology of a specific form of PUI. In this regard, it can be beneficial to complement the I-

PACE model with models that target the PUI form of interest. For example, the model proposed by Starcevic et al. (2021) for cyberchondria, and the dualistic model of passion for gaming disorder (Vallerand, 2010, 2015), coupled with the identification of their respective vulnerable factors, provide a deeper understanding of their conceptualization.

Table 20

Person's core characteristics highlighted in the studies of the present PhD thesis

	Person's core characteristics			
	General predisposing variables		**Behavior-specific predisposing variables**	
Cyberchondria	Health anxiety	*(Psychopathology)*	Collecting information	*(Need)*
	Reassurance seeking	*(Coping style)*	Fear of a specific disease; relieve anxiety	*(Motives)*
	Intolerance to uncertainty	*(Temperamental feature)*		
Gaming disorder	Depression	*(Psychopathology)*	Expressing a passion	*(Need)*
	Escape real life	*(Coping style)*	Motivation of gaming: escape/coping, competition, skill development, fantasy; Experiencing pleasure and enjoyment	*(Motives)*
	Lack of perseverance	*(Temperamental feature)*		

Brand, Rumpf, Demetrovics, et al. (2020) proposed a set of three meta-level criteria for considering the integration of a specific disorder into the ICD-11 category of "*other specified disorder due to addictive behaviors".* One of the criteria put forth by the authors is that "c*urrent theories and theoretical models belonging to the field of research on addictive behaviors describe and explain most appropriately the candidate phenomenon of a potential addictive behavior*" (Brand, Rumpf, Demetrovics, et al., 2020). In this regard, and as it has been argued previously, cyberchondria could fulfill this criterion through the theoretical framework of the I-PACE model. The consideration of the potential inclusion of cyberchondria and other forms of PUI in the ICD-11 category of "*other specified disorder due to addictive behaviors*" (Mestre-Bach & Potenza, 2023) raises questions about how to assess PUI in general.

The ICD-11 criteria of two disorders (compulsive sexual disorder and gaming disorder) that belong to different diagnostic categories, were compared by Wegmann et al. (2022). When comparing the criteria of both, the authors highlighted the fact that they share common core criteria: (a) there is a loss of control over behavior, (b) the behavior becomes more important, (c) the behavior continues or worsens despite negative consequences, and (d) there is noticeable distress and/or functional impairment (Wegmann et al., 2022). Because of this convergence of their core criteria, it may be useful to consider the criteria highlighted by Wegmann et al. (2022) as potentially transdiagnostic. These criteria could be used to assess PUI in its various forms, particularly since the ICD-11 already includes a form of PUI (i.e., the gaming disorder) and successfully addresses its core criteria through them. This contrasts with the DSM-5 which include both core and peripheral criteria of gaming disorder and thus might over-pathologize healthy gamers who are highly involved, as it is argued in studies 2 and 3 (see **Table 19**). Additionally, these criteria could be used to explore the prevalence of specific forms of PUI such as cyberchondria in the general population and their relevance in terms of public health.

In summary, although cyberchondria and gaming disorder can be understood within the same general framework (such as the I-PACE model), utilizing additional models specific to each condition can enhance their understanding and provide important insights for their treatment and prevention interventions. Regarding their assessment, the criteria proposed by the ICD-11 for the assessment of gaming disorder may have a transdiagnostic nature by tackling core features of addictive behaviors. In that sense, the present PhD thesis supports the idea of using these criteria to address the various forms of PUI. Furthermore, they could address the question of their potential inclusion within diagnostic manuals by assessing their potential prevalence and issues in public health.

6.1.2. On the use of machine learning in psychological research using psychometric data

The present PhD thesis capitalized on various forms using a combination of traditional statistical and ML analyses, as recommended by various authors (Dehghan et al., 2022; Orrù et al., 2020; Rajula et al., 2020; Rosenbusch et al., 2021). Moreover, because the quality of a given ML model is computed based on a new, independent sample with unknown variance, ML methods presents more reliable and more robust conclusions when compared to traditional statistics (Rosenbusch et al., 2019; Vabalas et al., 2019).

The ML analyses used in studies 1 and 3 capitalized on a robust methodology called repeated nested cross-validation that is known to be able, with less than 1000 participants, to produce reliable and unbiased performance estimates (Vabalas et al., 2019). Additionally, it allows for the optimization of a ML algorithm by tuning its hyperparameters while simultaneously reducing the risks of overfitting (Vabalas et al., 2019). Also, *Study 3* relied on the fact that ML algorithm can use predictors of different nature (i.e., categorical, continuous, ordinal) without making any underlying assumptions to determine a strong predictive model (Rajula et al., 2020; Vélez, 2021). These characteristics of ML represent, undeniably, a significant advantage in psychological research. It is common in psychological research to use both socio-demographic variables and variables from scales that assess psychological constructs and disorder, leading to a total score, and thus continuous or ordinal variable, or to the creation of categories (e.g., presence or absence of a disorder). The use of ML might then raise the possibility of implementing every measured variable in the context of a survey inside the same model without making any underlying assumptions, thus exploiting the entire potential of a given dataset.

In *Study 2*, ML clustering techniques were used to identify a gaming passion profile that characterizes risky gamers. Furthermore, ML regression tasks in Studies 2 and 3 helped in linking a specific psychopathology or type of passion with the criteria of gaming disorder according to the DSM-5. In this context, ML allowed us to combine person-centered and variable-centered approaches. The person-centered approach tackles the identification of psychological factors, provides helpful information to avoid the pathologization of highly involved but healthy gamers, and helps to elaborate adapted treatment or prevention interventions. For example, *Study 2* allows the identification of a specific gaming passion profile related to risky gamers and identifies important psychological factors (i.e., gaming motives, impulsivity trait) that can be addressed in the context of treatment or prevention. On the other side, the variable-centered approach allows the evaluation of gaming disorder criteria to identify the most discriminative one for the assessment of a potential gaming disorder. Thanks to the variable-centered approach, Studies 2 and 3 identified core criteria that could improve gaming disorder assessment. By doing so, the use of ML contributed to the conceptualization, assessment, and clinical approaches to the treatment of gaming disorder.

Lastly, *Study 4* highlights the risks associated with a liberal use of ML-based analytical approaches in psychological research. In particular, *Study 4* informs against the misinterpretation and overselling of ML output. It is important to highlight the necessity for researchers to understand ML methods to avoid any over-statement (Vélez, 2021). Moreover, it also addresses the challenge of ML classification tasks to accurately predict the presence of a specific mental disorder based on highly imbalanced data (i.e., a vast majority of participants belong to one specific group). In this regard, methods such as the K-NN SMOTE algorithm are proposed, but when correctly applied, these methods seem to present important limitations in psychological research. The literature recognizes the challenge of ML algorithms when dealing with highly imbalanced data (Orrù et al., 2020; Rosenbusch et al., 2021), and future research could focus on developing methods to address this issue.

To summarize, the current PhD thesis advocates the use of ML methods alongside traditional statistical approaches to overcome the limitations of the latter. This approach is aligned to so-called multiverse analyses in psychological science (e.g., Steegen et al., 2016). The thesis also demonstrates that ML methodologies offer a helpful and convenient instrument for psychological research topics such as the

PUI. They lead to more reliable and robust results that can be generalized and reproduced while simultaneously being able to handle different types (i.e., continuous, ordinal, categorical) of variables.

6.2. Strengths and limitations of the present PhD thesis

The present PhD thesis has several significant strengths, including the use of multiple ML methods through various studies. These studies employed ML methods of classification, regression, and clustering in PUI research using psychometric data. This large range of ML application contributed to gaining a comprehensive understanding of the use of ML in psychological research, providing an overall view of its potential. Moreover, the thesis used robust ML methods such as repeated nested cross-validation, which provided reliable and robust results, even with samples containing less than 1000 participants. It is also worth noting that two of the studies presented in the thesis contained more than 18,000 participants. Furthermore, the thesis made a major contribution to using ML methods in the context of PUI. To our knowledge, it contained the first study using ML in the context of cyberchondria, addressing the issue during the crucial moment that was the world pandemic of COVID-19. The present PhD thesis also has implications in providing guidelines to avoid misusing ML algorithms. Finally, the thesis addressed the gaming disorder PUI with samples composed by a good gender distribution. Moreover, the most prevalent PUI form (i.e., gaming disorder) was examined in different age groups, making the reported results more generalizable. While Study 2 consisted of a sample of adults, the Study *3* sample consisted of adolescents.

Despite these strengths, this PhD thesis also comes with limitations. First, it only focuses on two specific forms of PUI. However, it argues that it seems to be possible to use a general framework to conceptualize and understand PUI in its various forms. Moreover, it promotes the use of a global assessment tool using transdiagnostic criteria for PUI in its different forms to assess their prevalence and potential relevance regarding public health concerns. Another limitation of the thesis pertains to the use of psychometric data. As mentioned in *Section 1.3*, the accuracies of ML models are inherently limited by the nature of the tools used to train the models. Therefore, it highly depends on the limitations of the psychometric data themselves (e.g., social desirability, attention availability, test environment) (Fardouly et al., 2022). Additionally, psychometric data are usually assessed through self-reports that may be affected by response biases (e.g., social desirability, poor self-reflection abilities, and recall bias). The cross-sectional nature of the studies presented in the PhD thesis prevented the investigation of any causal relationships. Furthermore, although it is assumed that ML methods are more robust and reliable than traditional statistics, the present PhD thesis did not compare both approaches. It relied on the existing literature in this regard. Finally, it is worth noting that the samples used in the present PhD thesis consisted mostly of highly educated and European participants, which might not be representative of the general population.

6.3. Future perspective

Through its findings and limitations, the present thesis raises the potential for some avenues for future research to improve the conceptualization and assessment of the different forms of PUI. It also encourages future research to find solutions for better use of ML and to overcome the limits of ML in psychological research that have been raised regarding the classification of a clinical sample. Firstly, the present work proposes a scoping review of the use of ML in PUI research involving psychometric data. However, it highlights the importance of a potential systematic review using a strict methodological approach and involving multiple researchers for that purpose. This systematic review could, in addition to reporting the ML models used and their results, address the quality of the research and the ML analysis report. It has been observed during the scoping review that there is currently a lack of consistency regarding the reporting of ML analyses, and some manuscripts lack information or descriptions regarding the models that have been used. This observation has also been made in the current literature (Klement & El Emam, 2023). Moreover, another perspective would be to summarize the different ML methodologies and propose guidelines for good practice, but also for the report of each specific ML analysis. This type of research should promote more consistency and well-informed use of ML analyses in psychological research. Another potential research area is to combine longitudinal data and ML analyses to predict future problematic behavior. Machine learning models are known for their ability to predict unknown data. Therefore, this application may bring valuable contributions to psychological research and public health for prevention, early detection, or treatment purposes. Finally, regarding the conceptualization of PUI and its various forms, further studies are necessary to support or invalidate the current theoretical frameworks and assessment tools. Even though the present PhD thesis supports the use of transdiagnostic criteria to assess the diverse forms of PUI that are (a) a loss of control over behavior, (b) the behavior becoming more important, (c) the behavior that continues or worsens despite adverse consequences, and (d) noticeable distress and/or functional impairment (Wegmann et al., 2022), more research is still needed in this regard. Moreover, solutions regarding the precision and sensitivity of ML classification models are of great importance. Improving such ML models could lead to a new type of diagnostic and prevention tools through digital phenotyping, defined as "*the moment-by-moment, in situ quantification of the individual-level human phenotype using data from personal digital devices*" (Huckvale et al., 2019).

6.4. General conclusion

Based on several studies on two forms of PUI, namely gaming disorder, and cyberchondria, this PhD thesis suggests that it is possible to conceptualize different PUI forms within the same theoretical framework, such as the I-PACE model. Nevertheless, because of the complexity and versatility of such a model, the present thesis also acknowledges its potential limit and the need to consider additional models that target the PUI form of interest to understand its conceptualization optimally. The thesis also suggests that the criteria for gaming disorder proposed by the ICD-11 may have a transdiagnostic nature, which means that these criteria may be used to address various forms of PUI and, thus, cyberchondria. These criteria include: (a) an impaired control of a specific behavior or activity, (b) an increasing priority given to this behavior or activity to the extent that it takes precedence over other life interests and daily activities, (c) a continuation or escalation of this behavior or activity despite the occurrence of negative consequences, and (d) it results in noticeable distress and/or functional impairment in areas such as work, social life, or family relationships. These criteria could then be used to define a specific PUI and determine the potential prevalence and related public health issues, and whether it should be included in diagnostic manuals. The PhD thesis also advocates for the use of ML methods alongside traditional statistical approaches to overcome the latter's limitations. It supports the notion that ML methodologies are important tools for psychological research topics such as the PUI, as they lead to more reliable and robust results that can be generalized and reproduced. However, a limitation of ML pertains to its lack of precision and sensitivity in detecting PUI or other mental conditions. By overcoming this limitation new diagnostic and intervention tools could be developed using ML with digital phenotyping data.

6.5. References

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Scientific contribution

PUBLICATIONS

JOURNAL ARTICLES (peer-reviewed)
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7. **Infanti, A.***, Giardina, A.*, Razum, J., King, D.L., Baggio, S., Snodgrass, J.G., Vowels, M., Schimmenti, A., Király, O., Rumpf, H-J., Vögele, C., l Billieux, J. (2024). User-Avatar Bond as Diagnostic Indicator for Gaming Disorder: A Word on the Side of Caution. Commentary on: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning (Stavropoulos et al., 2023). *Journal of Behavioral Addictions. Accepted for publication.*

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2. Ortmann, J., **Infanti, A.**, van Dyck, Z., Vögele, C. (n.d). Psychometric validation of the English and French version of the Eating Disorder-specific Interoceptive Perception Questionnaire (EDIP-Q). *Submitted in the journal Appetit (under revision)*

1. Nogueira-López, A.*, **Infanti, A*.**, Rial-Boubeta, A., Vögele, C., and Billieux, B. (n.d). Playing with well-being: How problematic video game use affects emotional health and life satisfaction in Spanish adolescents. *Manuscript in preparation*

BOOK CHAPTER

1. **Infanti, A.**, Flayelle, M., Billieux, J., von Hammerstein, C. (n.d). Les motivations à jouer et leurs liens avec le trouble du jeu vidéo. Dans Khazaal, Y., Benyamina, A., & Billieux, J (dir.), *Trouble du jeu vidéo*. Ouvrages collectifs L'essentiel, RMS éditions. *Submitted*

SCIENTIFIC COMMUNICATIONS (* = speaker)

8. **Infanti, A.***, Nogueira-López, A., Rial-Boubeta, A., Vögele, C., & Billieux, J**.** Exploring the links between problematic gaming, emotional well-being, depression, and life satisfaction. Oral communication at the 9th International Conference on Behavioral Addictions (ICBA). Incheon, South Korea, 8-10 July 2024. (accepted)

7. **Infanti, A.***, Valls-Serrano, C., Perales, J.-C., Vögele, C., & Billieux, J. How gaming passion contributes to the definition and diagnosis of problem gaming: A combined person-centered and supervised machine-learning analysis. Oral communication at the 8th International Conference on Behavioral Addictions (ICBA). Incheon, South Korea, 23-25 August 2023.

6. **Infanti, A.***, Valls-Serrano, C., Perales, J, C., Vögele, C., & Billieux, J. The Dualistic Model of passion in the scope of problematic gaming. Oral communication at the Digital Games Research Association (DIGRA) conference. Seville, Spain, 19-23 June 2023.

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4. **Infanti, A.***, Valls-Serrano, C., Perales, J.C., Vögele, C., & Billieux, J. Contribution de la passion dans la définition et le diagnostic de l'usage problématique du jeu vidéo. Communication orale aux 17ème journées scientifiques du Groupe de Réflexion en Psychopathologie Cognitive (GREPACO). Louvain-La-Neuve, Belgium, 22-23 May 2023.

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2. **Infanti, A.***, Starcevic, V., Schimmenti, A., Khazaal, Y., Karila, l., Giardina, A., Flayelle, M., Baggio, S., Vögele, C., & Billieux, J. Les prédicteurs de la cyberchondrie durant la pandémie de COVID-19 : Une approche en apprentissage automatique supervisé. Communication orale aux 17ème journées scientifiques du Groupe de Réflexion en Psychopathologie Cognitive (GREPACO). Lausanne, Suisse, 30-31 May 2022.

1. **Infanti, A.***, Vögele, C., Deleuze, J., Baggio, S., & Billieux, J. Évaluation de la validité des critères du Trouble lié au Jeu Vidéo en ligne selon le DSM-5 : Une approche en “machine learning”. Communication orale (en ligne) aux 16èmes journées scientifiques du Groupe de Réflexion en Psychopathologie Cognitive (GREPACO). Caen, France, 31 May - 1 June 2021.

OTHER SCIENTIFIC ACTIVITIES

REVIEWING FOR THE FOLLOWING SCIENTIFIC JOURNALS

2. Addictive Behaviors

1. Cyberpsychology

STUDENTS SUPERVISION (reported in the relevant languages)

4. Nolan Pedro Fernando (2023). Adaptation et validation en français de la Smartphone Impact Scale (SIS). Mémoire de recherche de maîtrise ès Sciences en psychologie. *University of Lausanne, Switzerland.*

3. Noé Rossel & Stéphane Rohrer (2023). Why do you play League of Legends? High involvement VS Problematic involvement. Mémoire de recherche de maîtrise ès Sciences en psychologie. *University of Lausanne, Switzerland.*

2. Seyedeh Boshra Hedayatzadeh Razavi (2022). Impulsivité et Cyberchondrie dans le contexte de la pandémie de Covid-19. Mémoire de recherche de maîtrise ès Sciences en psychologie. *University of Lausanne, Switzerland.*

1. Hubertus Justine (2020). Validation of the French Smartphone Impact Scale (SIS) – A Study Protocol. Thesis for the Master of science in psychology, *University of Luxembourg, Luxembourg.*