



## Personality biomarkers of pathological gambling: A machine learning study



Antonio Cerasa<sup>a,j,\*</sup>, Danilo Lofaro<sup>b,h,1</sup>, Paolo Cavedini<sup>c</sup>, Iolanda Martino<sup>a</sup>, Antonella Bruni<sup>d</sup>, Alessia Sarica<sup>a</sup>, Domenico Mauro<sup>e</sup>, Giuseppe Merante<sup>f</sup>, Ilaria Rossomanno<sup>a</sup>, Maria Rizzuto<sup>a</sup>, Antonio Palmacci<sup>g</sup>, Benedetta Aquino<sup>h</sup>, Pasquale De Fazio<sup>d</sup>, Giampaolo R. Perna<sup>c,k,l</sup>, Elena Vanni<sup>c</sup>, Giuseppe Olivadese<sup>a</sup>, Domenico Conforti<sup>b</sup>, Gennarina Arabia<sup>i</sup>, Aldo Quattrone<sup>a,i</sup>

<sup>a</sup> Institute of Molecular Bioimaging and Physiology, National Research Council (IBFM-CNR), 88100 Catanzaro, Italy

<sup>b</sup> de-Health Lab, Department of Mechanical, Energy, Management Engineering, University of Calabria, 87036 Rende (CS), Italy

<sup>c</sup> Department of Clinical Neurosciences, Hermanas Hospitalarias, Villa San Benedetto Menni Hospital, FoRiPsi, 22032, Albese con Cassano, Como, Italy

<sup>d</sup> Psychiatric Unit, Department of Health Science, Magna Graecia University, 88100, Catanzaro, Italy

<sup>e</sup> Centro Clinico "San Vitaliano" – Malattie Neuromuscolari, Centro di Riabilitazione, 88100 Catanzaro, Italy

<sup>f</sup> Ascoc, Scuola di Psicoterapia cognitivo-comportamentale, 87040, Castrolibero (CS), Italy

<sup>g</sup> Innovation Lab, Infobyte@, 80124 Naples, Italy

<sup>h</sup> Kidney and Transplantation Research Center, Annunziata Hospital, 87100 Cosenza, Italy

<sup>i</sup> Institute of Neurology, Department of Medicine, "Magna Graecia" University, 88100 Catanzaro, Italy

<sup>j</sup> S. Anna Institute and Research in Advanced Neurorehabilitation (RAN), 88900 Crotona, Italy

<sup>k</sup> Department of Psychiatry and Neuropsychology, Faculty of Health, Medicine and Life Sciences, Maastricht University, 6200, Maastricht, The Netherlands

<sup>l</sup> Department of Psychiatry and Behavioral Sciences, Leonard Miller School of Medicine, Miami University, 33136 -1015, Miami, USA

### HIGHLIGHTS

- We applied artificial intelligence to extract markers of pathological gambling.
- Personality profile was used to train classification-regression trees algorithm.
- Classification algorithm discriminates gamblers with 77% of accuracy.
- Multidimensional construct of traits characterized gamblers from controls.

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### ABSTRACT

**Background:** The application of artificial intelligence to extract predictors of Gambling disorder (GD) is a new field of study. A plethora of studies have suggested that maladaptive personality dispositions may serve as risk factors for GD.

**New method:** Here, we used Classification and Regression Trees algorithm to identify multivariate predictive patterns of personality profiles that could identify GD patients from healthy controls at an individual level.

Forty psychiatric patients, recruited from specialized gambling clinics, without any additional comorbidity and 160 matched healthy controls completed the Five-Factor model of personality as measured by the NEO-PI-R, which were used to build the classification model.

**Results:** Classification algorithm was able to discriminate individuals with GD from controls with an AUC of 77.3% (95% CI 0.65–0.88,  $p < 0.0001$ ). A multidimensional construct of traits including sub-facets of openness, neuroticism and conscientiousness was employed by algorithm for classification detection.

\* Corresponding author at: Institute of Molecular Bioimaging and Physiology, National Research Council (IBFM-CNR), Viale Europa, 88100 Catanzaro, Italy.

E-mail address: [antonio.cerasa76@gmail.com](mailto:antonio.cerasa76@gmail.com) (A. Cerasa).

<sup>1</sup> These authors equally contributed to this work.

*Comparison with existing method(s):* To the best of our knowledge, this is the first study that combines behavioral data with machine learning approach useful to extract multidimensional features characterizing GD realm.

*Conclusion:* Our study provides a proof-of-concept demonstrating the potential of the proposed approach for GD diagnosis. The multivariate combination of personality facets characterizing individuals with GD can potentially be used to assess subjects' vulnerability in clinical setting.

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## 1. Introduction

Computational psychiatry is a new field of Machine Learning (ML) application born from pressing clinical needs to improve understanding, early detection and preventive strategies of several disorders, such as Gambling Disorder (GD), where etiology, underlying mental processes, and, subsequently, sub-differentiation and nosology, remain to be clarified (Huys et al., 2016). The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) replaced the previous diagnosis of Pathological Gambling with GD reclassifying them in a new category on behavioral addictions. Generally, GD is a heterogeneous disorder being highly comorbid with other psychiatric disorders such as substance abuse, major depression or anxiety disorders (Petry, 2005; Petry et al., 2013; Toneatto and Nguyen, 2007; Hodgins et al., 2011). Gambling disorders are also characterized by anatomical and metabolic alterations in specific brain regions involved in the reward system and emotional control (Grant et al., 2016; Meng et al., 2014). Gamblers showed dysfunctions in cognitive or executive processes, such as deficits in problem-solving (Marazziti et al., 2008), disruption of inhibition process (Goudriaan et al., 2006) or decision-making (Clark et al., 2013). The clinical picture is completed by the presence of maladaptive personality dimensions, which hampered the vulnerability to compulsive behavior.

In the past three decades, researchers have identified a plethora of predictive risk factors associated with the development of gambling disorders (Petry, 2005). The aforementioned clinical and biological factors together with young age, male gender and low socioeconomic status are all associated with the insurgence of GD (Johansson et al., 2009; Hodgins et al., 2011). However, the complex interaction among these factors is poorly known and highly heterogeneous.

ML can exploit the complex correlation and interaction between variables in a multivariate way highlighting differences that might otherwise remain undetected (Orriù et al., 2012; Huys et al., 2016). In the recent years, artificial intelligence has been proven a new effective way to automate the analysis of medical data and to extract new combination of biomarkers useful for early diagnosis (Segovia et al., 2012; Cerasa, 2016; Salvatore et al., 2016; Illan et al., 2012). With respect to the classical univariate perspective of the past studies where human behavior has been associated in a one to one fashion to clinical symptoms, the vast amount of information characterizing the GD realm might be used to train a multivariate classifier with the scope to predict a specific phenotype or behavior. Indeed, identifying potential risk factors for GD is of primary importance for planning preventive and therapeutic interventions. Overall, in clinical realm artificial intelligence has always been applied using neuroimaging data (Borgwardt and Fusar-Poli, 2012). Due to their invasiveness and high cost, there is a need for more inexpensive alternative techniques that could contribute to early diagnosis of GD.

In the last few years, a substantial body of empirical work indicates that particular combinations of personality traits (high neuroticism with low level of Openness and Consciousness) characterized patients with GD (Odlaug et al., 2013; Grant et al., 2016).

However, this kind of data originated from classical univariate statistical approach that identifies differences between patients and controls at a group level. The univariate approach markedly increases our knowledge about behavioral mechanisms underlying psychiatric symptoms, but with a very limited translation to individual diagnosis in a clinical setting.

Generally, personality traits are studied because these are enduring dispositions that underlie individuals' cognitive, emotional and behavioral tendencies (Costa et al., 2001). If there are changes in these traits along life this can serve as a possible hallmark to identify underlying pathology that may contribute to uncharacteristic actions by a person (Harris et al., 2012). Because of its relative consistency over ages, these traits are related to individuals' lifestyles and have been implicated as risk factor in several physical and mental health, such as drug users (Terracciano et al., 2008), obesity (Sutin et al., 2011) or Alzheimer's disease (Terracciano et al., 2014). For this reason, personality has been regarded as one of the most important topics in psychological research (Ozer and Benet-Martinez, 2006). Since personality is an implicit psychological construct, which cannot be observed directly, it has to be measured through valid behavioral indicators (Burger, 2008). Currently, the five-factor model (FFM; McCrae and Costa, 1997) is the most widely accepted theoretical framework for measuring personality (McCrae and John, 1992). In the past decades, a general worldwide consensus has emerged that variations in human personality may be best captured across five dimensions: Openness to Experience, Conscientiousness, Agreeableness, Extraversion and Neuroticism.

The building of classification algorithms based on personality data has widely been employed in the last few years (Lima and de Castro, 2014). At a computational level, data extracted from personality inventory can be easily translated in a multi-label classification problem because each of these factors may correspond to a class for a classifier useful to predict social orientations (Van Der Heide et al., 2012; Lima and de Castro, 2014; Eftekhar et al., 2014) or drug abuse predisposition (Ahn and Vassileva, 2016). To date, no studies have employed multiple dimensions of personality as predictors of GD in a machine-learning model approach. Among the high number of classification algorithms, decision trees showed its strengths in many clinical fields. In particular, classification and regression trees (CART) algorithms have been shown to achieve good classification performance similar to others approaches (Nisbet et al., 2009; Song and Lu, 2015; Cohen et al., 2016; Besga et al., 2015). The most important advantage of this method is its intrinsic and automatic variables selection, which provides the relative importance of features. The ranking of variables could be indeed used to formulate clinical hypotheses and to find, as in this case, psychological personality correlates.

The aim of the present work is twofold: first, to evaluate the contribution of psychological measures combined to artificial intelligence for the automated diagnosis of GD; second, to extract the multidimensional construct which might play a role in determining individual's risk of developing GD.

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