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PROBLEMATIC USE OF THE INTERNET AND SOCIAL NETWORKING SITES: A PSYCHO-PHYSIOLOGICAL PERSPECTIVE

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Gali May, L. (2018). Absorbed by light [Light Sculpture]. Amsterdam light festival

To my fox who changed my life

by inspiring my mind and my heart

"There is a light and it never goes out"

The Smiths (1986). There is a light that never goes out. On The Queen is Dead.

Table of contents

SECTION 2: MECHANISMS UNDERLYING PROBLEMATIC SOCIAL NETWORKING SITES USE

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List of Abbreviations

ACC: Anterior Cingulate Cortex

ADHD: Attention-Deficit/Hyperactivity Disorder

AIC: Akaike Information Criterion

APA: American Psychiatric Association

ATS: Addictive Tendencies Scale

AUC: Area Under the Curve

AUD: Alcohol Use Disorder

BFAS: Bergen Facebook Addiction Scale

BIC: Bayesian Information Criterion

BIS-11: Barratt Impulsiveness Scale

BSMAS: Bergen Social Media Addiction Scale

CAST: Cannabis Abuse Screening Test

CFA: Confirmatory Factor Analysis

CFI: Comparative Fit Index

CIUS: Compulsive Internet Use Scale

CRF: Corticotropin-Releasing Factor

CUD: Cannabis Use Disorder

DA: Dopamine

DASS-21: Depression Anxiety Stress Scales-21

DSM: Diagnostic and Statistical Manual for Mental Disorders

ECG: Electrocardiogram

EEG: Electroencephalogram

ERPs: Event-Related Potentials

FDQ: Facebook Dependence Questionnaire

GBT: Cognitive Behavioral Therapy

GBT-IA: Cognitive Behavioral Therapy for Internet Addiction

GLMM: Generalized Linear Mixed-Effects Model

GLMs: Generalized Linear Models

Glu: Glutamate

GPIU: Generalized Pathological Internet Use

GPIUS: Generalized Problematic Internet Use Scale

GPIUS2: Generalized Problematic Internet Use Scale 2

IAT: Internet Addiction Test

ICD: International Classification of Diseases

IGD: Internet Gaming Disorder

I-PACE: Person-Affect-Cognition-Execution

IRPS: Internet Related Problem Scale

ITI: intertrial interval

LMM: Linear Mixed-Effect Model

LMMs: Linear Mixed-Effect Models

LPP: Late Positive Potential

MA: methamphetamine

NAc: Nucleus Accumbens

NE: Norepinephrine

OCD: Obsessive-Compulsive Disorder

OCI-R: Obsessive-Compulsive Inventory-Revised

OCS: Online Cognition Scale

OFC: Orbitofrontal Cortex

PFC: Prefrontal Cortex

PFU: Problematic Facebook Use

PFUS: Problematic Facebook Use Scale

PFUs: Problematic Facebook Users

PIU: Problematic Internet Use

PIUQ-SF-6: Problematic Internet Use Questionnaire-Short Form

PIUs: Problematic Internet Users

POSI: Preference for Online Social Interaction

POSI: Preference for Online Social Interaction

P-P: Probability-Probability

PSNSU: Problematic Social Networking Sites Use

RMSEA: Root Mean Square Error of Approximation

rMSSD: root Mean Square of Successive Differences of normal-to-normal intervals

ROC: Receiver Operating Characteristic

RTs: Reaction Times

SDNN: Standard Deviation of all Normal-to-Normal intervals

SEM: Structural Equation Model

SNSs: Social Networking Sites

SNWAS: Social Networking Addiction Scale

S-S: stimulus-stimulus associations

SUDs: Substance Use Disorders

TLI: Tucker Lewis index

VIF: Variance Inflation Factor

VTA: Ventral Tegmental Area

WHO: World Health Organization

WLSMV: Weighted Least Squares Mean and Variance

Abstract

In the framework of the theoretical debate on whether it is appropriate to consider Problematic Internet Use (PIU) and problematic Social Networking sites use as addictive behaviors, the main aim of this work was to build on and extend previous findings about the psycho-physiological mechanisms underlying these problematic behaviors.

In the first study, self-report instruments in a cross-sectional design highlighted a pattern of symptoms related to anxiety/mood disorders and Obsessive-Compulsive Disorder (OCD) in PIU. Interestingly, only hoarding and obsessing symptoms predicted the condition of problematic vs. non-problematic Internet use, suggesting an altered mechanism shared by OCD and PIU that may lie at the basis of PIU development.

In the second study, the relationship between autonomic reactivity during a stressful task and craving was investigated in PIU. We found lower resting heart rate variability (HRV) before the stressful task in individuals with PIU vs. non-PIU. Moreover, after the stressful task, lower HRV in PIU was related to higher craving for Internet use, suggesting that, in PIU, reduced autonomic flexibility is a stable condition that is related to reduced capacity for self-regulating craving.

In the third study, inhibitory processes and their relationship with HRV were assessed in PIU by an emotional Go/Nogo task. Lower performance accuracy among problematic- than non-problematic users was found. Moreover, only among problematic Internet users lower HRV predicted less efficient task performance upon the presentation of unpleasant stimuli, suggesting reduced HRV to be a potential indicator of defective inhibitory control in PIU.

As for the fourth study, the cognitive-behavioral model of generalized PIU in the context of Problematic Facebook Use (PFU) was tested. The main result showed that using Facebook for mood regulation has a greater impact than preference for online social interaction on negative outcomes of PFU, suggesting that using Facebook to regulate mood is a core component of PFU.

Cue-reactivity and response inhibition in the presence of Facebook-related and affective stimuli in individuals with vs. without PFU were also investigated. In the fifth study, the Event-Related Potentials (ERPs) were recorded during the passive viewing of Facebook-related, pleasant, unpleasant and neutral pictures. The results did not provide evidence for cue-reactivity to Facebook-related cues in problematic users. Rather, Facebook-related cues elicited larger ERP positivity than neutral, and comparable to unpleasant stimuli, in all Facebook users. Interestingly though, only in problematic users the ERP positivity elicited by Facebook-related cues was inversely related to subjective arousal, suggesting that negative reinforcement processes might characterize PFU as a behavioral addiction. Moreover, similarly to drug addiction, in which enhanced and sustained reward reactivity would increase the likelihood of risky behavior, we found long-lasting larger ERP positivity to pleasant than unpleasant pictures only in problematic Facebook users.

In the sixth study, we investigated whether individuals with vs. without PFU show greater difficulties in inhibiting motor responses during an emotional Go/Nogo task. Overall, our findings suggest that problematic users are characterized by under-engagement of response inhibition processes in the context of natural reward- and Facebook-related stimuli, as indexed by reduced overall accuracy and Nogo-P3 amplitude to Facebook-related, pleasant and neutral stimuli than to unpleasant stimuli.

Overall, the findings of these studies seem to suggest that PIU and PFU share similar affective and cognitive processes with addictive behaviors. In order to overcome some methodological problems, identifying core symptomatology and reliable diagnostic criteria of PIU has become a priority.

SECTION 1: MECHANISMS UNDERLYING PROBLEMATIC INTERNET USE

Dong-kyu, K. (2013). Luncheon [based on: The luncheon on the grass by Édouard Manet (1862–1863)]. ART X SMART Project

“Given the recent surge in access to information technologies, we have a new generation of diverse computer users. As this case suggests, contrary to the stereotype of a young, male, computer-savvy on-line user as the prototypic Internet "addict", new consumers of the Internet who do not match this general stereotype are just as susceptible. Given the severity of the family impairment in this case, future research should focus on the prevalence, characteristics, and consequences of this type of addictive behavior”

(Young, 1996)

Characterizing Problematic Internet Use

Introduction

In the last two decades, the Internet has become part of our daily life, changing the way we work, communicate, shop, and so on. Despite its advantages, many people spend more time than necessary on the Internet and sometimes a psychopathological condition may result with psychological, social, school, and/or work difficulties in a person's life (Van Rooij & Prause, 2014; Young, 1998a). Despite the growing number of studies in this context, there is not yet an agreement on the conceptualization of Internet-related psychological problems (Chamberlain et al., 2016; Kardefelt-Winther, 2017). The reasons for this lack of consensus can be found in existing research gaps and controversies surrounding Internet-related behaviors. Psychological problems related to Internet use were first labeled as *Internet Addiction Disorder*, defined as an impulse-control disorder that does not involve an intoxicant (Young, 1998b). Since then, several different labels have been used in the scientific literature to capture Internet-related problematic behavior, including *Internet addiction*, *compulsive Internet use*, *computer addiction*, *pathological Internet use*, and *problematic Internet use* (Cash, Rae, Steel, & Winkler, 2012). Given these debates, we will use the term Problematic Internet Use (PIU) in this dissertation although other terms (e.g., Internet addiction) have been used in the literature.

The extent to which Internet overuse may represent a psychopathological condition is still under discussion, with some researchers proposing that Internet may work as a vehicle for expressing an individual's dependence on other behaviors (e.g., gaming, sex), which represent the "true" problematic feature (Davis, 2001; Griffiths, 2000; Yellowlees & Marks, 2007). In this perspective, Internet overuse would reflect an addiction *on* the Internet, it is content-specific and can occur even in the absence of Internet access (Caplan, 2010; Davis, 2001; Griffiths, 2000). As a consequence, PIU would be more appropriately acknowledged and diagnosed as an aspect of other psychopathological conditions, e.g., gambling disorder (Shaffer, Hall, & Vander Bilt, 2000). Moreover, in more than half of patients with excessive Internet use and a comorbid Diagnostic and Statistical Manual for Mental Disorders (DSM), Fourth Edition (American Psychiatric Association, 2000), PIU was considered as a symptom of another underlying psychopathological condition (Ahn, 2007).

Differently, many researchers in the field have considered PIU as a specific psychopathological condition that shares core components with addictive behaviors and with Impulse Control Disorder (Cheever, Moreno, & Rosen, 2018; Fu, Chan, Wong, & Yip, 2010; Potenza, 2006; Shapira, Goldsmith, Keck, Khosla, & McElroy, 2000; Shapira et al., 2003; Yellowlees & Marks, 2007; Young, 1998b). However, animal models and clinical studies suggest that behavioral addictions, including gambling, compulsive sex, compulsive buying, and PIU, are different from Impulse Control Disorder (ICD), since only the first are characterized by abnormalities in brain circuits underlying reward processing (Black, 2013; Clark & Limbrick-Oldfield, 2013; Karim & Chaudhri, 2012; van Holst, van den Brink, Veltman, & Goudriaan, 2010). This latter view suggests that PIU shares more characteristics with addictive behaviors, including craving, tolerance, and withdrawal (Block, 2008; Ko et al., 2008), than with ICD. In this context, PIU has been described as an addiction *to* the Internet, characterized by a general, multidimensional overuse of the Internet (e.g., wasting time online without a specific purpose), and thought to be mainly related to the social aspect of the Internet, i.e., the reinforcement obtained by online social interactions would result in an increased urge to stay in a virtual social life (Davis, 2001).

Anyway, once conceptualized as a disorder, whether or not to consider PIU as an addiction is still a matter of debate as well. Research findings are controversial, reporting both similarities and differences between PIU, gambling disorder, and substance use disorder (Weinstein & Lejoyeux, 2010). Indeed, research in this context is still at an early stage, often with several limitations, including small sample sizes (Banz, Yip, Yau, & Potenza, 2016).

Given these debates, in the present PhD dissertation it has been chosen to discuss Internet-related problematic behaviors by endorsing one of the most recent definition of PIU, i.e., as a condition involving the excessive or poorly controlled urges and behaviors relating to Internet use that lead to subjective distress and/or interference in major areas of life functioning. It is a heterogeneous construct that may include a multitude features relating to sexual, social networking, and gaming behaviors (Banz et al., 2016).

Which diagnostic criteria for problematic Internet use?

More than 20 years ago, Ivan Goldberg (Goldberg, 1995) provocatively described the diagnostic criteria for Internet overuse that included i) Tolerance (i.e., markedly increased amount of time on Internet to achieve satisfaction), withdrawal symptoms (i.e., obsessive thinking about what is happening on the Internet, fantasies or dreams about Internet, voluntary or involuntary typing movements of the fingers), spending a great deal of time in activities related to Internet use, and reducing important social, occupational, or recreational activities because of Internet use (Thurlow, Lengel, & Tomic, 2004). From that moment on, many researchers have tried to specify clinical criteria for PIU (Beard & Wolf, 2001; Block, 2008; Tao et al., 2010; Widyanto & Griffiths, 2006; Young, 1996, 1998b, 1998a). In 2008, four diagnostic criteria have been proposed for a diagnosis of PIU as an addictive behavior: (i) Internet overuse associated with a loss of sense of time/a neglect of basic motivations; (ii) withdrawal, i.e., feelings of anger, depression and tension when Internet is not available; (iii) tolerance, i.e., the need to get better computer equipment/more hours of use; and (iv) negative consequences, i.e., arguments, lying, poor school or vocational achievement, social isolation, and fatigue (Block, 2008). One year later, Ko, Yen, Chen, Yang et al. (2009) confirmed the diagnostic accuracy of nine criteria they had developed in 2005 (Ko, Yen, Chen, Chen, & Yen, 2005b), that could be summarized under Block's criteria structure (2008) and included recurrent failure to resist the impulse to use the Internet; preoccupation with Internet activities; use of Internet for a period of time longer than intended; persistent desire and/or unsuccessful attempts to cut down or reduce Internet use; excessive effort spent on activities necessary to obtain access to the Internet; excessive time spent on Internet activities and leaving the Internet; tolerance: a marked increase in the duration of Internet use needed to achieve satisfaction; withdrawal symptoms; continued Internet use despite knowledge of having a persistent or recurrent physical or psychological problem likely to have been caused or exacerbated by Internet use; recurrent Internet use resulting in a failure to fulfill major role obligations at school and home, impaired interpersonal relationships, and behaviors violating school rules or laws. However, the accuracy was tested in a cohort of 216 Taiwanese students, and this has limited the generalizability of the results (Ko, Yen, Chen, Yang, et al., 2009).

More recently, the findings obtained in a number of studies on video game-related behaviors led the American Psychiatric Association (APA) to include Internet Gaming Disorder (IGD, divided into online and offline IGD) in the research appendix of the fifth edition of the DSM (American Psychiatric Association, 2013; Petry et al., 2014). The DSM-5 noted that more studies are needed, both in the context of Internet gaming as well as more general Internet use, in order to confirm and/or update the proposed criteria. Specifically, reflecting the literature debates, the Substance Use Disorder Workgroup of the DSM-5 was split into those who considered excessive behavior patterns as not aligned to the concept of 'addiction' as a medical condition (Davies, 1998; Keane, 2004), and those who argued that excessive behavioral patterns are indeed psychopathological conditions that can lead to important functional impairments, similarly to other disorders (Martin & Petry, 2005). However, gambling disorder was voted to be moved to the *Substance-related and addictive disorders* section, and IGD was included as another putative *non-substance addiction* (Petry et al., 2014). As noted in the DSM-5, "*In addition to the substance-related disorders, this chapter also includes gambling disorder, reflecting evidence that gambling behaviors activate reward systems similar to those activated by drugs of abuse and produce some behavioral symptoms that appear comparable to those produced by the SUDs. Other excessive behavioral patterns, such as Internet gaming, have also been described, but the research on these and other behavioral syndromes is less clear (American Psychiatric Association, 2013)".*

The inclusion of IGD in the DSM-5 was based upon more than 250 studies in the field, that highlight the negative consequences (including death; Reuters, 2007) of excessive gaming on affected individuals' life (Chuang, 2006), and cultural similarities and differences in IGD, i.e., between Asian (Choo et al., 2010; Fu et al., 2010; Hur, 2006; Ko, Yen, Chen, Chen, & Yen, 2005a; Ko, Yen, Chen, Yeh, & Yen, 2009; Tao et al., 2010), European (Durkee et al., 2012; Festl, Scharkow, & Quandt, 2013; Rehbein, Psych, Kleimann, Mediasci, & Mößle, 2010; Rumpf et al., 2014), and US people (Desai, Krishnan-Sarin, Cavallo, & Potenza, 2010; Gentile, 2009). Age was also considered as a relevant variable in the majority of studies conducted on youth or young adults (Choo et al., 2010; Fu et al., 2010; Hur, 2006; Ko, Yen, Chen, Yeh, et al., 2009), with only a small number of studies on adults (Festl et al., 2013; Haagsma, Pieterse, & Peters, 2012; Mentzoni et al., 2011). Some studies focused on Internet gaming activities (Festl et al., 2013; Haagsma et al., 2012; Tejeiro Salguero & Morán, 2002), while others included several subtypes of Internet use (Durkee et al., 2012; Fu et al., 2010; Ko, Yen, Chen, Yeh, et al., 2009). Based on the findings of the few studies that compared specific types of Internet use, Internet gaming emerged as a distinct problematic behavior compared to other problematic Internet-related activities (e.g., social networking sites use, pornography viewing, etc). As a consequence, the Workgroup decided to recommend only IGD to be included in Section 3 of the DSM-5. As concern other PIU subtypes, the Workgroup decided to not include them because of limited studies, less documented negative consequences on the lives of affected individuals, or the lack of a clear alignment with SUDs (Petry et al., 2014).

Considering the clinical relevance and the demand of focused treatment and preventive programs (Rumpf et al., 2018), the World Health Organization (WHO) included both online and offline gaming in the 11th revision of the International Classification of Diseases (ICD-11). *"Disorders due to addictive behaviours are recognizable and clinically significant syndromes associated with distress or interference with personal functions that develop as a result of repetitive rewarding behaviours other than the use of dependence-producing substances. Disorders due to addictive behaviors include gambling disorder and gaming disorder, which may involve both online and offline behavior (ICD-11)"*.

To date, given the existing evidence of the similarities among addictive behavioral patterns, researchers are considering other Internet-related activities beside gaming for inclusion in diagnostic systems (Besser, Loerbroks, Bischof, Bischof, & Rumpf, 2019; Kuss & Griffiths, 2011; Rumpf et al., 2014; van Rooij, Schoenmakers, van de Eijnden, & van de Mheen, 2010). A growing number of studies are reporting some significant adverse consequences of PIU, including reduced scholastic achievement, missing work, interfering with personal functioning, isolation, and mental health sequelae including mood and anxiety disorders, thus highlighting the need to better understand and characterize PIU (Derbyshire et al., 2013; Ho et al., 2014; Ioannidis et al., 2018; Ko et al., 2005b). However, a consensus regarding the diagnostic criteria for PIU and specific problematic online activities (i.e., pornography viewing, social networking sites use, online shopping, etc.) seems not to be possible to achieve currently. Nevertheless, considering the updated findings in the field and the relevance for public health, identifying the diagnostic criteria for PIU should be one of the main aims of research communities in order to improve reliability across studies and to develop effective treatment approaches and prevention measures (Kuss & Lopez-Fernandez, 2016).

Current models and proposed mechanisms for problematic Internet use

In 2001, Davis introduced a **cognitive-behavioral model** of pathological Internet use and discerned specific- from generalized pathological Internet use (Davis, 2001). *Specific pathological Internet use* refers to the pathological use of the Internet for a specific purpose (e.g., online sex, online gambling). This kind of overuse is content-specific and can occur even in the absence of Internet access. *Generalized pathological Internet use* (GPIU), instead, refers to wasting time online without a specific purpose, or spending vast amounts of time in activities that are not content-specific (Davis, 2001). Generalized and specific pathological Internet use can be viewed as addiction *to* the Internet itself and addiction *on* the Internet, respectively (Widyanto & Griffiths, 2006, 2007). The cognitive-behavioral model of pathological Internet use (Davis, 2001) posits that GPIU results from a lack of social support and/or social isolation and low psychosocial well-being (e.g., mood disorders, SUDs). The need for social contact and the reinforcement obtained online would result in an increased desire to remain in a virtual social life (Davis, 2001). Existing psychopathology would act as a distal necessary cause of symptoms of GPIU, predisposing individuals to develop maladaptive Internet-related cognitions, such as ruminating about one's overuse of the Internet, low self-efficacy, and negative self-appraisal. In turn, maladaptive Internet-related cognitions would act as proximal sufficient causes of behavioral and affective symptoms of both specific and generalized pathological Internet use, leading to difficulties with impulse control, that ultimately results in negative outcomes associated with Internet use (Davis, 2001).

In 2002, (Caplan, 2002) described technology-related psychological problems as a type of behavioral addictions, and referred to Internet-related problematic behaviors as Internet addiction, featuring the core components of addiction. Specifically, Internet addicts would be characterized by the attribution of greater salience to online activities, craving feelings and preoccupations when offline, mood modification, tolerance, withdrawal when reducing Internet usage, conflict, and relapsing back to Internet overuse (Caplan, 2002). Aiming to update Davis' model, Caplan (2010) proposed a model of GPIU that incorporates some cognitive and behavioral variables that were identified by more recent research as key constructs associated with the negative outcomes of Internet use. According to **Caplan's model**, individuals with a preference for online social interactions are more likely to use computer-mediated communication for alleviating the affective distress associated with face-to-face interactions. Using online interactions to regulate mood would be associated with deficient self-regulation, manifested as obsessive thought patterns related to Internet use and compulsive use of the Internet. In turn, deficient self-regulation would lead to negative outcomes in daily life (Caplan, 2010).

In 2011, Young introduced the **cognitive-behavioral therapy for Internet addiction** (CBT-IA). Considering PIU as a behavioral addiction, it was proposed that controlled Internet usage is the most appropriate way to treat PIU (Greenfield, 1999; Young, 2007a). Based on the premise that thoughts determine feelings, cognitive-behavioral therapy (CBT) has been suggested as the main treatment approach for PIU (Young, 2007a). In CBT-IA, during the early stages of therapy the focus is on specific and severe Internet-related problematic behaviors resulting from low impulse-control. Later over the course of the therapy, there is more of a focus on Internet-related cognitive distortions and the effects of compulsive behavior (Young, 2007a). Based on these assumptions, CBT-IA gives particular attention to both individual characteristics and specific cognitions as key features to be addressed in the therapy.

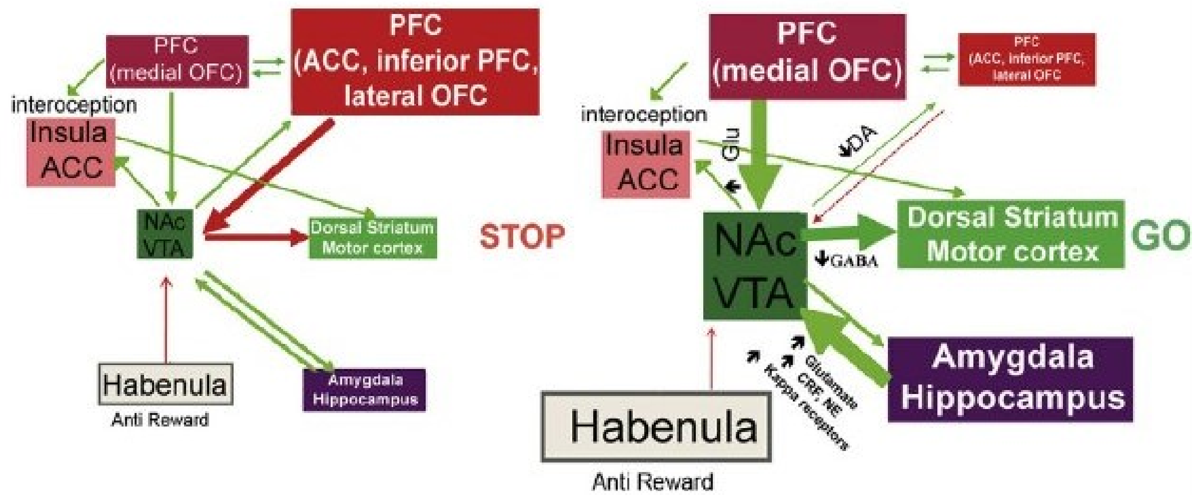
CBT-IA includes three main phases. During the first phase, the therapist monitors incidental situational, emotional, and cognitive aspects of Internet usage. The positive and negative reinforcing effects resulting from Internet usage are also considered in order to characterize cognitions and high-risk behaviors triggered by the Internet. In the second phase, cognitive restructuring and reframing are employed to modify maladaptive cognitions and treatment denial. The last phase is focused on understanding and changing personal, social, psychiatric, and occupational issues related to the development and maintenance of Internet-related problematic behaviors (Young, 2011; Young & De Abreu, 2010).

Some functions mediated mainly by the prefrontal cortex (i.e., executive functions, self-reflection, cognitive flexibility) have been described to be fundamental for the effectiveness of CBT-IA (Brand, Young, & Laier, 2014; Young, 2011). In 2014, **Brand, Young, & Laier (2014) proposed a model on the development and maintenance of generalized and specific Internet addiction** which combines the cognitive-behavioral model of GPIU (Davis, 2001) with a model of healthy Internet usage, and a global model of specific types of Internet addiction. Here, control processes and executive functions play a significant role on the person's coping style and Internet use expectancies. Specifically, reduced prefrontal control processes would underlie reduced coping and self-regulation abilities to deal with daily challenges, thus leading users to turn to the Internet. The experienced reinforcement when using the Internet (i.e., coping with negative feelings) may increase Internet-related expectancies, making Internet usage the only way to cope with negative mood (Brand et al., 2014). In this way, Internet users may engage in a loop where online activities increase their focus on maladaptive general and Internet-related cognitions that, in turn, are reinforced by using the Internet. Brand et al. (2014) stressed the importance of working on prefrontal control processes during treatment, in order to increase monitoring and controlling situational triggers, which would be fundamental for controlling Internet usage (Brand et al., 2014).

The model proposed by Brand et al. (2014) clearly highlights the connection between PIU and mechanisms underlying addictive behaviors, where deficient prefrontal control processes are one of the main factors implicated in the development and maintenance of addiction (Cerniglia et al., 2017; Robinson & Berridge, 2003). Among all the processes in which they are involved, prefrontal control processes have been described to be fundamental in the top-down guidance/regulation of behavior to achieve goals (Buschman & Miller, 2014; Pezzulo, Rigoli, & Friston, 2018). Such processes have been proposed as key factors involved in the transition from voluntary/goal-directed actions (with an appraisal of action consequences) to habitual (automatic and uncontrolled) actions at the basis of addictive behaviors (Everitt, Dickinson, & Robbins, 2001; Everitt & Robbins, 2005). This transition would reflect a parallel transition in neurobiological mechanisms, i.e., from cortical prefrontal to striatal control over behavior, and from ventral to more dorsal striatal subregions (see Figure 1). The ability to inhibit the urge to engage in consummatory/maladaptive behaviors is thought to reflect the proper functioning of top-down control of conditioned responses that both predict reward and drive the motivation to engage in addictive behaviors (Lee, Hoppenbrouwers, & Franken, 2019; Starcke, Antons, Trotzke, & Brand, 2018; Volkow, Wang, Fowler, Tomasi, & Telang, 2011). The modulation of these complex behavioral patterns seems to arise from the activity of six interacting circuits (Volkow & Baler, 2014; see Figure 1): reward/saliency (nucleus accumbens and ventral pallidum); memory/learning-conditioning/habits (amygdala and hippocampus); inhibitory control/executive functions (dorsolateral prefrontal cortex, inferior frontal cortex, orbitofrontal cortex and anterior cingulate cortex); motivation/drive (orbitofrontal cortex, subcallosal cortex, dorsal striatum and motor cortex); interoception (involved in the awareness of craving; insula and anterior cingulate cortex); and aversion avoidance/stress reactivity (habenula and amygdala). The balanced neural activity of these circuits results in proper inhibitory control and adaptive decision making. Differently, enhanced expectation value of drugs or of specific behaviors (e.g., Internet gaming) in the reward, motivation, and memory circuits results in overcoming the activity of control circuits, with consequential consummatory behaviors, craving, and relapse (Bickel et al., 2018; Volkow & Baler, 2014; Volkow et al., 2011; Wei, Zhang, Turel, Bechara, & He, 2017).

Figure 1. Brain circuits involved in addiction. From Volkow & Baler, 2014

Non-addicted brain	Addicted brain



PFC = Prefrontal cortex; ACC = Anterior cingulate cortex; OFC = Orbitofrontal cortex; NAc = Nucleus accumbens; VTA = Ventral tegmental area. DA = dopamine; Glu = Glutamate; CRF = corticotropin-releasing factor; NE = norepinephrine

As shown in Figure 1, these circuits also interact with those involved in mood regulation, stress reactivity and interoception (Volkow & Baler, 2014; Wei et al., 2017). Interestingly, the transition to problematic Internet usage has been proposed to mainly arise from the interaction between exaggerated learning/reward processes and reduced stress/mood regulation/interoceptive awareness processes (LaRose, 2010, 2015; LaRose, Lin, & Eastin, 2003; Wei et al., 2017).

Similarly to the aforementioned literature on SUD, the mechanisms that are thought to underlie addictive behaviors and PIU have been modeled in the recently updated version of the Interaction of **Person-Affect-Cognition-Execution (I-PACE) model of addictive behaviors** (Brand, Wegmann, et al., 2019; Brand, Young, Laier, Wölfling, & Potenza, 2016). This model takes into account the interactions among predisposing variables, affective and cognitive responses to internal or external stimuli, executive and inhibitory control, decision-making behavior resulting in the use of certain Internet applications/sites, and consequences of using the Internet applications/sites of choice. Specifically, Brand et al. (2019) have proposed that during the process of becoming addicted to a specific behavior, the associations between exaggerated cue-reactivity/craving and diminished inhibitory control processes would lead to the development of habitual (addictive) behaviors. At the neural level, this would be reflected in the imbalance between the activity of fronto-striatal circuits (i.e., dorsolateral PFC, ventral striatum, and amygdala; with decreased prefrontal activity and increased subcortical activity) during the early stages of problematic behavior, and the dominance of dorsal striatum activity during the later stages of addiction.

In its first formulation, the I-PACE model was developed as a theoretical framework for a process model of the temporal dynamics of specific PIU (Brand et al., 2016). According to the I-PACE model for specific PIU, coping styles and Internet-related cognitive biases would moderate the associations between predisposing factors and PIU characteristics. Moreover, coping styles and cognitive biases would be affected by the presence of psychopathological disorders and personality characteristics. A moderated mediation effect between predisposing factors and coping styles and Internet-related cognitive biases has been also proposed. Affective and cognitive responses to situational stimuli (e.g., cue-reactivity, craving) would be mediating variables, and would be mainly influenced by coping styles and Internet-related cognitive biases. They would develop as a result of conditioning processes governed by positive and negative reinforcement, and would reduce inhibitory control, and this, in turn, would lead to PIU (Brand et al., 2016).

The updated I-PACE model includes three main revisions of the first version, namely a more refined definition of the predisposing variables involved in different types of addictive behaviors, an update of the inner circle of the addiction process with recent findings in the field, a distinction between early and later stages of the addiction process and the related moderating and mediating variables (Brand, Wegmann, et al., 2019).

While several models of PIU have been proposed, many research gaps still exist, with arguably more gaps and controversies related to the mechanisms underlying the development and maintenance of Internet-related problematic behaviors.

Assessing problematic Internet use

Although clinical interviews in conjunction with standardized self-reports should be the most effective way to identify Internet-related psychological problems, many different self-report instruments have been developed and used to assess PIU (Beard, 2005; Laconi, Rodgers, & Chabrol, 2014; Lortie & Guitton, 2013). The following paragraph provides a brief description of the most widely used instruments that have been validated (at least) in English (Király, Nagygyörgy, Koronczai, Griffiths, & Demetrovics, 2015).

Almost all the available instruments assessing PIU have been developed following the DSM-IV criteria for pathological gambling and/or substance dependence (American Psychiatric Association, 2000), the cognitive-behavioral model of pathological Internet use (Davis, 2001), and the conceptual framework of behavioral addiction (arguing that all addictions consist of a number of distinct common components, namely salience, mood modification, tolerance, withdrawal, conflict and relapse (Griffiths, 2005a; Király et al., 2015).

The most widely employed instrument is the **Internet Addiction Test** (IAT; Young, 1998b). In its first formulation, i.e., the Internet Addiction Diagnostic Questionnaire (IADQ; Young, 1998b), it included 8 items reflecting the criteria for pathological gambling modified to the context of PIU. Based on the cut-off point for pathological gambling (i.e., meeting five or more diagnostic criteria), 60% of the 396 participants included in the IADQ validation study were classified as dependent on the Internet and reported more adverse consequences of Internet usage. Moreover, those who were classified as dependent reported engaging in different online activities and in more interactive Internet functions, such as chat rooms and news groups, as compared with non-dependent users. Interestingly, the time of Internet access was shorter for dependent than for non-dependent users, suggesting that "Internet addiction" was related to the type of online activity and not to the amount of time spent online (Young, 1998b).

Based on the results obtained using the IADQ, the IAT was then developed as a more comprehensive 20-item instrument (the 8 items of the IADQ plus 12 new items) to assess problematic Internet use (Young, 1998b). The IAT allows assessing i) among those already identified as problematic Internet users, the specific area in which PIU has impacted the individual's life; ii) in cases in which the presence of PIU is not certain, whether Young's criteria for Internet addiction (Young, 1998a) are met, and the consequences of Internet-related behavior on the individual's life. Moreover, people who believe that someone may be a problematic Internet user are recommended to use the IAT to assess the user's potential Internet addiction. A score of 70 or more means that Internet use is causing significant problems. The IAT has been extensively tested and translated into several languages; it is considered as the most valid (Laconi et al., 2014) and a highly reliable instrument to assess PIU (Moon et al., 2018; Widyanto & McMurran, 2004).

The **Internet Related Problem Scale** (IRPS; Armstrong, Phillips, & Saling, 2000) is a 20-item scale, based on the DSM-IV criteria for substance abuse in the context of PIU, including factors such as tolerance, craving, and negative impact of Internet use. The first validation of the scale (Armstrong et al., 2000) has been conducted on a small sample of participants (n = 50), however this preliminary study showed the IRPS to have a moderate level of internal consistency, i.e., the questions were homogenous and related to the construct of "Internet Addiction". The construct validity was also supported by the significant correlations between the IRPS scores and the number of hours spent online and the Minnesota Multiphasic Personality Inventory-2 scores (Hathaway & McKinley, 1951). The IRPS has been further tested on a sample of 79 participants, and showed a six-factor structure, including salience, negative effects, mood enhancement, productivity, loss of control, and lack of information. All factors provided good internal consistency and concurrent validity, with salience being the most reliable (Widyanto, Griffiths, Brunsden, & McMurran, 2008). However, the study had some limitations, e.g., the small sample size (as in the first validation study) and the gender imbalance, i.e., more than 80% of participants were women (Widyanto et al., 2008).

The **Online Cognition Scale** (OCS; Davis, Flett, & Besser, 2002) was developed focusing on cognitions-related rather than behaviors-related PIU symptoms, and adapting some items from measures of procrastination, depression, impulsivity, and pathological gambling. This questionnaire is the operationalization of a cognitive-behavioral model of PIU (Davis, 2001), that is based on the idea that maladaptive Internet-related cognitions would act as proximal sufficient causes of behavioral and affective symptoms of PIU, leading to difficulties with impulse control that ultimately results in negative outcomes associated with Internet use. It is a 36-item questionnaire that provides a global measure of PIU. It was tested for the first time on a sample of 211 undergraduate students, and showed a four-factor structure, i.e., loneliness/depression, diminished impulse control, social comfort, and distraction. Although the first validation study did not report any analysis of the internal factor structure (Charlton & Danforth, 2007), the psychometric qualities of the questionnaire have been ascertained (Davis et al., 2002; Laconi et al., 2014; Ozcan & Buzlu, 2005).

The **Compulsive Internet Use Scale** (CIUS; Meerkerk, Van Den Eijnden, Vermulst, & Garretsen, 2008) is a 14-item scale developed to assess compulsive Internet use. It is based on the criteria for Substance Dependence and Obsessive-Compulsive disorder (American Psychiatric Association, 2000), the findings on behavioral addictions (Griffiths, 1999), and clinical interviews with self-declared Internet addicts. The scale has been validated on three different samples and the one-factor structure provided factorial invariance across time, gender, age, and heavy vs. non-heavy Internet use, with reported high reliability, concurrent and construct validity (Meerkerk et al., 2009).

The **Generalized Problematic Internet Use Scale 2** (GPIUS2; Caplan, 2010) was developed to revise and update the first version of the Generalized Problematic Internet Use Scale (GPIUS; Caplan, 2002). The GPIUS was designed to assess both cognitive and behavioral dimensions of generalized pathological Internet use, including their negative outcomes on the individual's life. This first version included seven dimensions: i) mood alteration, i.e., Internet usage for regulating negative moods; ii) social benefits perceived when using the Internet; iii) social control, i.e., the perception of controlling individual self-presentation during online social interactions; iv) withdrawal, i.e., Internet-related preoccupations; v) compulsive use, i.e., uncontrolled online behavior; vi) excessive time online, i.e., feelings about excessive amount of time spent online, and vii) negative outcomes, i.e., personal, social, and professional problems due to Internet use. Based on findings from studies on the combination of the social benefits and social control factors into a single dimension, on the Preference for Online Social Interaction (POSI; Caplan, 2003) and on compulsive Internet use and cognitive preoccupation as both symptoms of deficient self-regulation (LaRose, 2006; LaRose et al., 2003), the GPIUS was updated to GPIUS2. The main changes to the instrument were the inclusion of a subscale that operationalizes POSI and two first-order sub-scales that, taken together, constitute deficient self-regulation. Thus, the GPIUS2 includes four constructs: i) POSI; ii) mood regulation; iii) deficient self-regulation, i.e., a compulsive use subscale and a cognitive preoccupation subscale; and iv) negative outcomes. It consists of 15 items that assess the separate sub-dimensions and an overall composite index (Caplan, 2010). The GPIUS2 has been described as an adequate measure of GPIU cognitions, behaviors, and outcomes (Fioravanti, Primi, & Casale, 2013).

The **Problematic Internet Use Questionnaire-Short Form** (PIUQ-SF-6, Demetrovics et al., 2016) is the last, 6-item version of the Problematic Internet Use Questionnaire (PIUQ, Demetrovics, Szeredi, & Rózsa, 2008). The PIUQ was originally a 18-item scale developed on a Hungarian sample and then validated in various countries (Demetrovics et al., 2016, 2008; Koronczai et al., 2011; Mazhari, 2012). It includes three factors, i.e., obsession (obsessive thinking about the Internet and mental withdrawal symptoms caused by the lack of Internet use), neglect (neglect of basic needs and everyday activities) and control disorder (difficulties in controlling Internet use). The PIUQ-SF-6 was developed by selecting two items from each of the three factors. Scores range from 6 to 30, with higher scores indicating more severe PIU. The short version has been developed in order to obtain a measure of PIU brief enough to be useful in time-limited surveys. A cut-off score of 15 (out of 30) is suggested to differentiate between people at risk of developing PIU and people who are not at risk.

Despite all the self-report instruments described before have been tested at least once and provided satisfactory validity and reliability indices, the criterion validity was not assessed and therefore existing instruments do not allow discerning overuse from problematic use of clinical relevance (Lortie & Guitton, 2013). To differentiate between non-problematic and problematic Internet users, a control group should also be assessed and strict selection criteria must be used to detect excessive Internet users (e.g, a score of 70 or higher on IAT, Lortie & Guitton, 2013; Young, 1998b). Additional tests of reliability have been also recommended in order to improve the predictive value of current self-report instruments (Lortie & Guitton, 2013).

“I feel the “normal” need to check whether I received any mail/messages

and to look at Facebook”

(Participant 211, 25 years old)

Study 1: Identifying Problematic Internet Users by their symptoms

Introduction

To understand and conceptualize problematic Internet use (PIU), several studies assessing specific psychological characteristics of PIU have been conducted (Davis et al., 2002; Morahan-Martin & Schumacher, 2000; Orzack & Orzack, 1999; Peterka-Bonetta, Sindermann, Elhai, & Montag, 2019; Shapira et al., 2003). Different psychopathological features have been found to be often associated with PIU and PIU subtypes (Anderson, Steen, & Stavropoulos, 2017; Choi et al., 2019; Elhai, Levine, & Hall, 2019; Gentile et al., 2011; Montag, Kirsch, Sauer, Markett, & Reuter, 2012; Peterka-Bonetta et al., 2019). It has been mainly reported that **individuals with PIU are more likely to have symptoms associated with substance addictions, mood and anxiety disorders, and obsessive-compulsive disorder, and to be characterized by highly impulsive behavior**. The interaction between high impulsivity/poor inhibitory control, low mood regulation and high stress reactivity has been suggested to be a key aspect of both behavioral addiction and PIU. Specifically, individuals who are highly responsive to stressors and employ impulsive coping strategies would be more inclined to use the Internet for mood regulation. Indeed, they seem to hold false beliefs about the power of the Internet to regulate their negative mood (Brand, Wegmann, et al., 2019; Brand et al., 2016). Moreover, in PIU, the incidence of symptoms associated with substance addictions and obsessive-compulsive disorder has been argued to be determined by common alterations of reward-related processing and behaviors (Brand, Wegmann, et al., 2019; Figee et al., 2011; Fontenelle, Oostermeijer, Harrison, Pantelis, & Yücel, 2011; Ko et al., 2008). However, the predictive and diagnostic power of such variables, as well as whether problematic vs. non-problematic users are characterized by different networks of relationships remain to be clarified.

PIU & impulsivity

Impulsivity has been broadly conceptualized as a personality trait, characterized by the tendency to engage in risky, inappropriate or maladaptive behaviors (Bari & Robbins, 2013). High levels of impulsivity have been found to be associated with several psychopathological conditions, including substance use disorder (de Wit, 2009), gambling disorder (Chowdhury, Livesey, Blaszczynski, & Harris, 2017), Attention Deficit/Hyperactivity Disorder (ADHD; Ahmad & Hinshaw, 2017), psychopathy (Gray, Weidacker, & Snowden, 2019), and bulimia nervosa (del Pino-Gutiérrez et al., 2017).

A large number of studies has also shown that impulsivity levels are positively associated with- or are predictive of PIU (Cao, Su, Liu, & Gao, 2007; Ioannidis et al., 2016; Koo & Kwon, 2014; Liu, Lan, Wu, & Yan, 2019; Mottram & Fleming, 2009; Peterka-Bonetta et al., 2019; Shokri, Potenza, & Sanaeepour, 2017), suggesting that impulsivity may be a core personality trait in problematic Internet users (Brand, Wegmann, et al., 2019; Brand et al., 2016; Choi et al., 2014).

PIU & depression, anxiety, and stress symptoms

Depression has been found to be one of the main risk factors associated with PIU (Kitazawa et al., 2018; Ko, Yen, Chen, Yeh, et al., 2009; Yen, Ko, Yen, Wu, & Yang, 2007), as well as with PIU subtypes (Tian et al., 2018), i.e., problematic use of social networking sites (Mamun & Griffiths, 2019; Yoon, Kleinman, Mertz, & Brannick, 2019), Internet gaming disorder (IGD; González-Bueso et al., 2018; Torres-Rodríguez, Griffiths, Carbonell, & Oberst, 2018; Wang, Cho, & Kim, 2018), and addictive cybersex (Varfi et al., 2019).

Similarly to what reported for depression, higher levels of anxiety were found to be significantly associated with higher PIU (Kitazawa et al., 2018; Ostovar et al., 2016; Vasileios Stavropoulos et al., 2017; Younes et al., 2016) and with IGD (Torres-Rodríguez et al., 2018).

Stress occurs when an individual perceives that environmental demands exceed his or her adaptive capacity (Cohen, Kessler, & Gordon, 1995). In the literature, the majority of studies have investigated the relationship between stress and PIU indirectly, by assessing the link between PIU and the number of stressful events in the individual's life. Specifically, stressful life events were found to be significantly positively associated with PIU (Li et al., 2016) and with some PIU subtypes, including WeChat addiction (Li, Wu, Jiang, & Zhai, 2018) and IGD (Torres-Rodríguez et al., 2018). Furthermore, interpersonal and school-related stressors and anxiety symptoms were found to be significantly associated with PIU, with negative coping style as the mediator of this association (Tang et al., 2014). Similarly, academic stress among adolescents was reported to influence PIU through negative emotions (Jun & Choi, 2015). Interestingly, Internet abuse for sexual purposes was found to be predicted by both disinhibition and perceived stress (Velezmoro, Lacefield, & Roberti, 2010).

Of note, while some studies found mood disorders to be consequences of PIU (Dong, Lu, Zhou, & Zhao, 2011), the majority of studies in this context have suggested that Internet use may be a mean to escape from daily problems and to regulate negative mood. After experiencing stressful life events, some individuals might attempt to reduce negative emotion by engaging in Internet related-behaviors, using the Internet as an emotion regulation strategy (Brand, Wegmann, et al., 2019; Elhai et al., 2019; Young, 1998b, 2009). Moreover, mood-related disorders and anxiety symptoms in PIU may be related to seeking relationships online and have been proposed as relevant screening factors in clinical practice to detect people with PIU (Tonioni et al., 2012).

PIU & obsessive-compulsive symptoms

Obsessive-compulsive disorder (OCD) is a severe and disabling disorder characterized by the occurrence of either obsessions and/or compulsions (American Psychiatric Association, 2013). Certain obsessions and compulsions tend to co-occur to form five main dimensions: obsessions about being responsible for causing or failing to prevent harm; checking compulsions and reassurance-seeking; symmetry obsessions, and ordering and counting rituals; contamination obsessions, and washing and cleaning rituals; repugnant obsessions concerning sex, violence, and religion; hoarding, which are obsessions about acquiring and retaining objects, and associated collecting compulsions (Abramowitz, Taylor, & McKay, 2009; McKay et al., 2004).

An association between PIU and obsessive-compulsive symptoms has been observed (Ha et al., 2006; Pies, 2009), and a study reported 7% of adults with PIU to have obsessive-compulsive personality, with PIU appearing to be more compulsory than rewarding or mood driven (Bernardi & Pallanti, 2009). Importantly, a longitudinal study found obsessive-compulsive symptoms to be present *before* individuals became addicted to the Internet (Dong et al., 2011). A review of 20 studies reported high comorbidity rates for PIU with some mental disorders, including obsessive-compulsive disorder, depression, anxiety, and ADHD (Carli et al., 2013). However, no study to our knowledge investigated the relationship between PIU and specific OCD dimensions.

PIU & alcohol and cannabis use

Alcohol use disorder (AUD) and Cannabis use disorder (CUD) are defined as problematic alcohol and cannabis use, respectively, that lead to clinically significant impairment or distress manifested by impaired control, continued use despite social/medical problems, craving, tolerance, and withdrawal (American Psychiatric Association, 2013). Both AUD and CUD tend to be manifested during adolescence and early adulthood (D'Alessio, Baiocco, & Laghi, 2006; Degenhardt et al., 2013; Martinotti et al., 2017), and represent major public health challenges (Peacock et al., 2018). A recent study on Italian young people (age 13-20) showed high rates of alcohol consumption and a common co-occurrence of drugs use, with cannabis reported as the most used (Addolorato et al., 2018). Moreover, it has been estimated that there are about 128-238 million annual cannabis users worldwide, with cannabis use being most prevalent among young people aged 15-34 years in Europe (EMCDDA, 2016; United Nations Office on Drugs and Crime, 2017). The incidence of abuse of alcohol and other drugs among young people has been proposed as the consequence of a hedonistic youth culture (Addolorato et al., 2018). Moreover, the co-occurrence of AUD and CUD has been conceptualized by the problem-behavior theory (Hays, Stacy, & Dimatteo, 1987), where alcohol, smoking, and illicit substance use are problematic behaviors that usually coexist since they share the same social and perceived environment, personality, and behavior (Ko et al., 2008).

PIU has been proposed to be included as an additional problematic behavior contemplated by the problem-behavior theory (Ko et al., 2008), and several studies have been conducted in order to investigate its relationship with AUD. Adolescents with PIU have been reported to be more likely to have substance use experience (Ko et al., 2006; Rücker, Akre, Berchtold, & Suris, 2015) and, among substance abuse, problematic alcohol use has been suggested to share the same psychosocial vulnerability with PIU (Ko et al., 2008). Moreover, alcohol abuse seems to be positively associated with PIU (Ho et al., 2014; Lee, Han, Kim, & Renshaw, 2013; Yen, Ko, Yen, Chen, & Chen, 2009), and adolescents who experience adverse consequences of PIU seem to be more vulnerable to problematic alcohol use (Gámez-Guadix, Calvete, Orue, & Las Hayas, 2015). Interestingly, it has been recently found that cocaine and cannabis users spend more hours online than opioid and alcohol abusers (Baroni, Marazziti, Mucci, Diadema, & Dell'Osso, 2019). However, despite the high incidence of both PIU and CUD in young people, there is not much research on the relationship between these two problematic behaviors.

The goals of the present study were: (i) to assess impulsivity, depression, anxiety, stress, obsessive-compulsive symptoms, and alcohol and cannabis abuse (i.e., study variables) in individuals with- vs. without PIU; (ii) to investigate the power of study variables to predict PIU, and iii) their diagnostic efficiency, and (iv) to examine whether a specific network of associations among study variables characterizes individuals with- vs without PIU.

The following hypotheses were formulated: i) individuals with PIU would show higher scores on self-reports of impulsivity, depression, anxiety, stress, obsessive-compulsive symptoms, and alcohol and cannabis use as compared with individuals without PIU; ii) all study variables would be statistically predictive of PIU vs. non-PIU, and iii) because the diagnostic efficiency of study variables was an empirical question to be answered by this study, we did not make specific predictions regarding how well the variables would discern problematic from non-problematic Internet users; iv) problematic Internet users would be characterized by positive stronger intercorrelations between depression, anxiety and stress symptoms, as well as between obsessive-compulsive symptoms and alcohol and cannabis abuse than non-problematic users.

Method

Participants

The current study is part of a larger research project that examined psychophysiological mechanisms underlying PIU (Moretta & Buodo, 2018a; Moretta, Sarlo, & Buodo, 2019) and social networking sites use (Moretta, Sarlo, Palomba, & Buodo, 2019). Students of the University of Padua, Italy, were contacted informally at university facilities and asked about their Internet usage. Those who declared to use the Internet were asked to complete the Italian version of the Internet Addiction Test (IAT; Ferraro, Caci, D'Amico, & Blasi, 2007; Young, 1998b). The IAT is a 20-item questionnaire that assesses the extent to which Internet use affects social and individual quality of life, career, and time control, and excitatory/compensatory usage of the Internet (see further details in *Assessing problematic Internet use* of the *Characterizing problematic Internet use* subsection, Section 1). Participants are required to answer on a 6-point Likert scale (0 = 'it does not concern me' to 5 = 'always'). The minimum score is 20, and the maximum is 100; higher scores indicate more severe problems related to Internet use. Considering the Italian cut-off scores (Poli & Agrimi, 2012), Internet usage was defined as non-problematic (scores 20-50), mild to moderate problematic (scores 50-80), and severe problematic (scores 80-100).

Based on their IAT scores, 70 participants were classified as non-problematic Internet users (non-PIUs, F = 54, mean IAT score = 34.69±7.30, mean age = 23.13±2.89, sleep hours = 7.27±0.71, daily cigarettes consumption = 1.73±3.49), and 34 as mild to moderate problematic Internet users (PIUs; F = 24, mean IAT score = 57.68±7.00, mean age = 23.38±3.17, sleep hours = 7.15 ±0.80, daily cigarettes consumption = 1.97±4.03). IAT scores among PIUs were significantly higher than among non-PIUs ($t = 15.3$, $p < .001$). No differences between groups were found for age, gender, sleep hours, and cigarettes consumption.

The study was approved by the ethics committee of Psychological Research, Area 17, University of Padova. The ethical principles of the Helsinki and its amendments or comparable ethical standards were followed.

Self-report measures

The *Alcohol Use Disorders Identification Test* (AUDIT; Saunders, Aasland, Babor, de la Fuente, & Grant, 1993; Italian version by Addolorato, Caputo, Mioni, Patussi, & Zavan, 1999) was used to assess the frequency and quantity of alcohol consumption (Reinert & Allen, 2002). It includes 10 items divided into three domains: alcohol consumption, dependence, and alcohol-related consequences. Scores range from 0 to 40, with higher scores indicating more problematic alcohol use. Based on Italian cut-offs, scores in the range of 8-12 represent a medium level of alcohol-related problems, whereas scores of 13 and above represent a high level of alcohol-related problems (Addolorato et al., 1999).

The *Cannabis Abuse Screening Test* (CAST; Legleye, Piontek, & Kraus, 2011; Italian version by Bastiani et al., 2013) was administered to assess cannabis use with reference to the past 12 months. It is a 7-item self-report, with scores ranging from 0 to 24. Based on Italian cut-offs, scores of 7 and above indicate problematic cannabis use.

The *Depression Anxiety-Stress Scales* (DASS-21; Lovibond & Lovibond, 1995; Italian version by Bottesi et al., 2015) is a 21-item self-report that assesses general distress through three separate subscales (i.e., anxiety, depression, and stress). The depression subscale assesses lack of motivation, low self-esteem, and dysphoria; the anxiety subscales measures somatic and subjective symptoms of anxiety, and acute fear responses; the stress subscale assesses irritability, tension, and persistent arousal. Scores are considered as clinically significant when equal to or over 5 for the depression subscale, equal to or over 4 for the anxiety subscale, and equal to or over 8 for the stress scale (Henry & Crawford, 2005).

The *Barratt Impulsiveness Scale* (BIS-11; Patton, Stanford, & Barratt, 1995; Italian version by Fossati, Di Ceglie, Acquarini, & Barratt, 2001) was administered to assess impulsivity. It is a 30-item self-report, with scores ranging from 30 to 120. The higher the score, the higher the impulsiveness level.

The *Obsessive-Compulsive Inventory-Revised* (OCI-R; Foa et al., 2002; Italian version by Sica et al., 2009) was used to measure obsessive-compulsive symptoms. It is an 18-item self-report that provides separate scores on six subscales, i.e., washing, checking, ordering, obsessing, hoarding, and mental neutralizing, and a total score of Obsessive-Compulsive-related symptoms. Based on the cut-offs of the Italian version, a total score between 16 and 20 indicates the presence of obsessions and compulsions bordering on clinically relevant symptoms with further investigations suggested. A total score in the range of 21-23 means that obsessions and compulsions are causing significant problems. Lastly, scores of 24 and above indicate clinically relevant OCD symptoms. Considering the different subscales, scores in the range of 4-5 on the checking and ordering subscales indicate symptoms bordering on psychopathology that require clinical attention, while scores of 6 and above indicate the presence of clinically significant symptoms. Scores in the range of 3-4 on the washing subscale indicate symptoms bordering on psychopathology that require clinical attention, while scores of 5 and above indicate the presence of a clinically significant condition. As for the hoarding and the mental neutralizing subscales, scores greater than or equal to 6 and 3, respectively, indicate the presence of a clinically significant condition (Marchetti, Chiri, Ghisi, & Sica, 2010).

Procedure

Upon arrival at the laboratory, participants signed an informed consent form and were asked to complete an ad-hoc questionnaire about their demographic characteristics, health status, and medical history, and the self-reports measuring impulsivity, anxiety/depression/stress, obsessive-compulsive symptoms, and use of alcohol and cannabis. The entire procedure took about 30 min.

Statistical analysis

Pearson's correlation coefficients between study variables were calculated in PIUs and non-PIUs separately.

Linear model analysis considering Group (PIUs and non-PIUs) as a predictor was performed to compare study variables (i.e., Impulsivity, Anxiety, Depression, Stress, Obsessive-compulsive symptoms, Alcohol and Cannabis abuse) between groups, and effect sizes were reported in terms of Cohen's d, with a $d \geq 0.50$ indicating a moderate or greater effect size and a $d \geq 0.80$ indicating a large effect size (Cohen, 1988). Prior to running linear models, data were examined for skewness, kurtosis, outliers, and normalcy by both exploratory analyses and graphs, i.e., violin plots and boxplots (Pastore, Lionetti, & Altoè, 2017).

The normal Probability-Probability (P-P) plot of the standardized residuals showed points that were not completely on the line, but close, and the scatterplot of the standardized residuals showed that the data met the assumptions of homogeneity of variance and linearity for the majority of dependent variables. The Washing, Checking and Mental neutralizing subscales scores, and the cannabis abuse scores were positively skewed, thus the associated log-transformed scores were used. Outliers were identified in Depression ($n = 1$), Stress ($n = 1$), Hoarding ($n = 1$), Washing ($n = 1$), Checking ($n = 1$), Mental neutralizing ($n = 2$), and Cannabis abuse ($n = 2$), and removed to study group differences (PIUs and non-PIUs); see Figure 2. However, the results did not change if the analyses were re-run by including the outliers.

To study the relative predictive power of Impulsivity, Anxiety, Depression, Stress, Obsessive-compulsive symptom dimensions (Washing, Checking, Ordering, Obsessing, Hoarding, And Mental neutralizing), Alcohol and Cannabis abuse in PIUs vs non-PIUs, a multiple logistic regression analysis was employed with forward variable selection by using together $p < .05$, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) as the selection criteria to determine the most parsimonious model (Burnham & Anderson, 2002;

Vrieze, 2012). That is, the simplest model with the greatest explanatory predictive power was selected. Within the selected model, the maximum likelihood method was employed to analyze the contribution of each predictor in explaining PIU, and effect sizes were reported in terms of Odds Ratio (OR). Moreover, the strength of evidence of predictors was estimated as the difference in AIC and BIC between the model with and the model without the parameter (ΔAIC and ΔBIC, respectively).

Multicollinearity was monitored by examining the variance inflation factor (VIF, Craney & Surles, 2002). In this study, the VIF indicated that multicollinearity was not a concern (Impulsivity, VIF = 1.24; Anxiety, VIF = 1.78; Depression, VIF = 2.09; Stress, VIF = 2.33; Washing, VIF = 1.32; Checking, VIF = 1.96; Ordering, VIF = 1.75; Obsessing, VIF = 1.71; Hoarding, VIF = 1.56; Mental neutralizing, VIF = 1.30; Alcohol abuse, VIF = 1.32; Cannabis abuse, VIF = 1.20).

A receiver operating characteristic (ROC) analysis was conducted, and the area under the curve (AUC) was calculated as a measure of the accuracy of diagnostic power of each study variable and each model. The larger the area, the more accurate the diagnostic power, with low AUC if in the 0.50–0.70 range, moderate AUC in the 0.70-0.90 range, while an AUC over 0.90 indicates high accuracy (Pintea & Moldovan, 2009).

Intercorrelations among study variables within PIUs and non-PIUs were visualized and interpreted by a network plot (Csárdi & Nepusz, 2014). To test for differences between correlations higher than $r = 0.30$ in PIUs and non-PIUs, the correlations were transformed into z-scores using Fisher's r-to-z transformation, and effect sizes were reported in terms of Cohen's q (Cohen, 1988).

All analyses were performed using R software (R Development Core Team, 2016).

Results

Mean scores (and standard deviations) for the study variables and Pearson's correlations are reported in Table 1, for PIUs and non-PIUs separately.

Table 1. Descriptive statistics and intercorrelations in problematic (PIUs) and non-problematic Internet users (Non-PIUs). Red color indicates p < .05

PIUs (n = 34)

	Mean±sd	1	2	3	4	5	6	7	8	9	10	11	12
1.Impulsivity	61.24±8.63	1											
2.Anxiety	5.71±3.93	.32	1										
3.Depression	8.09±5.62	.19	.65	1									
4.Stress	10.21±4.75	.15	.59	.70	1								
5.Washing	1.47±1.81	.00	.17	.07	.10	1							
6.Checking	3.44±3.74	.06	.53	.44	.39	.50	1						
7.Ordering	4.50±3.30	-.15	.14	.19	.26	.35	.59	1					
8.Obsessing	5.12±3.33	.20	.67	.62	.62	.41	.33	.22	1				
9.Hoarding	4.15±2.82	.23	.32	.25	.50	.25	.35	.30	.37	1			
10.Neutralizing	1.71±2.56	-.14	.18	.26	.27	.50	.26	.28	.38	-.01	1		
11.Alcohol abuse	7.15±4.55	.32	-.02	-.06	-.04	-.19	-.20	-.07	-.06	.01	-.01	1	
12.Cannabis abuse	1.24±2.73	.19	.16	.20	.16	.21	.16	-.25	.25	-.04	-.05	.18	1

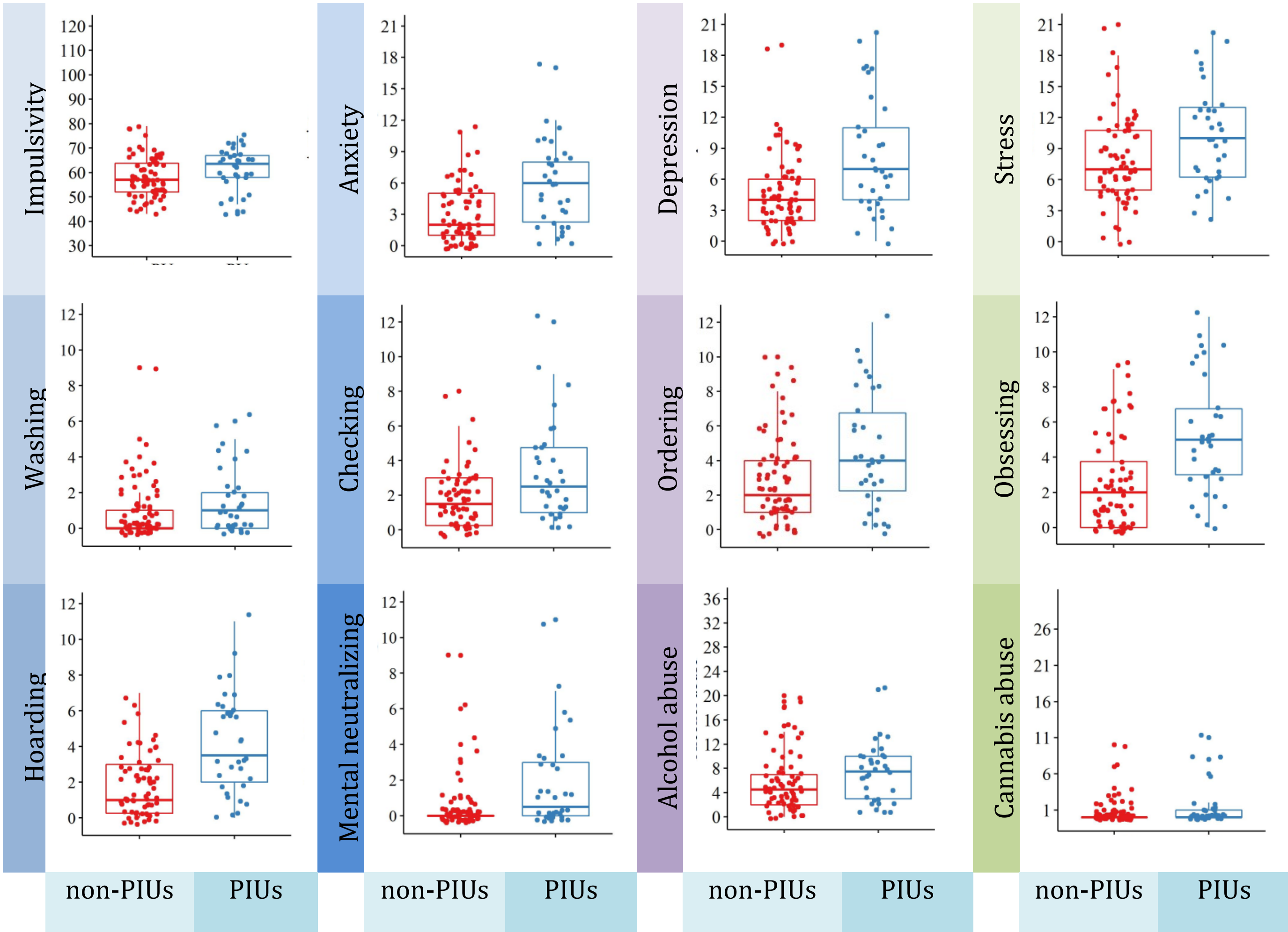
Non-PIUs (n = 70)

	Mean±sd	1	2	3	4	5	6	7	8	9	10	11	12
1.Impulsivity	57.91±8.52	1											
2.Anxiety	2.91±2.82	.14	1										
3.Depression	4.54±3.31	.14	.48	1									
4.Stress	7.69±4.20	.03	.64	.57	1								
5.Washing	0.91±1.55	.03	.29	.13	.13	1							
6.Checking	1.76±1.63	-.21	0	-.05	.02	.14	1						
7.Ordering	2.91±2.47	-.09	.22	.26	.16	.26	.48	1					
8.Obsessing	2.51±2.67	.20	.30	.29	.20	.32	.11	.23	1				
9.Hoarding	1.84±1.71	.12	.27	.19	.27	.30	.40	.26	.30	1			
10.Neutralizing	0.51±1.48	.04	.13	.07	.12	.01	.12	.24	.32	.10	1		
11.Alcohol abuse	5.61±4.79	.27	.13	.27	-.01	.19	.06	.10	.22	.33	.14	1	
12.Cannabis abuse	0.63±1.63	.17	.17	.07	-.02	0	-.09	-.07	-.02	.1	.03	.33	1

As showed in Figure 2, the linear model analysis revealed significantly higher scores in the PIUs than the non-PIUs group in Anxiety ($t(1) = 4.15$, $p < .001$, $d = -0.87$), Depression ($t(1) = 4.52$, $p < .001$, $d = -0.95$), Stress ($t(1) = 3.09$, $p = .002$, $d = -0.65$), Washing ($t(1) = 2.08$, $p = .04$, $d = -0.43$), Checking ($t(1) = 2.71$, $p = .007$, $d = -0.57$), Ordering ($t(1) = 2.74$, $p = .007$, $d = -0.57$), Obsessing ($t(1) = 4.30$, $p < .001$, $d = -0.90$), Hoarding ($t(1) = 4.90$, $p < .001$, $d = -1.03$), and Mental neutralizing symptoms ($t(1) = 3.59$, $p < .001$, $d = -0.76$).

Groups did not significantly differ on Impulsivity (t(1) = 1.86, p = .07, *d* = -0.39), Alcohol abuse (t(1) = 1.84, p = .07, *d* = -0.39), and Cannabis abuse (t(1) = 1.03, p = .30, *d* = -0.22).

Figure 2. Differences between non-Problematic (non-PIUs) vs. Problematic (PIUs) Internet users for study variables



To test the predictive power of study variables in PIUs and non-PIUs, a multiple logistic regression was employed. As shown in Table 2, only Hoarding and Obsessing symptoms remained independent statistical predictors of PIUs vs non-PIUs group. Each one-score increase in Hoarding significantly increases the log odds of being Problematic vs. non-problematic Internet user by 0.37 (Deviance = 22.1, p < .001, OR = 1.44, ΔAIC = -9.41, ΔBIC = -

6.77). Similarly, each one-score increase in Obsessing increases the log odds of being Problematic vs. non-problematic Internet user by 0.19 (Deviance = 5.20, p = .02, OR = 1.21, ΔAIC = -3.20, ΔBIC = -0.55). However, the effect of Obsessing is much smaller than that of Hoarding.

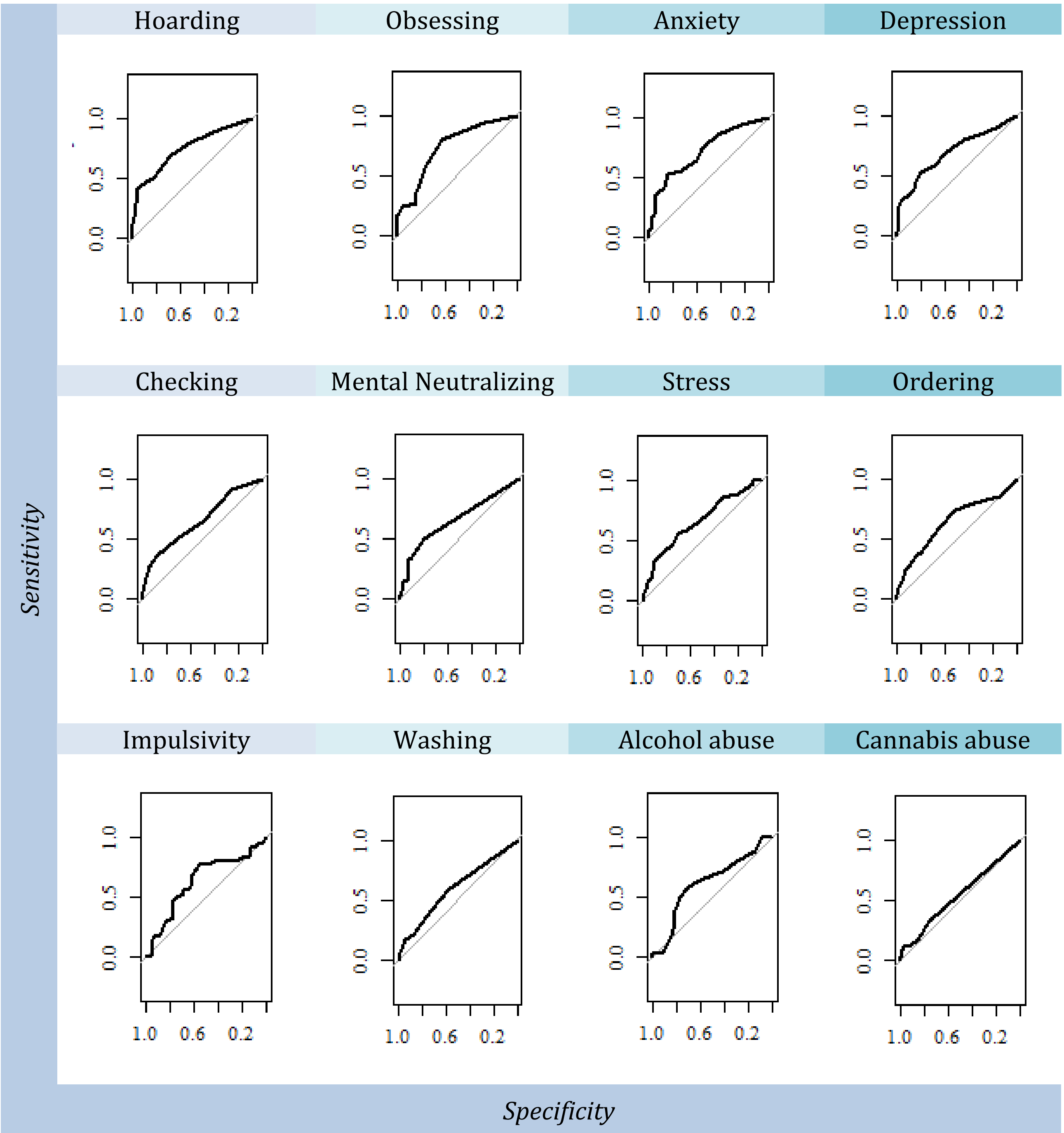
Table 2. Stepwise multiple logistic regression analysis and Area Under the Curve (AUC)

n = 104

		Predictors	Deviance	p	AIC	BIC	AUC
Step 1	*+ Hoarding*	1	22.1	<.001	113.35	118.64	0.745
Step 2	*+ Obsessing*	2	5.2	0.02	110.15	118.09	0.792
Step 3	*+ Anxiety*	3	2.08	0.15	110.07	120.64	0.799
Step 4	*+ Depression*	4	1.1	0.29	110.97	124.19	0.797
Step 5	*+ Checking*	5	0.61	0.44	112.36	128.23	0.804
Step 6	*+ Mental neutralizing*	6	1.63	0.20	112.73	131.24	0.811
Step 7	*+ Stress*	7	1.89	0.17	112.84	133.99	0.811
Step 8	*+ Ordering*	8	0.05	0.83	114.79	138.59	0.813
Step 9	*+ Impulsivity*	9	0.19	0.67	116.61	143.05	0.817
Step 10	*+ Washing*	10	0.66	0.42	117.95	147.04	0.822
Step 11	*+ Alcohol abuse*	11	0.02	0.90	119.93	151.67	0.821
Step 12	*+ Cannabis abuse*	12	0.84	0.36	121.1	155.48	0.828

Only Hoarding (AUC = 0.75), Obsessing (AUC = 0.74), and Anxiety (AUC = 0.72) presented AUC significantly different from 0.5 (p = 0.009, p = 0.011 and p = 0.03, respectively) and > 0.70, indicating that these variables can distinguish between individuals with and without PIU (see Figure 3).

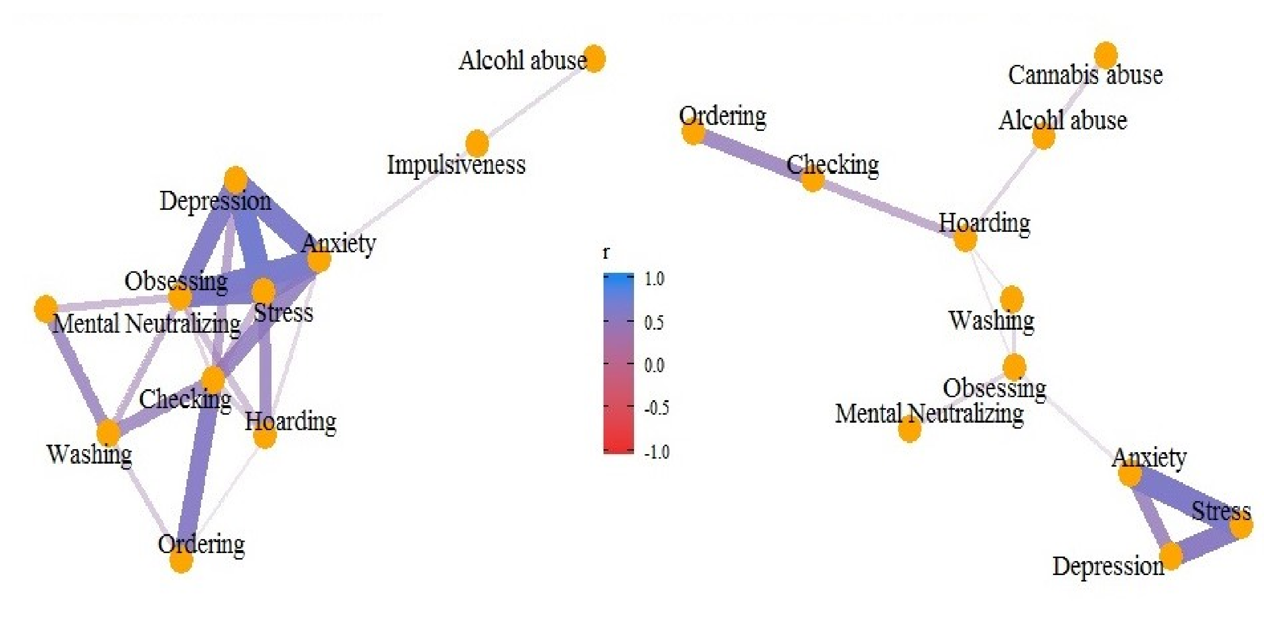
Figure 2. Receiver Operating Characteristic (ROC) plots for each study variable. Larger areas under the curve indicate better global performance of the variable in discriminating PIUs from Non-PIUs



In the correlation networks in PIUs and Non-PIUs, correlations were considered as meaningful when $p < .05$ and $r \geq |0.30|$ (Taylor, 1990, see Figure 4). The following correlations were stronger in PIUs than in non-PIUs: Stress and Checking symptoms ($z = 1.80$, $p = .04$, Cohen's q = 0.39), Stress and Obsessing symptoms (z = 2.40, p = .01, Cohen's q = 0.52), Anxiety and Checking symptoms (z = 2.72, p = .01, Cohen's q = 0.59), Anxiety and Obsessing symptoms (z = 2.31, p = .01, Cohen's q = 0.50), Depression and Checking symptoms (z = 1.94, p = .03, Cohen's q = 0.42), Depression and Obsessing symptoms (z = 1.96, p = .03, Cohen's q = 0.43), Washing and Checking symptoms (z = 1.88, p = .03, Cohen's q = 0.41), Washing and Mental neutralizing symptoms (z = 2.48, p = .01, Cohen's q = 0.54).

Figure 3. Correlation network plot for problematic (PIUs) and Non-problematic Internet users (Non-PIUs). Only Pearson's rs ≥ |0.30| were included. Variables that are more strongly correlated appear closer together and are connected by stronger paths. Paths are colored by their sign (blue for positive and red for negative). The proximity of the points is determined using multidimensional clustering.

PIUs	non-PIUs



Discussion

The present study was aimed at characterizing individuals with PIU in terms of impulsivity, depression, anxiety, stress, obsessive-compulsive symptoms, alcohol and cannabis abuse, and examining both the predictive and the diagnostic power of these variables in discerning individuals with vs. without PIU.

The pattern of findings that emerged in individuals with PIU partially supports the results of previous research on the occurrence of some psychopathological symptoms in PIU. Specifically, in accordance with our hypothesis, individuals with PIU did endorse more anxiety, depression, stress, and obsessive symptoms, and more compulsive behaviors (with the exception of compulsive washing, that showed a low effect size). Of note, in the group of individuals with PIU mean levels of anxiety, depression, and stress were all above the questionnaires' cut-off values for these psychopathological symptoms. Moreover, the severity of obsessing and ordering symptoms was above the cut-off values that indicate a condition requiring clinical attention. Overall, these findings suggest that PIU may be characterized by a pattern of symptoms resulting from a disturbance of networks and mechanisms underlying anxiety/mood disorders and OCD. Among such networks, the reward network might play a fundamental role. The reward network is at the basis of motivated behavior, and alterations in its functionality are associated with addiction, depression, and OCD (Park et al., 2019). Similarly to behavioral addictions, it has been shown that both PIU and IGD are related to abnormalities in reward processing, inhibition, and impulse control (Brand et al., 2016; Dong, Hu, & Lin, 2013; Dong & Potenza, 2014; Kuss & Lopez-Fernandez, 2016; Younes et al., 2016), with increased reward sensitivity and sensitivity to punishment in individuals with PIU (Vargas et al., 2019). Neurobiological overlaps between behavioral addictions, OCD, and mood disorders have been hypothesized, and a shared dysfunction in the reward network has been identified for these disorders. Specifically, it has been suggested that addictions, OCD (Alves-Pinto et al., 2019;

Figee et al., 2016; Rădulescu & Marra, 2017), and mood disorders (Gong et al., 2017; Ironside, Kumar, Kang, & Pizzagalli, 2018) are all related to altered reward processing, with dopamine abnormalities in limbic structures and imbalances between ventral and dorsal frontostriatal activities (Figee et al., 2016, 2011). Studies on functional connectivity have shown similar impairments of reward network connectivity in OCD and depression (Alves-Pinto et al., 2019; Gong et al., 2017). Moreover, a relationship between stress and the activity of the reward network has been extensively described. Both preclinical and clinical studies suggest that stress affects reward anticipation and dopamine signaling in the medial prefrontal cortex and ventral striatum (Ironside et al., 2018), and stress seems to be a significant risk factor for the development and maintenance of addictive behaviors (Schwabe, Tegenthoff, Hoffken, & Wolf, 2012; Schwabe, Dickinson, & Wolf, 2011; Schwabe, Schächinger, de Kloet, & Oitzl, 2010). However, evidence of shared dysfunctions in brain networks activity does not clarify whether these abnormalities are risk factors for PIU, or their onset is a consequence of Internet abuse. Since the present study was cross-sectional, it does not allow discussing the results in terms of cause-effect relationships. However, it is noteworthy that a longitudinal study on the precursors and sequelae of PIU in Chinese people found that across a number of psychopathological symptoms (i.e., obsessive-compulsive, somatisation, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, and psychoticism), only OCD symptoms were higher in Internet addicts than the norm values for Chinese people, before these individuals developed Internet addiction. The Authors argued that since OCD symptoms were much higher than the norm values before Internet addiction, OCD could be considered as a predictor for Internet addiction (Dong et al., 2011). Further longitudinal studies are needed to better characterize the mechanisms underlying PIU, the commonalities with those underlying mood disorders and OCD, as well as the timeline of symptom onset.

Contrary to our expectations, we did not find higher levels of impulsivity in individuals with vs. without PIU. Similar results have been previously reported in studies that assessed impulsivity in PIU using self-report measures (Armstrong et al., 2000) and behavioral tasks (Lee et al., 2019). However, a number of studies has also shown that impulsivity levels are positively associated with- or are predictive of PIU (Cao et al., 2007; Ioannidis et al., 2016; Koo & Kwon, 2014; Liu et al., 2019; Mottram & Fleming, 2009; Peterka-Bonetta et al., 2019; Shokri et al., 2017), suggesting that further studies are necessary to eventually replicate and to expand our findings for clarifying the role of impulsivity in PIU (Lee et al., 2019).

As for alcohol and cannabis use, we did not find any significant differences between PIUs and non-PIUs. Despite the similarities between PIU and substance use disorder (SUDs) in the underlying psychobiological mechanisms, some neurobiological differences between addictive substances as well as between IGD and SUDs have been extensively described (Park, Han, & Roh, 2017). It may be speculated that PIU shares core psychological and neurobiological aspects of psychostimulants use disorders rather than of AUD and CUD. Future studies should investigate similarities and differences between PIU and different substance use disorders, including psychostimulants use disorder, AUD, CUD, heroin use disorder, etc.

Interestingly, when the predictive power of study variables for PIU was examined, we found that only hoarding and obsessing symptoms were significant in predicting a condition of problematic vs. non-problematic Internet use, with hoarding having a higher predictive power and greater accuracy than obsessing to discern problematic from non-problematic Internet users. While a number of studies have focused on the relationship between OCD and PIU, this is the first study to our knowledge that investigated specific OCD dimensions in problematic Internet users. Of note, hoarding has been reported to have a positive relationship with online/offline compulsive buying (Claes, Müller, & Luyckx, 2016), and similar results were found in a qualitative study aimed at evaluating a pilot treatment program for Internet addiction in Holland (van Rooij, Zinn, Schoenmakers, & van de Mheen, 2012). Specifically, van Rooij and colleagues (2012) found that individuals with PIU frequently reported of hoarding porn, photos, and other Internet-related materials. Moreover, an overview on sexual addiction reported that sexually compulsive gay men are likely to hoard sexually explicit photographs on their computer or disk for future use (Dew & Chaney, 2004). Hoarding has also been described as one of the main aspects of online/offline child pornography use (O'Donnell & Milner, 2012). Of note, despite Hoarding disorder is included among Obsessive-compulsive related disorders (American Psychiatric Association, 2013), its appetitive aspects, e.g. the affection and pleasure related to the inanimate objects to be hoarded, are thought to be more akin to behavioral addictions (Grisham & Norberg, 2010; Yap & Grisham, 2019). Moreover, similarly to behavioral addictions, hoarding seems to arise from the anticipation of pleasure and impaired self-regulation (Grisham, Brown, Liverant, & Campbell-Sills, 2005; Grisham & Norberg, 2010).

Quite recently, the notion of "digital hoarding" has been proposed. It has been described as a subtype of hoarding disorder, characterized by the accumulation of digital information to the point of loss of perspective, eventually resulting in stress symptoms and disorganization, with adverse consequences on the individual's functioning in daily life (van Bennekom, Blom, Vulink, & Denys, 2015). A qualitative study on digital hoarding behavior showed that people that engage in digital hoarding experience several difficulties, e.g. they fail to delete hoarded digital information. Specifically, despite digital hoarders are surprised about the amount of digital information they have accumulated, they refuse to delete useless material. This behavior seems to be related to the belief that hoarded information have potential value and might be useful in the future (Sweeten, Sillence, & Neave, 2018). If hoarding or, more specifically, "digital hoarding", is one of the core elements that characterize PIU, and/or if it is a consequence of altered mechanisms that also determine PIU, is yet to be determined. Given our findings on the predictive power of hoarding levels and their accuracy in discerning problematic from non-problematic Internet users, future studies should further explore the nature of hoarding behaviors in PIU and their clinical relevance for the diagnosis of PIU.

Our findings on the predictive power of obsessing in PIU are in accordance with previous studies that described obsessing as one of the main factors underlying PIU (Demetrovics et al., 2008). These findings are also similar to what reported for IGD (Young, 2007b), SUDs (O'Brien, Childress, Ehrman, & Robbins, 1998; Redish & Johnson, 2007), sexual and food addiction (Leedes, 2001; Pelchat, 2002), suggesting that obsessing might be a shared feature between PIU and other addictive behaviors.

Of note, anxiety showed only a moderate accuracy to discern between problematic and non-problematic Internet users. Future studies should further explore the role of anxiety in PU, not only as a possible outcome of PIU, but also as a potentially useful variable in the context of clinical assessment and diagnosis formulation (Pintea & Moldovan, 2009).

Lastly, we found PIUs to be characterized by a pattern of stronger and positive associations of stress, anxiety, and depression with both checking and obsessing, and of washing with both checking and mental neutralizing than non-PIUs. In PIUs, the strong and positive associations between stress, anxiety, and depression with some OCD dimensions seems in line with the idea of an altered mechanism shared by OCD and PIU that may lie at the basis of PIU. It should be noted that although obsessions in OCD have been described to be related to anxiety, emotional distress in subclinical OCD may be of clinical relevance as well, as it may exacerbate compulsive behaviors (Spinella, 2005). As mentioned before, it has been described both OCD symptoms and mood disorders to share underlying psychopathological mechanisms including aberrant activity in reward network/prefrontal-striatal/limbic circuits. As a consequence, maladaptive emotional and behavioral patterns would emerge (Park et al., 2019; Spinella, 2005). As a consequence of these modifications, several problematic behaviors would emerge, including IGD (Han et al., 2018), gambling (Potenza, 2013), and SUDs (Volkow et al., 2010). Thus, OCD seems to be strongly related to behavioral addictions (including PIU and other addictive behaviors), with neurobiological overlaps between SUDs, OCD and behavioral addictions, including attenuated dopamine release in the ventral striatum as reflected in altered reward and punishment processing, dysregulated limbic activity with consequential abnormal negative reinforcement processes, reduced serotonergic prefrontal control reflected in cognitive and behavioral inflexibility, and imbalances between ventral and dorsal frontostriatal recruitment resulting in habitual responding (Figee et al., 2016). Future research should explore possibly altered psychobiological mechanisms that may underlie the pattern of interassociated psychopathological symptoms in PIU.

The present study has three main limitations. Firstly, this study was implemented using a cross-sectional design. This makes it difficult to infer cause-effect relationships between variables. Secondly, only self-report data were collected, Future research should include both behavioral and psychophysiological measures to further investigate the relationships between study variables. Lastly, participants were classified as mild to moderate problematic Internet users on the basis of IAT scores, such that our sample may not be adequately representative of problematic Internet users.

Despite these limitations, this study provides new insight into the characterization of PIU, by suggesting that PIU is characterized by a network of interassociated psychopathological symptoms that may reflect a disturbance of mechanisms underlying affective disorders and OCD. Interestingly, hoarding and obsessing are significant variables in characterizing PIU, with hoarding having greater accuracy than obsessing to discern problematic from non-problematic Internet users. These findings are of significance for the assessment of PIU and should be considered in the discussion about potential clinical criteria for the diagnosis of PIU. The results on anxiety suggest that future studies are needed to clarify if, besides hoarding and obsessing, anxiety is a useful variable in the clinical assessment and diagnosis of PIU.

"I feel tired and stressed but I need to use the Internet by my smartphone"

(Participant 108, 20 years old)

Study 2: Stress, craving and problematic Internet use

Introduction

It has been reported that individuals with problematic Internet use (PIU) are more likely to have psychopathological disorders or symptoms, including mood and anxiety disorders (Kitazawa et al., 2018; Ostovar et al., 2016; Vasileios Stavropoulos et al., 2017; Younes et al., 2016); obsessive-compulsive symptoms (Vasilis Stavropoulos, Gentile, & Motti-Stefanidi, 2016), and alexithymia (Taylor, Koerber, Parker, & Maitland, 2014). Controversial findings were found on the relationship of PIU with impulsivity and substance use disorders (SUDs), with some studies finding high impulsivity (Cao et al., 2007; Ioannidis et al., 2016; Koo & Kwon, 2014; Liu et al., 2019; Mottram & Fleming, 2009; Peterka-Bonetta et al., 2019; Shokri et al., 2017) and SUDs symptoms in PIU (Ho et al., 2014; Lee et al., 2013; Yen et al., 2009) while some others did not (Armstrong et al., 2000; Lee et al., 2019; see the Results of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection in Section 1) Such findings emphasize the importance of carefully assessing the presence of such conditions in individuals with PIU.

In addition to assessing comorbidities, identifying the factors that precipitate and maintain PIU is of fundamental importance. Studies on SUDs have shown that **craving** is a key factor in the maintenance of addictive behaviors (Tiffany & Wray, 2012). Craving is defined as a subjective motivational state involving an intense urge to engage in a specific behavior, and is thought to reflect a conditioned response resulting from repeated pairing of (previously neutral) stimuli with reward (Everitt et al., 2001). A recent study showed that, among individuals with PIU, exposure to Internet-related words was followed by an increase in self-reported craving, suggesting that PIU may share similar underlying mechanisms with other addiction disorders (Niu et al., 2016).

Research has increasingly recognized the importance of understanding the relationship between PIU and **stress**, including the role of potential mediators and moderators (Li et al., 2016). Stress occurs when an individual perceives that environmental demands exceed his or her adaptive capacity (Cohen et al., 1995). Studies on addictions suggest that acute and/or chronic stress can determine the attribution of additional salience to reward-related stimuli (Mantsch, Baker, Funk, Lê, & Shaham, 2016; Sinha et al., 2009), favoring the formation of conditioned responses without an appraisal of response consequences, i.e., habits (Balleine & O'Doherty, 2010). Habits are believed to be at the basis of craving (Schwabe et al., 2011, 2012; Sinha, Fuse, Aubin, & O'Malley, 2000). Specifically, Schwabe and colleagues (Schwabe et al., 2011, 2010, 2012) proposed that acute or chronic stress cause the release of several hormones, including glucocorticoids, noradrenaline and adrenaline, that facilitate striatum-dependent memory processes by favoring dorsolateral striatum-based habits.

The link between stress reactivity and craving has been less systematically examined in behavioral addictions than in SUDs. However, it can be hypothesized that Internet-related habits are potentiated and reinstated by stress, leading to craving symptoms and PIU development. In other words, an exaggerated reactivity to stressors may lead to an excessive engagement of habit processes in instrumental action, thus promoting conditioned habitual responses to Internet-related stimuli that lie at the basis of compulsive Internet use (LaRose, 2010, 2015).

Few studies have investigated the relationship between stress reactivity and PIU using self-report measures. Specifically, it has been shown that stressful life events are positively correlated with Internet addiction (Li, O'Brien, Snyder, & Howard, 2016). Furthermore, perceived stress has been found to be one of the predictors of PIU for sexual purposes (Velezmoro et al., 2010), and PIU appears to be associated with stress, depression and anxiety symptoms (Akin & Iskender, 2011). No study to our knowledge has yet investigated stress reactivity in individuals with PIU using psychophysiological indices in addition to self-report instruments. In the assessment of psychophysiological indices of the stress response, both the magnitude of response and the capacity to recover (i.e., the degree to which a psychophysiological response returns to pre-stress levels following a stressor) have been commonly considered as relevant parameters. Classical laboratory stress tasks used to investigate psychophysiological stress responses include public speaking and mental arithmetic, and the most commonly assessed indices include autonomic measures such as heart rate and heart rate variability (HRV) and skin conductance (SC).

HRV consists in the variations over time of the period between consecutive heartbeats (RR intervals). Such variations represent a fine tuning of the beat-to-beat control mechanisms by vagal and sympathetic activity directed to the sinus node of the heart (Malik et al., 1996). High HRV reflects the autonomic nervous system (ANS) ability to adapt to changing circumstances, and it seems to be associated with goal-based control of emotions, context-appropriate responses and recovery after stressor (Thayer, Åhs, Fredrikson, Sollers, & Wager, 2012). In contrast, low HRV reflects the ANS inability to adapt to stressful events, and is associated with delayed recovery from psychological stress (Weber et al., 2010).

The analysis of the spectral components of HRV allows to understand the modulatory effects of neural mechanisms on the sinus node. In particular, the high frequency (HF; .15-.40 Hz) component is mainly determined by efferent vagal activity, whereas the low frequency (LF; .04-.15 Hz) component is considered as a marker of sympathetic modulation or as a parameter that includes both sympathetic and vagal influences (Malik et al., 1996). In response to stressors, an increase in sympathetic cardiac control, a decrease in parasympathetic control, or both, are often observed, as reflected by increase in LF, a decrease in HF power, and/or an increase in the LF/HF ratio (Berntson & Cacioppo, 2007).

Skin conductance (SC) is a non-invasive measure of the variations in electrical conductance of the skin depending on the changes in the levels of sweat in the ducts (Cacioppo, Tassinary, & Berntson, 2016). SC reflects only the activity of the sympathetic component of the ANS, due to the absence of parasympathetic innervation on eccrine sweat glands. SC has been largely measured to assess sympathetic activation during challenging situations (Jacobs et al., 1994; Lazarus, Speisman, & Mordkoff, 1963).

The goals of the present study were to investigate (i) whether individuals with PIU show enhanced autonomic reactivity to a standardized psychosocial stress task; (ii) whether greater autonomic reactivity is related to higher craving ratings; and (iii) whether the presence of PIU is associated with high levels of anxiety, depression, impulsivity, alexithymia, obsessive-compulsive symptoms and more frequent use of alcohol and cannabis.

We hypothesized that PIU individuals would be characterized by lower HRV and higher SC level during the stress task as compared with individuals without PIU. Furthermore, we expected to observe an increase of craving ratings after the stress task in individuals with, but not in individuals without, PIU. Lastly, we expected that individuals with PIU would show higher scores on self-reports of anxiety, depression, alexithymia, and obsessive-compulsive symptoms than individuals without PIU. Based on the results of Study 1 (see *Results* of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection, Section 1), we did not expect group differences in impulsivity and in the use of alcohol and cannabis.

Method

Participants

Students of the University of Padova, Italy, were contacted informally at university facilities and asked to fill in an anonymous online version of the IAT (Ferraro et al., 2007; Young, 1998b. See further details in Assessing problematic Internet use of the Characterizing problematic Internet use subsection, Section 1). Based on Italian cut-off scores, Internet usage was defined as non-problematic (scores 20-50), mild to moderate (scores 50-80), and severe problematic (scores 80-100. Poli & Agrimi, 2012). One hundred eighty-eight students filled in the online questionnaire. Twenty-four students who qualified as problematic Internet users (PU; 15 females; mean age = 23.04 ± 3.57; mean IAT score = 58 ± 7.2, range = 49-71), and 21 who qualified as non-problematic Internet users (non-PIUs; 17 females, mean age = 23.29 ± 2.87; mean IAT score = 31 ± 4.6, range = 23-39) accepted to participate in the study. No differences between groups were found for age, gender, sleep hours, and cigarettes consumption.

Approval for the study was obtained from the Ethical Committee of Psychological Research, Area 17, University of Padova. The ethical principles of the Helsinki and its amendments or comparable ethical standards were followed.

Self-report measures

The following questionnaires were administered: the Italian version of *the Alcohol Use Disorders Identification Test* (AUDIT; Struzzo, De Faccio, Moscatelli, & Scafato, 2006) to assess the frequency and quantity of alcohol consumption (Reinert & Allen, 2002); the Italian version of the *Cannabis Abuse Screening Test* (CAST; Bastiani et al., 2013) to assess cannabis use with reference to the past 12 months. The Italian version of the *Depression Anxiety Stress Scales-21* (DASS-21; Bottesi et al., 2015) to assess general distress through three separate subscales (i.e., anxiety, depression, and stress); the Italian version of the *Barratt Impulsiveness Scale* (BIS-11; Fossati, Di Ceglie, Acquarini, & Barratt, 2001) to assess impulsivity; the Italian version of the *Obsessive-Compulsive Inventory-Revised* (OCI-R; Sica et al., 2009) to measure obsessive-compulsive symptoms (see further details on these self-reported measures in *Method* of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection, Section 1).

The Italian version of the *short UPPS-P Impulsive Behaviour Scale* (S-UPPS-P; D'Orta et al., 2015) is a 20-item questionnaire that was administered to further assess impulsivity by considering five different components: positive urgency, negative urgency, lack of perseverance, lack of premeditation, and sensation seeking. All items are scored on a Likert scale from 1 ("I agree strongly") to 4 ("I disagree strongly"). The Italian S-UPPS-P showed adequate psychometric properties like solid and theory-driven factor structures and good internal consistency of the subscales.

The Italian version of the *Toronto Alexithymia Scale* (TAS-20; Bressi et al., 1996) is a 20-item self-report measure that was used to assess alexithymia. All items are scored on a Likert scale form 1 ("strongly disagree") to 5 ("strongly agree") and five items are negatively keyed. It provides a total alexithymia score and also three subscales scores, i.e., Difficulty Identifying Feelings, Difficulty Describing Feelings, and Externally Oriented Thinking. A higher score on the TAS-20 indicates a greater level of alexithymia. The Italian TAS-20 showed adequate estimates of internal reliability, test-retest reliability, and good internal consistency of the total score.

Craving measure

To assess craving for Internet use, participants were asked to respond to a single question ("How much would you like to use the Internet now?") using a Likert scale (range 1-5; 1 = not at all, 5 = very much; Cano et al., 2014; Dawkins, Munafò, Christoforou, Olumegbon, & Soar, 2016).

Stress task

A modified version of the Trier Social Stress Test (TSST, Kirschbaum, Pirke, & Hellhammer, 1993) was employed. Participants were first invited to remain quiet (Phase 1; 3 minute-baseline). Then, they were asked to prepare an oral speech about their personal traits qualifying them for their "dream" job position (Phase 2; 3 minutes). In the following phase, they were asked to speak in front of a video camera (Phase 3; 5 minutes). Participants were informed that video camera was connected to a monitor in another room, where an evaluation commission would judge their performance. Then the experimenter invited participants to rest again for six minutes (Phase 4, 3-minute recovery; and Phase 5, 3-minute baseline). In the following phase (Phase 6, 5 minutes), participants were asked to start counting backwards in steps of 13, starting at 2011. Upon each error, the experimenter asked them to start over. Lastly, participants were invited to rest again for three minutes (Phase 7).

Autonomic measures

The electrocardiogram (ECG) and skin conductance (SC) were recorded continuously using a ProComp Infiniti system (Thought Technology; Montreal, Canada). To record the ECG, three disposable Ag/AgCl electrodes were placed on the participant's chest in a modified Lead II configuration. The ECG signal was sampled at 256 Hz, band-pass filtered (1-100 Hz), and amplified. A digital trigger detecting R-waves was applied to the ECG signal to obtain inter-beat intervals (IBIs). All ECG data were visually examined and artifacts were corrected. Time domain and frequency domain indices of HRV were compute by Kubios HRV Analysis Software 2.0 (The Biomedical Signal Analysis Group, Department of Applied Physics, University of Kuopio, Finland). Fourier analysis was used to calculate frequency domain indices, i.e., low frequency power (LF: 0.04 to 0.15 Hz) in ms^2, considered as an index of both ANS branches activity, and high frequency power (HF: 0.15 to 0.40 Hz) in ms^2, an index of cardiac parasympathetic tone.

As time domain indices, the standard deviation of all normal-to-normal intervals (SDNN) was calculated as an index of the total HRV, and the root mean square of successive difference of N-to-N intervals (rMSSD), expressed in ms, was calculated as an index of vagal control on the heart (Malik et al., 1996).

Skin Conductance Level (SCL) was recorded by two Ag/AgCl electrodes fixed to the medial phalanx surface of the first and middle finger of the nondominant hand. The sampling rate was 256 Hz.

Procedure

After participants provided a written informed consent, they were asked to rate their Internet craving using the Likert scale. Then, ECG and SC sensors were placed and participants were given instructions about the task. After completion of the task, participants were asked again to rate their Internet craving on the Likert scale, and sensors were removed. After the experimental session, the participants were asked to fill-in the questionnaires. The entire procedure took about 40 min.

Statistical analysis

All statistical analyses were conducted on the mean values of SDNN, rMSSD, HF, LF, HF/LF ratio, and SCL, calculated over the 3-min interval of Phases 1, 2, 4, 5 and 7, and the central 3 minutes in the 5-min Phases 3 and 6.

All analyses were performed using R software (R Development Core Team, 2016). Specifically, Pearson's r (Harrell, 2017) was calculated to assess the strengths of correlations between self-report measures in both PIUs and non-PIUs.

To test autonomic reactivity during the TSST we estimated fifty mixed-models (Mn in the Appendix by R package: lme4; Bates et al., 2014) and the best-fitting model was selected using the AIC criteria (Bolker et al., 2009; Wagenmakers & Farrell, 2004), i.e., the model with the smallest AIC and the highest AIC weight is considered as the most appropriate model for reproducing the observed data. Mixed-effects models are considered as a powerful procedure for repeated-measures designs in psychophysiology (Bagiella, Sloan, & Heitjan, 2000). Considering autonomic indices as dependent variables, the mixed-models were defined by starting from a simple model with individuals (i) random intercept only (Model 0 in the Appendix: $Y_{ij} = b_0 + v_i + e_{ij}$, where Y_{ij} was the response for j^{th} measurement of i^{th} individual; b_0 was the fixed intercept; v_i was the random intercept for the i^{th} individual and e_{ij} was a Gaussian error term), and adding one fixed predictor to each subsequent model. Fixed predictors included Group (PIUs and non-PIUs), Phase (TSST phases), their interaction, and self-report measures that had been observed to be significantly reciprocally correlated in each Group. Hypothesized group differences in stress reactivity were fitted adding Group, Phase, and their interaction as fixed factors (Model 46; M46 in the Appendix) to Model 0. The maximum likelihood method was employed to analyze the contribution of parameters within the selected model (the modeling approach utilized data of all participants, except for SCL, for which one participant was excluded due to marked deviation from all other observations in the sample).

To assess whether Group (PIUs and non-PIUs), Time (before and after the TSST) and their interaction predict craving ratings (R package: MASS, Venables & Ripley, 2002) we estimated five nested ordinal logistic models, and the AIC criteria were employed to select the model that more appropriately described our data (Bolker et al., 2009; Wagenmakers & Farrell, 2004).

Linear model analysis considering Group (PIUs and non-PIUs) as predictor was performed to compare scores on self-reports between groups. Bayes factor analysis was run to quantify the predictive success of linear models with Group as predictor relative to an intercept-only model (R package: BayesFactor; Morey & Rouder, 2015).

Autonomic measures

Descriptive statistics of autonomic indices are reported in Table 3.

Table 4 shows the AIC and AIC weights of fitted mixed-models for each considered autonomic index. The mixed-model with fixed Phase predictor (M48 in the Appendix) resulted the preferred model to fit rMSSD, LF, HF and SCL (see Table 4).

The effect of fixed predictor was tested by the maximum likelihood method. The inclusion of Phase predictor improved the fit of the model for rMSSD, LF, HF, and SCL (rMSSD: $\Delta AIC = 26.03$, $X2\ (6, N = 9) = 38.03$, $p < .001$; LF: $\Delta AIC = 10.91$, $X2(6, N = 9) = 22.91$ $p < .01$; HF: $\Delta AIC = 5.29$, $X2(6, N = 9) = 17.289$ $p < .01$; SCL: $\Delta AIC = 185.51$, $X2(6, N = 9) = 197.51$, $p < .001$). The Phase effect for these autonomic indices is shown in Figure 5. Both rMSSD and HF were lower during Phase 3 than Phase 5. On the contrary, no significant differences between Phases were found for LF. Lastly, SCL was lower during Phase 1 than Phase 3 and Phase 4.

Different results were obtained considering SDNN. Our modeled expectations that considered Group, Phase and their interaction as fixed predictors (Model 46, M46 in the Appendix) resulted the best to describe the data. The inclusion of Phase predictor improved the fit of the model ($\Delta AIC = 29.91$, $X2(6, N = 10) = 41.91$, $p < .001$), SDNN was higher during Phase 1 than any other TSST phase.

No improvement in the fit of the model was found when Group was included as a predictor, however including the *Group×Phase* interaction resulted in an improvement in the fit of the model ($\Delta AIC = 1.83$, $X2(6, N = 16) = 13.83$, $p = .03$). As shown in Figure 6, during the first rest period (Phase 1) SDNN was lower in PIUs than non-PIUs. Moreover, SDNN during Phase 1 was higher than during any other TSST phase only among non-PIUs.

Table 3. Descriptive Statistics of autonomic measures

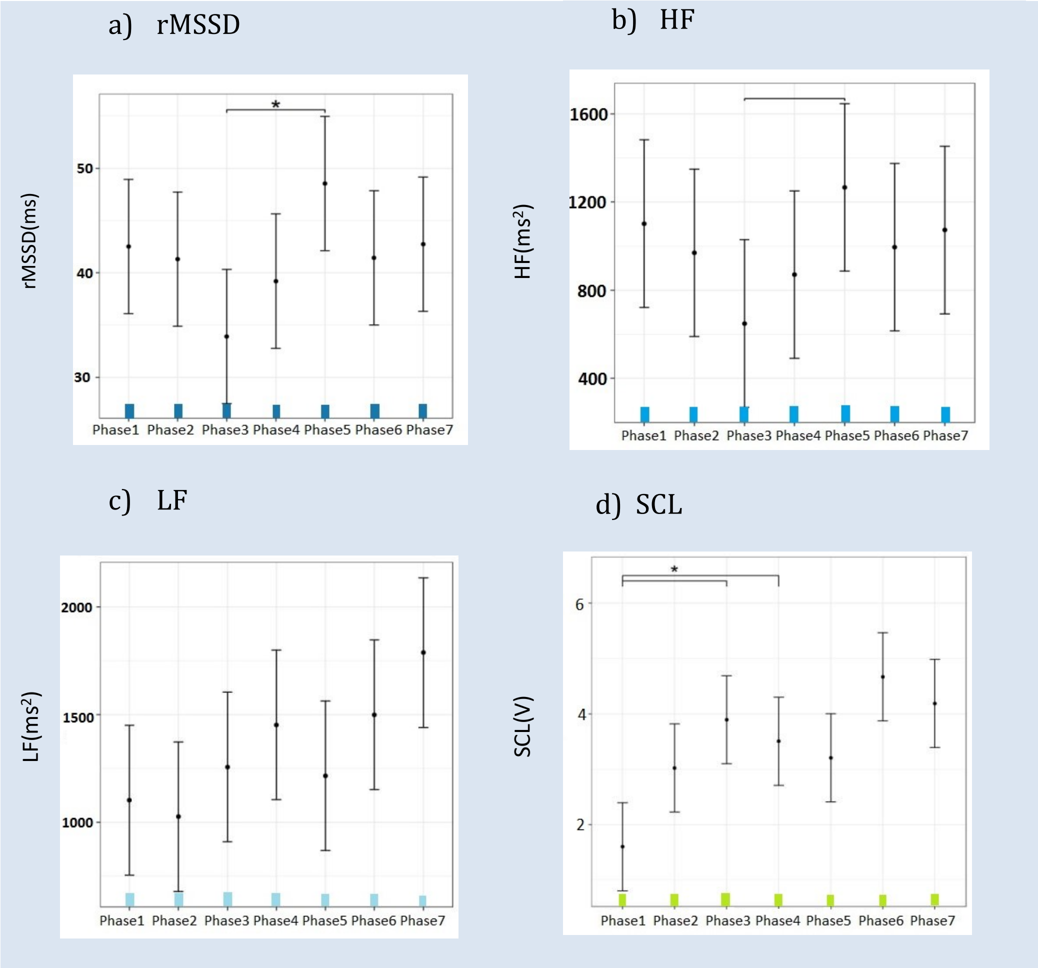
		PIUs			non-PIUs		
TSST phases	Index	mean	sd	median	mean	sd	median
Phase 1	SDNN (ms)	66.23	28.38	63.06	80.21	32.6	78.08
	rMSSD	39.95	18.69	38.24	45.43	28.43	33.98
	LF (ms^2)	915.43	455.43	901.08	1317.8	1140.2	1023
	HF (ms^2)	932.06	957.74	783.96	1296.5	2365.4	733.59
	SCL	1.93	2.21	1.43	1.7	1.48	1.42
Phase 2	SDNN	58.55	16.63	54.19	56.24	20.59	50.75
	rMSSD	40.44	17.73	38.2	42.28	23.61	35.42
	LF (ms^2)	1058.05	847.64	694.28	990.88	978.25	639.55
	HF (ms^2)	1025.46	1312.99	547.31	905.71	949.02	570.17
	SCL	3.54	3.28	2.54	3.06	2.33	2.3
Phase 3	SDNN	54.61	18.83	53.82	53.06	20.63	50.87
	rMSSD	32.41	13.98	31.5795	35.63	18.46	33.32
	LF (ms^2)	1148	856.9	1098.42	1381.6	1614	523.71
	HF (ms^2)	616.1	508.21	604.81	685.93	914.53	466.46
	SCL	4.53	4.17	2.96	3.97	3.34	2.84
Phase 4	SDNN	57.56	16.79	55.48	64.36	22.91	59.26
	rMSSD	37.35	20.78	30.04	41.33	27.3	33.41
	LF (ms^2)	1365.97	1058.1	976.86	1551.4	1035.4	1203.7
	HF (ms^2)	716.55	809.94	449.58	1046.1	1694.9	426.96
	SCL	4.22	4.58	2.91	3.61	3.28	2.24
Phase 5	SDNN	60.12	22.02	54.86	61.95	17.08	63.11
	rMSSD	47.51	30.69	39.5	49.72	22.12	46.64
	LF (ms^2)	1253.99	1111.24	770.8	1173.6	1351.2	697.82
	HF (ms^2)	1178.72	1400.36	750.63	1367	1550.2	1010.7
	SCL	3.92	4.67	2.74	3.34	3.40	1.75
Phase 6	SDNN	58.59	14.6	56.97	57.76	19.64	54.06
	rMSSD	39.84	15.76	41.39	43.25	18.06	36.77
	LF (ms^2)	1561.15	1087.48	1306.3	1428.9	1693.9	949.61
	HF (ms^2)	1022.81	892.13	672.71	963.51	840.33	778.6
	SCL	5.51	4.99	3.89	4.66	3.83	3.22
Phase 7	SDNN	62.35	18.51	59.86	62.94	22.40	64.72
	rMSSD	41.86	23.86	38.17	43.75	27.1	38.97
	LF (ms^2)	1761.95	1273.08	1580.55	1818.2	1856.8	1336.7
	HF (ms^2)	1102.03	1543	591.42	1040	1729.4	424.41
	SCL	5.19	5.38	3.76	4.12	3.76	2.45

Table 4. The AIC model comparison analysis of the mixed-effects models (Mn)

SDNN			rMSSD			LF			HF			SCL		
M_n	AIC	AIC_w	M_n	AIC	AIC_w	M_n	AIC	AIC_w	M_n	AIC	AIC_w	M_n	AIC	AIC_w
M46	2740.9	23.10%	M48	2573.0	38.47%	M48	5270.7	42.69%	M48	5208.7	37.04%	M48	1026.6	35.63%
M48	2741.2	19.38%	M47	2574.7	16.44%	M47	5272.6	16.61%	M47	5210.6	14.30%	M47	1028.6	13.22%
M47	2742.7	9.24%	M42	2574.8	15.39%	M42	5272.7	16.06%	M42	5210.6	14.26%	M42	1028.6	13.12%
M41	2742.7	9.21%	M44	2576.6	6.15%	M44	5274.6	6.12%	M44	5212.6	5.35%	M39	1029.2	9.89%
M42	2742.8	8.98%	M32	2576.9	5.43%	M27	5275.7	3.49%	M22	5213.2	4.02%	M32	1030.1	6.36%
M36	2743.2	7.30%	M39	2577.4	4.22%	M17	5276.2	2.72%	M32	5213.2	3.95%	M34	1030.4	5.42%
M32	2744.5	3.77%	M22	2578.1	3.02%	M34	5276.3	2.64%	M39	5213.4	3.63%	M44	1030.6	4.89%
M44	2744.5	3.68%	M27	2578.7	2.25%	M24	5276.4	2.50%	M0	5214.0	2.63%	M27	1032.1	2.34%
M31	2744.7	3.47%	M34	2578.9	2.00%	M19	5277.7	1.29%				M29	1032.4	1.99%
M39	2745.0	2.92%	M17	2578.9	1.95%	M12	5277.7	1.28%				M22	1032.7	1.68%
M27	2746.4	1.43%	M24	2579.9	1.21%	M14	5278.2	1.00%				M24	1033.5	1.12%
M34	2746.5	1.39%	M29	2580.7	0.83%	M46	5278.2	0.99%				M17	1034.3	0.78%
M26	2746.6	1.32%	M12	2580.7	0.81%	M7	5279.4	0.55%				M7	1034.4	0.72%
M22	2747.3	0.91%	M19	2580.9	0.73%	M0	5279.5	0.53%				M4	1034.6	0.66%
M21	2747.5	0.85%	M7	2582.4	0.34%							M2	1034.6	0.65%
M17	2748.1	0.61%	M14	2582.6	0.31%							M19	1035.3	0.47%
M16	2748.3	0.56%	M9	2584.3	0.13%							M9	1035.6	0.40%
M29	2748.4	0.53%	M2	2584.4	0.13%							M12	1036.3	0.29%
M24	2749.3	0.34%	M46	2585.8	0.06%							M14	1037.2	0.18%
M12	2750.1	0.23%	M4	2586.3	0.05%							M46	1039.2	0.06%
M19	2750.1	0.23%	M41	2587.7	0.02%							M36	1039.8	0.05%
M11	2750.3	0.21%	M36	2588.5	0.02%							M31	1041.0	0.03%
M7	2752.1	0.08%	M31	2590.0	0.01%							M41	1041.2	0.02%
M14	2752.1	0.08%	M21	2591.0	0.00%							M26	1043.0	0.01%
M6	2752.3	0.08%	M26	2591.7	0.00%							M21	1044.2	0.01%
M2	2754.0	0.03%	M16	2592.0	0.00%							M1	1045.2	0.00%
M9	2754.1	0.03%	M11	2593.7	0.00%							M16	1045.9	0.00%
M1	2754.1	0.03%	M6	2595.4	0.00%							M6	1046.3	0.00%
M4	2756.0	0.01%	M1	2597.4	0.00%							M11	1047.9	0.00%
M0	2771.1	0.00%	M0	2599.0	0.00%							M0	1212.1	0.00%

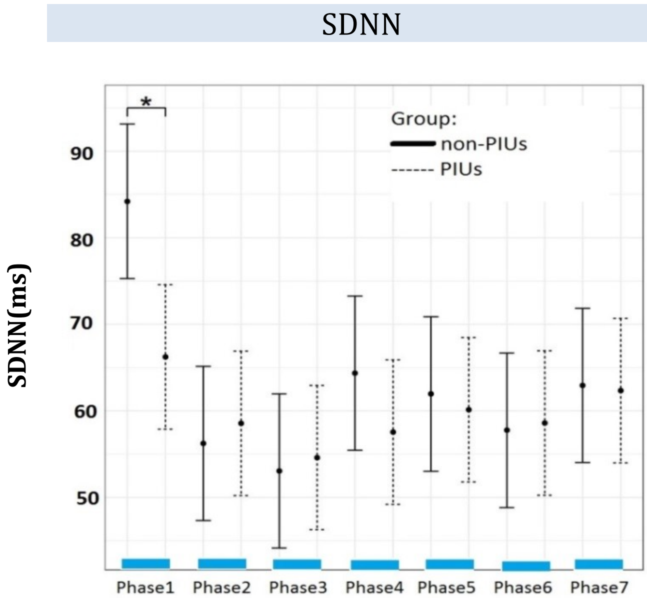
Given 50 candidate mixed-effects models (Mn; see Formulae A in S1 File), the best fitting models are reported in terms of AIC and AIC_{weight}. Considering SDNN, the best fitting model was our modeled expectation (Code M46, Formula: SDNN~Phase*Group+ (1|Individual)). Conversely, considering rMSSD, LF, HF, and SCL, M48 (Formula: Index~Phase+(1|Individual)) was the best fitting model.

Figure 5. The effect of Phase on rMSSD (a), HF (b), LF (c), and SCL (d)



The bars at each data point represent the confidence limits computed at .95. Asterisks and lines indicate significant differences between Phase levels

*Figure 6. The Phase*Group interaction for SDNN*



SDNN in each Phase and Group. The bars at each data point represent the confidence limits computed at .95. SDNN during Phase 1 was significantly greater in the non-PIUs than in the PIUs group

Craving ratings

As indicated by the AIC selection method, the model without the *Group×Time* interaction term (L2 in the Appendix) best fitted the data (see Table 5).

Table 5. The AIC model comparison analysis of the ordinal logistic models (Ln)

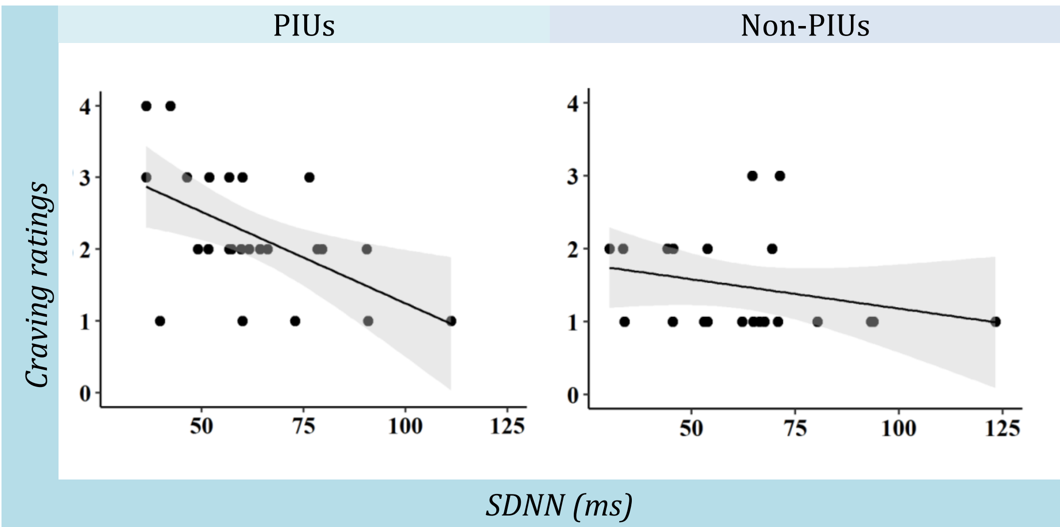
L_n	L2	L4	L1	L3	L0
AIC	191.5	192.2	193.5	206.2	206.4
AIC_w	47%	34%	18%	0.3%	0.3%

Based on the AIC and the AICweight of the ordinal logistic models (Ln; see Formulae B in S1 File), L2 (Formula: $Craving{\sim}Time + Group$) was the preferred model, indicating insufficient evidence to support a $Group \times Time$ interaction

The ordinal logistic regression was significant only using Group to predict craving ratings: t = 3.89, p < .001, OR = 5.65, 95% CI = [0.88, 2.64]), indicating that PIUs were more likely to report higher craving ratings then non-PIUs. Time was found not to predict craving ratings (t = 1.62, p > .05, OR = 1.98, 95% CI = [-0.13, 1.52]).

Finally, a strong negative correlation between SDNN measured during Phase 7 and craving ratings after the TSST was found only among PIUs (r(24) = - .53, p < .01; see Figure 7).

Figure 7. Correlation between craving ratings and SDNN after the stress task



Self-report measures

Descriptive statistics of self-report measures are reported in Table 6.

Table 6. Descriptive statistics of self-report questionnaires

	PIUs (n = 24)			Non-PIUs (n = 21)		
	mean	sd	median	mean	sd	median
AUDIT	8.08	4.26	8	4.48	4.24	3
CAST	0.75	2.25	0	0.67	1.6	0
DASS-21	21.88	11.67	17	12	6.83	12
BIS-11	61.75	9.43	63.5	54.95	6.5	56
NU[a]	11.04	2.36	11	10.14	2.99	10
PU[b]	10.04	2.37	10	9.1	2.59	8
LoPRE[c]	8.63	3.46	8.5	6.33	1.83	6
LoPER[d]	9.25	3.19	9.5	5.9	2.21	5
SS[e]	10.21	2.96	10.5	8.86	2.87	9
OCI-R	16.67	7.04	16.5	8.24	3.67	8
TAS-20	47.67	10.37	46.5	38.1	8.94	35

[a] The negative urgency subscale of the S-UPPS-P; [b] The positive urgency subscale of the S-UPPS-P; [c] The lack of premeditation subscale of the S-UPPS-P; [d] The lack of perseverance subscale of the S-UPPS-P; [e] The sensation seeking subscale of the S-UPPS-P

Linear model analysis revealed higher scorings in PIUs than in non-PIUs in the AUDIT ($F(1) = 8.06$, $p < .01$, $R^2 = .16$, BF = 6.57), the DASS-21 total score ($F(1) = 11.54$, $p < .01$, $R^2 = .21$, BF = 22.62 ±0%), the BIS-11 ($F(1) = 7.7$, $p < .01$, $R^2 = .15$, BF = 5.74 ±0%); the lack of premeditation ($F(1) = 7.39$, $p < .01$, $R^2 = .15$, BF = 5.13 ±0%) and lack of perseverance ($F(1) = 16.22$, $p < .001$, $R^2 = .27$, BF = 108.86 ±0%) subscales of the S-UPPS-P, the OCI-R ($F(1) = 24.28$, $p < .001$, Multiple $R^2 = .36$, BF = 1308.96 ±0) and the TAS-20 ($F(1) = 10.84$, $p < .01$, $R^2 = .2$, BF = 17.69 ±0%).

Discussion

This is the first study to our knowledge to investigate the relationship between autonomic stress reactivity and Internet craving in PIU. Specifically, we wanted to investigate (i) whether individuals with PIU show enhanced autonomic reactivity (i.e., lower HRV and higher SCL) to a standardized psychosocial stress task, (ii) whether greater autonomic reactivity is related to higher craving ratings, and (iii) whether PIU is associated with high impulsivity, and with alexithymia depression, anxiety, stress, and obsessive-compulsive symptoms.

Contrary to our expectations, we did not find any group difference during the stress tasks. It may be hypothesized that the version of the TSST used in this study was not stressful enough to highlight possible differences in autonomic reactivity between individuals with vs. without PIU. Moreover, the participants with PIU were recruited using the cut-off scores of the IAT and were classified as mild to moderate problematic Internet users. As such, they may not be fully representative of problematic Internet users. Future studies should include participants with severe problematic Internet usage to better elucidate autonomic stress reactivity in PIU.

We found that SDNN, that reflects the activity of all the cyclic components responsible for HRV (Malik et al., 1996), was lower in PIUs than non-PIUs before, but not during and after, the stress task. Lower HRV before the stress task suggests that, in PIU, reduced autonomic flexibility and impaired control of emotions may represent a stable condition, that is evidenced even in non-stressful conditions. Studies on SUDs suggest that regular and chronic use of drugs is associated with adaptations in stress-related brain pathways (specifically, the hypothalamic-pituitary-adrenal axis and autonomic nervous system pathways; Sinha, 2008). It might be hypothesized that, similarly to substance addictions, behavioral addictions (including PIU) adversely impact autonomic functioning, reducing HRV at rest. On the other hand, low HRV in PIUs might be a vulnerability factor that underlies difficulty in self-regulation and inhibitory capacity (Thayer & Lane, 2000), leading to problems in controlling one's use of the Internet. Future research aimed at preventing and treating PIU should investigate whether low HRV represents a risk factor or a consequence of PIU.

The fact that we found group differences only for SDNN, reflecting both sympathetic and parasympathetic activity, but neither for other HRV indices nor for SCL, suggests that PIU is associated with an overall autonomic unbalance, rather than a specific dysregulation related to the sympathetic or the parasympathetic nervous system.

As regards the second research question, self-reported craving for Internet usage was higher in individuals with PIU than those without PIU, both before and after the stress task. Furthermore, after the stressful task, higher craving ratings were related to lower HRV only in PU. These findings support our hypothesis about the relationship between lower HRV and higher craving for Internet usage, suggesting that lower HRV in PIUs may be related to reduced capacity for self-regulation and ability to inhibit craving. Of note, these results fit with previous research showing that lower resting-state HRV predicted higher craving in alcohol dependent outpatients (Quintana, Guastella, McGregor, Hickie, & Kemp, 2013). Overall, our findings generate new insight into the study of PIU by adding further support to the existence of a relationship between HRV and craving. However, the nature of the relationship between these variables is not currently understood. Future studies should further investigate the nature of this relationship in both behavioral and substance addictions.

Lastly, we found that PIUs endorsed more mood, obsessive and compulsive symptoms. Overall, these results are in line with previous findings showing that Internet addiction is associated with depression, anxiety, and stress (Akin & Iskender, 2011; Shapira et al., 2000); and obsessive-compulsive symptoms (Vasilis Stavropoulos et al., 2016). Moreover, PIUs endorsed more alcohol-related problems. These findings differ from those of Study 1 (see *Results* of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection, Section 1) where we did not find any significant differences between PIUs and non-PIUs in alcohol abuse. However, the results of the present study are in line with previous findings showing that Internet addiction is associated with problematic alcohol use (Ko et al., 2008). Further studies are needed to better characterize the relationship between PIU and alcohol-related problems.

In addition to the above-mentioned limitations related to the task and to the criteria employed for sample selection, a further limitation of the current study is represented by the fact that we employed a single-item scale to collect Internet craving ratings (Cano et al., 2014; Dawkins et al., 2016). Although this is considered as a sensitive method to measure craving, the combination with a questionnaire that explores the construct of craving through multiple items would improve the accuracy of the measure (Davey, Barratt, Butow, & Deeks, 2007).

In conclusion, our findings provide new insights into the relationship between stress reactivity and craving in PIU, by supporting the existence of a relationship between reduced autonomic flexibility and Internet craving. Also, our results confirm the previously reported associations of PIU with mood, obsessive-compulsive, and alcohol-related problems.

“I want to use the Internet right now because

I would like to talk to someone, to feel human warmth”

(Participant 208, 21 years old)

STUDY 3: EMOTIONAL MODULATION OF INHIBITORY CONTROL IN PROBLEMATIC INTERNET USE

Introduction

One of the key features of substance dependence, which has also been investigated in the context of problematic Internet use (PIU), is a deficit in cognitive control. fMRI and ERP studies, where the Stroop and Go/Nogo tasks were used, consistently highlight cognitive inefficiency and reduced response-inhibition capacity among problematic Internet users (PIUs) relative to non-problematic users (non-PIUs), as indicated by greater recruitment of anterior and posterior cingulate cortex, dorsolateral prefrontal, premotor, and parietal cortices (Ding et al., 2014), and reduced amplitude of the N2 component of the ERPs in the Nogo condition (Dong, Lu, Zhou, & Zhao, 2010; Luijten et al., 2014; Zhou, Yuan, Yao, Li, & Cheng, 2010), which reflect impaired conflict monitoring and inhibitory control. By contrast, and of considerable interest, behavioral evidence of reduced inhibitory control in PIU is equivocal (Ding et al., 2014; Dong et al., 2010; Sun et al., 2009; Zhou et al., 2010). However, neuroimaging and electrophysiological measures may be used to detect meaningful differences in cognitive processes that are too subtle to produce robust and unequivocal behavioral effects.

The majority of studies on inhibitory control in PIU have relied on a standard Go/Nogo task with neutral stimuli (e.g., letters or numbers) as Go and Nogo cues (Sun et al., 2009; Zhou et al., 2010). To our knowledge, few studies have examined whether inhibitory control difficulties in PIU may emerge in emotionally-laden contexts. Indeed, emotional situations can impact behavioral control, with important consequences on effective impulse inhibition and decision making in the context of both substance and behavioral addictions (Bechara, 2003).

Inhibitory control in emotional contexts can be investigated using the emotional Go/Nogo task, where affective stimuli (e.g., emotionally salient words or pictures) are used in place of standard neutral stimuli, thereby providing a reliable measure of the emotional modulation of behavioral response (Schulz et al., 2007). The only studies that, to our knowledge, have investigated inhibitory control in PIU, in the context of emotionally salient stimuli, have only included individuals addicted to online video game playing (Liu et al., 2014; Yao et al., 2015), and only disorder-related stimuli were employed as emotionally salient cues. In those studies, individuals with Internet gaming disorder made more commission errors (i.e., responses to Nogo stimuli) in the presence of gaming-related stimuli, suggesting poor response inhibition specifically related to gaming cues (Liu et al., 2014; Yao et al., 2015). However, it would be important to investigate whether the processing of non-disorder-related, highly arousing pleasant and unpleasant stimuli modulates response inhibition in behavioral addictions, in PIU in particular, as it does in substance addiction (Goldstein & Volkow, 2011). Given that a deficit in the modulation of emotional arousal and in the ability to act in desired ways, regardless of emotional state (Gratz & Roemer, 2004), is currently regarded as critically implicated in the development and maintenance of PIU (Casale, Caplan, & Fioravanti, 2016; LaRose et al., 2003; Spada & Marino, 2017; Yu, Kim, & Hay, 2013), the investigation of inhibitory control in emotional contexts that are not specifically related to Internet use would contribute to a better understanding of emotional regulation abilities in PIU.

A psychophysiological index of efficient inhibition of prepotent but inappropriate responses is heart rate variability (HRV, Thayer & Brosschot, 2005; Thayer, Hansen, Saus-Rose, & Johnsen, 2009). HRV consists of the variations, over time, of the period between consecutive heartbeats (R-R intervals). Such variations represent a fine tuning of the beat-to-beat control mechanisms, by sympathetic and parasympathetic activity directed to the sinus node of the heart (Malik et al., 1996). Relevant for the use of HRV as an index of inhibitory control is the fact that direct and indirect pathways connect brain circuits that are critical for affective, cognitive, and autonomic regulation of vagal motor output regions (Bredikis, 2000; Jellinger, 1998). In particular, these brain structures and areas are critically related to inhibitory control of cardiac behavior in particular (Verberne & Owens, 1998), and of behavior more generally (Roberts & Wallis, 2000). Low tonic vagally-mediated HRV, as indexed by the high-frequency spectral power of HRV (HF-HRV), and by the square root of the mean-squared differences of successive normal-to-normal intervals (rMSSD), is associated with a wide range of psychopathological syndromes, thus functioning as a broad indicator of behavioral and emotional dysregulation (Beauchaine & Thayer, 2015).

Individuals who engage in excessive online gaming showed significant reductions in HF-HRV during gaming, but no difference from healthy controls in resting HRV, suggesting that altered central control over autonomic responses only emerges in the context of reward seeking (i.e., game play), and may reflect reduced executive control over gaming (Chang et al., 2015; Hong et al., 2018; Lee et al., 2018). By contrast, HRV has recently been reported to be significantly lower in problematic Internet users than in non-problematic Internet users at rest, but not during or after a non-Internet-related stressful task (Moretta & Buodo, 2018a). This finding suggests that, in PIU, reduced autonomic flexibility may represent a stable condition. However, to our knowledge, no study has yet investigated the relationship between resting HRV and the capacity to inhibit inappropriate behavioral responses in an emotional context in individuals with PIU.

The present study aimed to investigate whether individuals with vs. without PIU show greater difficulties in inhibiting prepotent motor responses in an emotional context, and whether, in PIU, inhibitory control is related to resting HRV. We sought to broaden the knowledge base by selecting participants on the basis of their scores on the Internet Addiction Test (Young, 1998b), a self-report that uses "Internet" to denote all types of online activity.

We hypothesized that, in an implicit emotional Go/Nogo task (Albert, López-Martín, & Carretié, 2010; Buodo, Sarlo, Mento, Messerotti Benvenuti, & Palomba, 2017), the following would obtain: i) problematic Internet users would be characterized by lower resting HRV, relative to non-problematic users; ii) in the presence of high-arousal affective visual stimuli, it would be more difficult to activate inhibitory control mechanisms for withholding prepotent responses in individuals with vs. without PIU, as indicated by lower accuracy on Nogo trials; and iii) poorer response inhibition in individuals with PIU would be related to reduced resting HRV.

Method

Participants

Participants were recruited at the University of Padova, Italy, and also by means of advertisements on several open Facebook groups, and asked to complete an online version of the Internet Addiction Test (Ferraro et al., 2007; Young, 1998b. See further details in *Assessing problematic Internet use* of the *Characterizing problematic Internet use* subsection, Section 1). Based on Italian cut-off scores, Internet usage was defined as non-problematic (scores 20-50), mild to moderate problematic (scores 50-80), and severe problematic (scores 80-100. Poli & Agrimi, 2012).

Forty students agreed to participate in the study. Based on their IAT scores, 20 were classified as non-problematic Internet users (non-PIUs, F = 17), and 20 as mild to moderate problematic Internet users (PIUs; F = 12). As reported in Table 7, IAT scores among PIUs were significantly higher than among non-PIUs, and indicative of mild to moderate problematic and non-problematic use of the Internet, respectively (Poli & Agrimi, 2012).

Approval for the study was obtained from the Ethical Committee of Psychological Research, Area 17, University of Padova. The ethical principles of the Helsinki and its amendments or comparable ethical standards were followed.

Self-report measure

Given that trait impulsivity, which reflects inhibitory dyscontrol (Enticott, Ogloff, & Bradshaw, 2006; Logan, Schachar, & Tannock, 1997), has been found to be increased among individuals with PIU (Cao et al., 2007; Lee et al., 2012), the participants' trait impulsivity was measured and controlled for in data analysis.

Trait impulsivity was assessed by the Barratt Impulsiveness Scale (BIS-11, Fossati et al., 2001; Patton, Stanford, & Barratt, 1995, see further details in *Method* of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection, Section 1). The higher the total score (range = 30-120), the higher the level of trait impulsiveness.

Emotional Go/Nogo task

Ninety digitized color pictures (650 × 850 pixel) were presented as Go and Nogo stimuli. Pictures were selected from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2008) and were divided into three categories, pleasant, unpleasant, and neutral, each of which included 30 stimuli. Pleasant and unpleasant pictures were matched for mean normative arousal ratings (6.37±0.19 and 6.44±0.23, respectively), which were significantly higher than those for neutral pictures (2.93±0.27; both $ps < .001$).

Each picture was presented in a pink or blue frame, which cued the participant to either press a key (Go trials) as quickly as possible or withhold the key press response (Nogo trials). The frame colors indicating Go and Nogo conditions were counterbalanced across participants. Nogo trials represented 30% of the total, and within each category. Each picture was presented five times, so that for each category there were 105 Go trials and 45 Nogo trials. Go and Nogo stimuli were displayed for 600 ms. Responses were collected up to 1,000 ms. The intertrial interval varied randomly between 500 and 800 ms.

The task was presented by a Pentium IV computer on a 19-in. computer screen, using E-prime 2.0 presentation software (Psychology Software Tools, Pittsburgh, PA).

Behavioral measures

Response accuracy in both Go and Nogo trials (i.e., button presses in Go trials and no responses in Nogo trials, respectively) and RTs for Go trials were calculated. RTs below 150 ms were excluded from analyses.

To obtain a measure of the efficiency of response inhibition for each participant, an efficiency index was calculated as the difference (i.e., the residual) in Nogo accuracy between the individual performance and the performance of an ordinarily efficient subject, at a given RT. The ordinarily efficient performance is represented by the regression line between RTs on Go trials and accuracy on Nogo trials across all participants (Hirose et al., 2012).

HRV

The electrocardiogram (ECG) was recorded at rest for 3 minutes, using a ProComp Infiniti system (Thought Technology; Montreal, Canada). Three disposable Ag/AgCl electrodes were placed on the participant's chest in a modified Lead II configuration. The ECG signal was sampled at 256 Hz, band-pass filtered (1-100 Hz), and amplified. ECG data were visually examined and artifacts were corrected.

Time-domain indices of HRV were computed as mean values over the 3-min resting phase by Kubios HRV Analysis Software 2.0 (The Biomedical Signal Analysis Group, Department of Applied Physics, University of Kuopio, Finland). The standard deviation of all normal-to-normal intervals (SDNN) was calculated as an index of all cyclic components responsible for HRV, and the root mean square of successive differences of normal-to-normal intervals (rMSSD), expressed in ms, was calculated as an index of vagal control on the heart (Malik et al., 1996).

Procedure

Upon arrival at the laboratory, participants signed an informed consent form and were asked to complete a questionnaire about their demographic characteristics, health status, and medical history. Each participant was subsequently seated on a chair, placed 100 cm away from a computer monitor; ECG sensors were then attached to the participant's chest. After ECG recording, sensors were removed and instructions for the task were given. Participants had to press a key with their right finger as rapidly and accurately as possible, whenever a picture surrounded by the Go color frame was presented, and to withhold pressing the key when the picture was surrounded by the Nogo color frame. Ten trials with neutral pictures served for practice. After completing the task, the participants completed the BIS-11. The entire procedure took about 30 min.

Statistical Analysis

As the groups differed significantly with regard to gender distribution and BIS-11 total score, with a higher number of males and a higher BIS-11 total score in the PIU group (see Table 7), both gender and BIS-11 total score were included as covariates in all analyses.

Linear model analysis, considering group (PIUs, non-PIUs) as predictor, was performed to compare resting HRV between groups.

To investigate whether SDNN and/or rMSSD predicted response accuracy to Go and Nogo trials, we estimated two non-nested generalized linear models (GLMs) with binomial error distribution, and the extent to which each model accounted for the dependent variables was quantified by means of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The model with the smallest AIC and BIC was regarded as the best-fitting to the data (Vrieze, 2012). In considering response accuracy to Go and Nogo trials as dependent variables, the GLMs included Condition (Go, Nogo), Category (pleasant, unpleasant, and neutral), Group (PIUs, non-PIUs), resting HRV (SDNN or rMSSD), their interactions (*Condition×Category×Group× HRV*), sex, and BIS-11 total score as predictors. The two GLMs differed only on resting HRV predictors, i.e., SDNN and rMSSD. To test the effect of each predictor on the dependent variables, parameters were added sequentially to the simplest model, which included the intercept only.

To investigate whether SDNN and/or rMSSD predicted RTs to Go trials as well as the efficiency index, we estimated two non-nested linear mixed-effect models (LMMs) with individual random intercept (R package: lme4, Bates et al., 2014). The extent to which the model accounted for dependent variables was quantified by means of the AIC and the BIC.44 For both RTs and the efficiency index, the LMMs included Category (i.e., pleasant, unpleasant and neutral), Group (non-PIUs and PIUs), resting HRV (SDNN or rMSSD), their interactions (Category×Group× HRV), sex, and BIS-11 total score as fixed factors. The two LMMs differed only in resting HRV predictors, i.e., SDNN and rMSSD.

The maximum likelihood method was employed to analyze the respective contribution of parameters within the selected model, and the strength of their evidence was estimated as the difference in AIC between the model with and the model without the parameter (ΔAIC), as well as the Akaike weights (AICw, Burnham & Anderson, 2002).

All analyses were performed using R statistical software (R Development Core Team, 2016).

For resting HRV, response accuracy for Go and Nogo trials, and RTs to Go trials, only significant effects have been reported.

Resting HRV in problematic vs. non-problematic Internet users

SDNN at rest ($R^2 = .21$) and rMSSD at rest ($R^2 = .11$) were significantly lower in PIUs than in non-PIUs (see Table 7).

Table 7. Descriptive statistics and differences between Problematic (PIUs) and non-problematic (non-PIUs) Internet users

	Non-PIUs (n=20)	PIUs (n=20)	Test-statistic	p-value
Sex (females/males)	17/3	12/8	7889.2 $^{\chi 2\ test}$	<.001
age	23.4 (±2.9)	23.4 (±3.6)	0.7$^{t\ test}$	.5
BIS-11 score[a]	54.9 (±6.5)	62.2 (±9.4)	37.99 $^{t\ test}$	<.001
IAT score[b]	30.9 (±4.3)	57.4 (±6.7)	200.4 $^{t\ test}$	<.001
SDNN[c]	80.8(±29.3)	56.9(±19.4)	1725.6$^{F\ test}$	<.001
rMSSD[d]	47.1(±15)	35.2(±14.4)	261.84$^{F\ test}$	<.001

[a] Barratt Impulsiveness Scale; [b] Internet Addiction Test; [c] standard deviation of normal-to-normal intervals; [d] root mean square of successive difference of normal-to-normal intervals

Response accuracy and HRV in problematic vs. non-problematic Internet users

As indicated by the model selection method on accuracy for Go and Nogo trials, the GLM that considered Condition, Category, Group, resting SDNN, their interactions, sex, and BIS-11 total score as predictors best fitted the data (see Table 8). As non-nested GLMs differed only for one predictor, i.e. SDNN vs RMSSD, model comparison analysis revealed SDNN as preferable to rMSSD in predicting response accuracy ($\Delta AIC = 34$; $\Delta BIC = 34$).

Table 8. Model selection method by AIC and BIC, considering accuracy to Go and Nogo trials, RTs to Go trials, and efficiency index as dependent variables

		Accuracy				RTs				Efficiency Index			
		SDNN		rMSSD		SDNN		rMSSD		SDNN		rMSSD	
		AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
GLM	Condition[a]× Category[b]× Group[c]× HRV[d]+Sex+BIS-11[e]	**3473**	**3652**	3507	3686								
LMM	Category[b]× Group[c]× HRV[d]+ Sex+BIS-11[e]+(1|Individual)					**37676**	**37775**	37678	37777				
LMM	Category[b]× Group[c]× HRV[d]+ Sex+BIS-11[e]+(1|Individual)									**8659**	**8758**	8670	8769

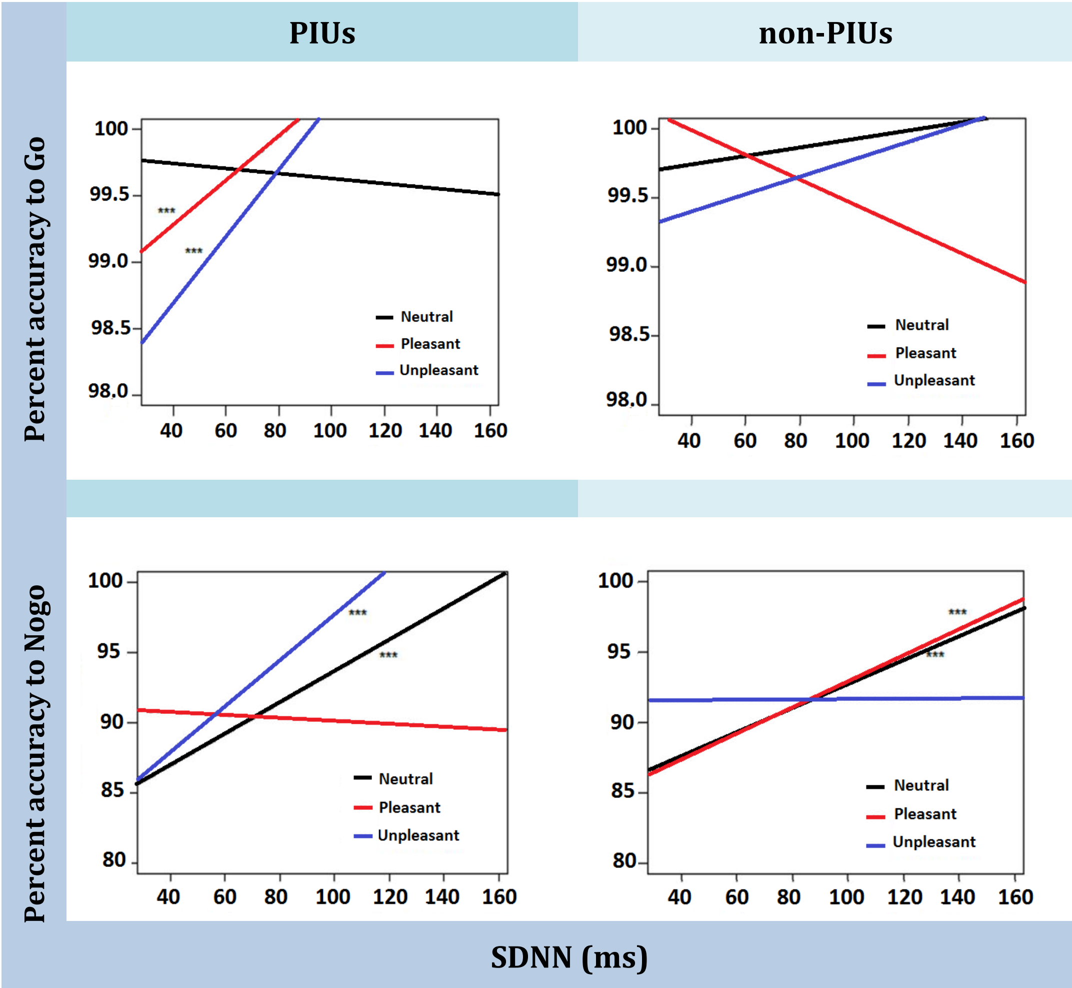
Two non-nested models were considered to fit Accuracy, RTs, and Efficiency Index by AIC and BIC indices. The two models differed only in the considered HRV index (SDNN in one case and rMSSD in the other) included in the model as one of the independent predictors. AIC and BIC values of the two non-nested models are reported for each dependent variable. [a] Go and Nogo trials; [b] Pleasant, unpleasant, and neutral; [c] PIUs and non-PIUs; [d] SDNN or rMSSD; [e] Barratt Impulsiveness Scale

The effect of predictors was tested by the maximum likelihood method. A statistically significant effect of Condition was found (Deviance Resid. (1) = 3061.6, p < .001, OR = 0.12, 95% CI = [0.00, 27.77]), indicating that accuracy was lower in Nogo (mean = 90.68%, sd = 25.85) than in Go trials (mean = 99.59%, sd = 3.48).

A significant main effect of Group was also found (Deviance Resid.(1) = 3056.7, p = .03, OR = 16.25, , 95% CI = [0.16, 1974.79]), indicating that PIUs were likelier to be significantly less accurate (mean = 94.76, sd = 19.57) than non-PIUs (mean = 95.51, sd = 18.51).

The significant main effect of SDNN (Deviance Resid.(1) = 3032.6, p < .001, OR = 1.04, 95% CI = [0.99, 1.13]) showed that a one unit increase in SDNN led to a 1.04-fold increase in the odds of giving an accurate response.

Figure 8. Effect of the Category, Group and resting SDNN interaction on response accuracy for Go and Nogo trials



A significant *Condition* × *Category* × *Group* × *SDNN* interaction was found (Deviance Resid(6) = 2980.5, $p = .003$). In the Go condition, the regression slope of SDNN differed significantly from zero in predicting response accuracy for pleasant ($z = 2.19$, $p = .03$, OR = 1.07, 95% CI = [1.02, 1.15]) and unpleasant stimuli ($z = 2.28$, $p = .02$, OR = 1.04,95% CI = [1.01, 1.08]) only in PU. Specifically, among PU, lower resting SDNN predicted poorer response accuracy upon presentation of pleasant and unpleasant Go stimuli (see Figure 8).

In the Nogo condition, the regression slope of SDNN differed significantly from zero in predicting response accuracy for unpleasant ($z = 3.79$, $p < .001$, OR = 1.03, 95% CI = [1.02, 1.05]) and neutral pictures ($z = 2.02$, $p = .04$, OR = 1.01, 95% CI = [1.001, 1.03]) in PIUs, and to pleasant ($z = 2.87$, $p = .004$, OR = 1.02, 95% CI = [1.01, 1.02]) and neutral pictures ($z = 2.19$, $p = .03$, OR = 1.01, 95% CI = [1.001, 1.02]) in non-PIUs, indicating that lower resting SDNN predicted more commission errors for unpleasant and neutral trials in PIUs, and for pleasant and neutral trials in non-PIUs.

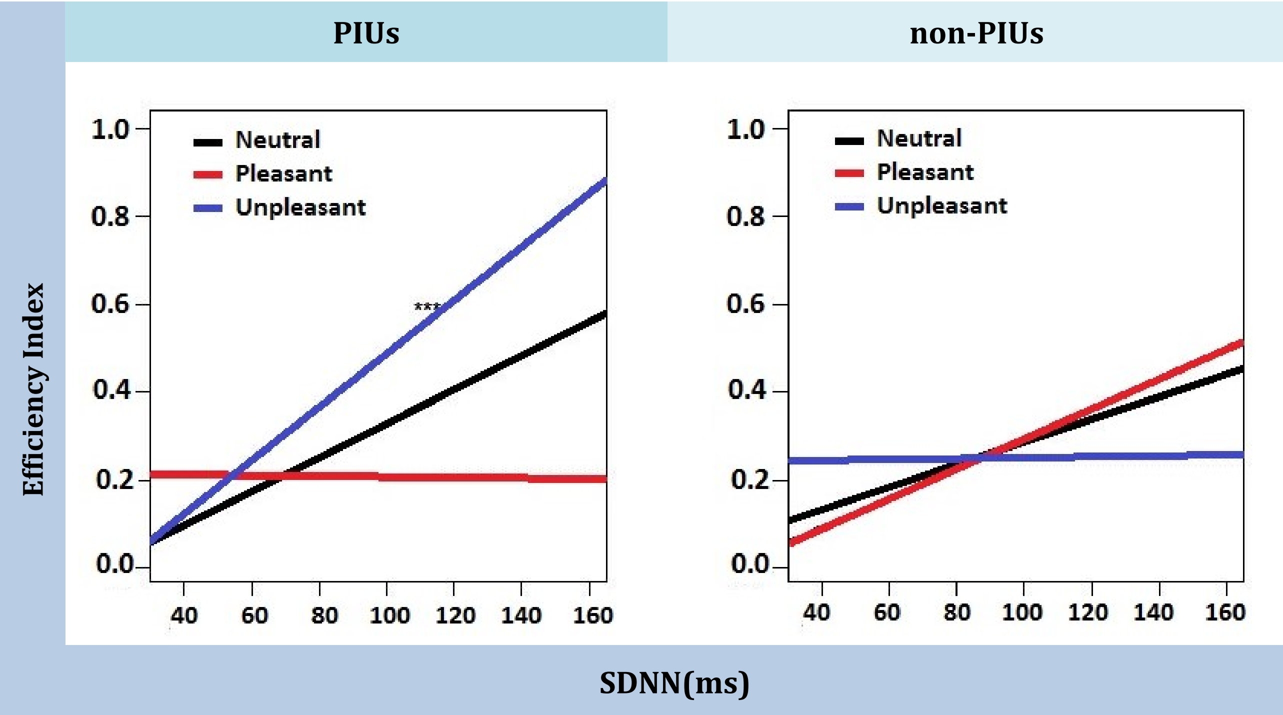
RTs and HRV in problematic vs. non-problematic Internet users

As indicated by the model selection method on RTs, the LMM that considered Category, Group, resting SDNN, their interactions, sex, and BIS-11 total score as predictors best fitted RTs to Go trials (see Table 8), i.e., SDNN was preferable to RMSSD in predicting RTs (ΔAIC = 2; ΔBIC = 99). The effect of fixed predictors was tested using the maximum likelihood ratio test. A significant main effect of Category was found to improve the fit of the model ($X^2(2) = 14.56$, $p < .001$, ΔAIC = -0.19, AICw = .52). RTs were faster to unpleasant Go stimuli (mean = 353.77, sd = 60.44) than to pleasant Go stimuli (mean = 360.53, sd = 60.01). A significant improvement in the fit of the model was found by including resting SDNN as a predictor (X2(1) = 7.78, $p = .01$). Lower resting SDNN predicted faster RTs to Go trials. However, no strong evidence was found to support resting SDNN as a predictor within the model (ΔAIC = 3.18, AICw = .17).

Efficiency and HRV in problematic vs. non-problematic Internet users

The LMM that considered Category, Group, resting SDNN, their interactions, sex, and BIS-11 total score as predictors best fitted efficiency index data (see Table 8), i.e., SDNN was preferable to RMSSD in predicting efficiency (ΔAIC = 11; ΔBIC = 11). A significant improvement in the fit of the model was found by including the Category ×Group ×SDNN interaction (X2(1) = 12.14, $p = .02$, ΔAIC = -4.11, AICw = .89). In testing the regression slope within groups, a significant effect of SDNN emerged in predicting the efficiency index in response to unpleasant stimuli only in PIUs (t = 2.11, p = .03), indicating that in PIUs, lower resting SDNN predicted less efficient performance upon presentation of unpleasant stimuli (see Figure 9).

Figure 9. Effect of the Category, Group and resting SDNN interaction on Efficiency Index



Discussion

The pattern of findings that emerged in the present study on problematic Internet users provides support to results of previous research on resting HRV and inhibitory control in the context of addiction. Despite the heterogeneity with respect to the experimental tasks and stimuli, and the disorder under investigation (e.g., substance and behavioral addictions), previous studies had reported autonomic imbalance at rest (Ingjaldsson, Laberg, & Thayer, 2003; Kim, Hughes, Park, Quinn, & Kong, 2016; Lin, Kuo, Lee, Sheen, & Chen, 2014; Yuksel,

Yuksel, Sengezer, & Dane, 2016) and impaired inhibitory control in individuals with addictions (Smith, Mattick, Jamadar, & Iredale, 2014; Zhou et al., 2010). In accordance with our hypothesis, problematic Internet users showed lower resting HRV, relative to non-problematic users, as indicated by lower SDNN and rMSSD. Lower resting HRV, as compared with healthy controls, has been previously reported in both individuals with substance use disorders (Ingjaldsson et al., 2003; Yuksel et al., 2016), and individuals with addiction-like behavioral disorders, including Internet gaming disorder (Kim et al., 2016) and PIU (Lin et al., 2014; Moretta & Buodo, 2018a). The importance of HRV in cognitive, affective, and physiological regulation has long been recognized. A relative reduction in vagally-mediated HRV is consistent with symptoms of poor attentional control, ineffective emotional regulation, and behavioral inflexibility (Friedman & Thayer, 1998). A reduction of the fast-vagal modulation of cardiac activity serves to disinhibit the relatively slow sympathetic excitatory influences on the heart, overall resulting in decreased ability to track the rapid changes in environmental demands and organize appropriate responses (Friedman & Thayer, 1998; Thayer & Friedman, 2002; Thayer et al., 2009; Thayer & Lane, 2000; Thayer & Siegle, 2002). From this perspective, maladaptive perseverative behavior and poor emotion regulation, such as those manifested in PIU, may result from reduced resting HRV.

Although RTs to Go stimuli were not significantly faster in problematic vs. non-problematic Internet users, which suggests that motor response execution was not specifically facilitated in PU, accuracy rates were significantly lower in PIUs vs. non-PIUs, both when they had to respond to Go stimuli and when they had to withhold from responding to NoGo stimuli, irrespective of the pictures' emotional content. This seems to suggest an overall greater difficulty with adjusting behavior to contextual demands. Our findings are consistent with those of Zhou et al. (2010), reporting both higher false alarm and miss rates in PIU vs. control participants. Other studies that used a standard Go/NoGo task to investigate inhibitory control in individuals with PIU (Ding et al., 2014; Dong et al., 2010; Sun et al., 2009) did not report reduced performance accuracy in either Go or NoGo trials in excessive vs. casual Internet users. It may be hypothesized that difficulties in inhibitory control only emerge in PIU when the effort required to suppress inappropriate responses exceeds a certain threshold, i.e., when prepotent responses must be inhibited pursuant to complex rules (Zhou et al., 2010), or in an emotional context.

When modelling resting HRV as a predictor of performance efficiency, SDNN, a global index of HRV (Malik et al., 1996), differently predicted performance efficiency in problematic vs. non-problematic users, as a function of the affective content of picture stimuli. Lower resting SDNN predicted lower response accuracy to pleasant and unpleasant Go trials only in individuals with PIU. As the rate of omission errors reflects lapses in attention or vigilance, or task disengagement (Halperin, Wolf, Greenblatt, & Young, 1991), our finding seems to suggest that, in individuals with PIU, lower overall HRV is related to poorer response adjustment in the presence of non-Internet-specific yet emotionally arousing affective stimuli, irrespective of valence. When considering the efficiency index, which combined response speed to Go trials and the rate of "no responses" to NoGo trials (i.e., faster RTs to Go trials combined with a higher percentage of correctly suppressed responses to NoGo trials as indicative of better performance), a more specific pattern of findings emerged, lower resting SDNN predicted less efficient task performance upon the presentation of unpleasant stimuli only in individuals with PIU. This finding suggests that, in problematic users, the alteration of the sympathetic/parasympathetic balance may specifically affect the ability to suppress prepotent but inappropriate responses during the processing of unpleasant emotional material. Previous research has suggested that negative emotions are strongly associated with PIU (Spada, Langston, Nikčević, & Moneta, 2008), and that Internet overuse seems to be characterized by difficulty in self-regulating stress and negative feelings (Leung, 2007). Diminished tonic HRV appears to lead to a decrease in restraint of cardiac rate necessary for cardiac stability, responsiveness, and flexibility. As a consequence of reduced HRV, a rigid behavioral pattern seems likely to emerge, associated with perseverative behavior, manifesting in attentional, affective, and autonomic inflexibility (Thayer & Siegle, 2002). From this perspective, reduced tonic HRV may represent a marker for poor attentional control, defective emotion regulation, and behavioral inflexibility in both substance addictions (Yuksel et al., 2016) and behavioral addictions, including PIU. Further studies should determine whether resting HRV in PIU may be a treatment target to improve inhibitory control under aversive motivational states.

The present results should be interpreted with three main limitations taken into account. The first is the small sample size. The second is the criteria employed for sample selection. As participants were classified as mild to moderate problematic Internet users on the basis of IAT scores, they may not be fully representative of problematic Internet users. Future studies should include participants with severe problematic Internet usage to better elucidate the relationship between autonomic balance and inhibitory control in PIU. Last, previous studies showed gender differences in the use of the Internet and Internet-related applications, as well as in the risk of addiction (Fattore, Melis, Fadda, & Fratta, 2014). Due to the difference in gender distribution in our samples of problematic and non-problematic Internet users, we were unable to investigate gender differences. Future studies, including larger samples and equal gender distributions between groups, should be undertaken to explore whether gender affects the relationship between autonomic balance and emotional modulation of inhibitory control in PIU.

SECTION 2: MECHANISMS UNDERLYING PROBLEMATIC SOCIAL NETWORKING SITES USE

Dong-kyu, K. (2013). When you see the amazing sight [based on: Wanderer above the sea of fog by Caspar David Friedrich (1818)]. ART X SMART Project

"I'd like to see the Government and social media platforms take responsibility, so we never see another child lose their life due to the virtual world before they've lived a life in a real world"

Julie, the mother of Ruby Seal (The SUN a news UK company, 2019)

Characterizing problematic Social Networking sites use

Introduction

With the exponential growth of Internet usage, research has increasingly focused on the degree to which the types of behaviors performed on the Internet might become problematic (Potenza, 2017). Recently, a large body of work has involved Problematic Social Networking Sites Use (PSNSU).

The era of social network traces back to the Usenet, an Internet discussion system created in 1979, that allowed users to post and share public messages (Kaplan & Haenlein, 2010). After almost forty years, social networking sites (SNSs) have become integral parts of the daily life of billions of users around the globe, changing the way they communicate, socially interact, and learn information. SNSs (e.g., Facebook, Twitter, Instagram) are Internet-based applications characterized by three elements: each user has a personal profile; lists of connections are publicly visible; a stream of frequently updated content is shown, which is primarily populated by posts from one's connections (Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017). Although the relevant literature suggests that engaging in social interaction through SNSs has the potential to increase subjective well-being (Verduyn et al., 2017), there is mounting evidence that SNSs usage patterns can become problematic (Ryan, Chester, Reece, & Xenos, 2016). It has been argued that excessive online behaviors and constant connections are associated with poor social skills, reduced sustained attention, and impaired ability to retain information, leaving people unable to engage in meaningful conversations (Fernández Pedemonte, 2012). Individuals engaging in excessive SNSs use have come to be described as "alone together": always connected via technology, but in fact isolated (Fernández Pedemonte, 2012). SNSs use has been also showed to, at times, adversely affect psychological well-being

(Yuen et al., 2019), and for some people become an addictive behavior (Griffiths, Kuss, & Demetrovics, 2014). Moreover, PSNSU have a dramatic impact on public health, since it seems to be linked to a string of teenage suicides including Molly Russell, 14, who took her life after viewing self-harm content on Instagram; Jessica Scatterson, 12, who killed herself "*after claiming she was being bullied had struggled to cope with the pressure of social media*"; Ruby Seal, 15, "*after becoming hooked on a desperate mission for social media likes*" (Mirror, 2019; The SUN, a news UK company, 2019).

With over 2.41 billion monthly active users, Facebook is the most popular SNSs in the world (Facebook, 2019). In the last ten years, the reasons for the exponential growth of the number of people using Facebook have been largely investigated, and two main motivations underlying Facebook use have been identified (Wilson, Gosling, & Graham, 2012): the external press that encourages people to engage in Facebook-related behaviors (e.g., birthday reminders, automatic e-mails sent by Facebook to users) and internal motivations (e.g., the need for social engagement). Internal motivations seem to be related to the gratifications provided by media content and use, i.e., social connection, joining groups and organizing events, posting and viewing photographs, etc. (Pai & Arnott, 2013). Considering that Facebook is by far the most popular among SNSs, it is not surprising that many studies of problematic SNSs use have focused specifically on Facebook (Hong, Huang, Lin, & Chiu, 2014; Zaremohzzabieh et al., 2014). While some scholars (Kuss & Griffiths, 2011; 2017) have argued that Problematic Facebook Use (PFU) is only one example of problematic SNSs use, and therefore a specific focus on Facebook is unwarranted, others have suggested that there may be unique factors associated with Facebook use and abuse, and that the specific motivations of problematic Facebook users may differ from those of problematic users of other SNSs (Ryan, Chester, Reece, & Xenos, 2014; Ryan et al., 2016). Overall, Facebook can be considered as an 'egocentric' SNS, since Facebook users represent themselves on this SNS by individual profiles and wall posts. These can contain text, visual, and video contents, friend connections (reflecting both virtual and real-life friendships), and are related to the motivation of using SNSs to maintain friend connections (Kuss & Griffiths, 2011).

Although there is no universal consensus on the conceptualization of problematic SNSs use as a behavioral addiction, it has been suggested that excessive and compulsive online social networking behavior (including PFU) shares core components of other behavioral and substance addictions, including tolerance, withdrawal, conflict, salience, relapse, and mood modification (Andreassen, 2015; Andreassen & Pallesen, 2014; Andreassen, Torsheim, Brunborg, & Pallesen, 2012; Griffiths, 2005b; Griffiths et al., 2014; Hormes, Kearns, & Timko, 2014), and has negative consequences on personal and occupational functioning (Moqbel & Kock, 2018).

Behavioral addictions are thought to arise from short-term reward engendered by engaging in a specific behavior, and have been described as the persistence of problem behavior despite knowledge of its adverse consequences (Grant, Potenza, Weinstein, & Gorelick, 2010). Similarly to what argued for problematic Internet use (PIU), in the case of PSNSU it is somehow difficult to understand what specific behavior produces short-term reward, and even more difficult to discern people addicted *to* SNSs because of the rewards provided by social networking from those addicted *on* SNSs because of the rewards provided by other online activities that are made available on SNSs (e.g., gaming; Griffiths, 2012). Moreover, given that this research field is still in its infancy, studies investigating PSNSU suffer from a number of methodological problems, i.e., the lack of reliable estimations of the worldwide prevalence of PSNSU, small and unrepresentative samples (Kuss & Griffiths, 2011) and, similar to what described previously for the more general problematic Internet use (PIU, see *Which diagnostic criteria for problematic Internet use?* of the *Characterizing problematic Internet use* subsection,

Section 1), the absence of diagnostic criteria. Such problematic issues have led to marked heterogeneity in assessment tools as well as to varying questionnaire cut-offs employed to assess PSNSU, thus making generalizations and cross-comparisons difficult (Griffiths et al., 2014; Kuss & Griffiths, 2017). Accordingly, developing criteria that are clinically sensitive to identify individuals with PSNSU is required for making reliable and valid diagnosis in terms of identification of research samples, treatment development, and treatment delivery.

The understanding and the conceptualization of PSNSU is also made difficult by the existing gaps in some important fields of clinical research. There are relatively few studies investigating the psychophysiological mechanisms underlying this problematic behavior, with the majority of theoretical models arising from psychosocial research only. Anyway, even once conceptualized as a disorder, whether or not to consider PSNSU as an addiction is still a matter of debate as well. Although researchers have extensively used the behavioral addiction conceptual framework to define PSNSU, controversies about the traditional conceptualization of behavioral addictions have emerged, with some disagreeing with this view and suggesting the possibility of an overpathologization of new habitual behaviors (Pontes, Taylor, & Stavropoulos, 2018).

While the existence of PSNSU as an addictive behavior is debatable, the evidence that a minority of SNSs users experience severe negative consequences because of their online behavior is well documented (Moqbel & Kock, 2018). The need of future research aimed at clarifying the conceptual nature of PIU and its underlying mechanisms, is even more true for PSNSU. To increase our understanding of these phenomena, research should focus on the presence of specific addiction symptoms beyond the negative consequences of PSNSU only, select large representative samples to increase the validity of the results, and include psychophysiological indices to investigate the underlying psychobiological mechanisms (Griffiths et al., 2014).

Current models and proposed mechanisms for problematic Social Networking Sites use

The **biopsychosocial framework** for the etiology and syndrome model of addictions (Griffiths, 2005a; Shaffer et al., 2004) posits that multiple and interacting biopsychosocial antecedents, manifestations, and consequents within and among behavioral and substance-related patterns of excess, reflect an underlying addiction syndrome. As a consequence, the symptoms of PSNSU are viewed as similar to those of other behavioral addictions and of Substance Use Disorders (SUDs), and include *salience*, referring to the experience that a specific behavior becomes the most important activity in the person's life and dominates their thinking, feelings and behavior; *mood modification*, referring to the subjective experience that people report as a consequence of engaging in the specific behavior (e.g. a tranquillizing and/or distressing feeling); *tolerance*, referring to the process whereby increasing amounts of the specific behavior are required to achieve the former reinforcing effects; *withdrawal symptoms,* referring to the unpleasant feelings and/or physical effects which occur when the specific behavior is ceased or suddenly reduced; *conflict*, referring to conflicts between the addicted individual and other people (interpersonal conflict) or within the individuals themselves (intrapsychic conflict), which are concerned with the specific behavior; and *relapse,* referring to the tendency to reinstate the specific behavior after its cessation (even after many years).

PSNSU has been also described as **arising by the positive reinforcement that SNSs generate**, which lies at the basis of strong habit formation, that in turn may result in maladaptive psychological dependency on SNSs use (Turel & Serenko, 2012). This hypothesis has been formulated by integrating three overarching theoretical perspectives: i) the cognitive-behavioral model (Davis, 2001), ii) the social skill model (Caplan, 2005), and iii) the socio-cognitive model of unregulated media use (LaRose et al., 2003). **The cognitive-behavioral model** suggests that some Internet users (e.g., SNSs users) can develop maladaptive cognitions that are amplified by several environmental factors (e.g., social isolation), leading to the development of maladaptive obsessive use patterns (Davis, 2001; for further details see *Current models and proposed mechanisms for problematic Internet use* of the *Characterizing problematic Internet use* subsection, Section 1). **The social skill model** suggests that Internet users who lack self-presentational skills are especially likely to prefer online social interaction over face-to-face communication "*because they perceive their self-presentational skill in online social interaction to be greater than in face to face interaction*" (Caplan, 2005). Online social interaction would favor compulsive Internet use and its related negative outcomes (Caplan, 2005). Lastly, the **socio-cognitive model** of unregulated use suggests that the expectation of positive outcomes, combined with Internet self-efficacy and deficient Internet self-regulation, favors compulsive social networking behavior (LaRose et al., 2003).

Based on these three models and on the definition of general technology addiction, PSNSU has been described as a condition occurring when social networking is viewed by the individual as an important (or even exclusive) mechanism to relieve stress, loneliness, or depression (Xu & Tan, 2012). Here, **SNSs use is viewed as a self-medication strategy** that favors an addictive use by providing continuous rewards (e.g., self-efficacy, satisfaction) and helping individuals to escape from their dysphoric mood states.

The **Dual-System Theory** in the Context of PSNSU (Turel & Qahri-Saremi, 2016) is based on the assumption that human behavior is guided by two structurally and conceptually different brain systems: an impulsive, automatic, and reflexive (reactive) brain system (System

1), and a controlled, inhibitory, and reflective (prudent) brain system (System 2; Evans, 2008; Turel & Qahri-Saremi, 2016). While System 1 generates impulsions to engage in (or avoid) a specific behavior, System 2 determines whether impulsion and behavior are aligned with one's long-term goals, and modulate behavior to reach these goals (Turel & Bechara, 2016). PSNSU would reflect an imbalance between these two systems, involving strong cognitive-emotional preoccupation with using the SNSs and weak cognitive-behavioral control over using the SNS.

Bandura's reciprocal determinism model within the social cognitive theory (Bandura, 1986) has also been used to describe PSNSU (LaRose & Eastin, 2004; Moqbel & Kock, 2018). The model consists of triadic factors (i.e., the person, the behavior, and the environment) that interactively determinate each other (Bandura, 1986). The reciprocal determinism concept assumes that the individual's behavior changes how the environment is perceived and how that individual in turn interacts with the environment. In this perspective, individuals with PSNSU would not only be affected by their environment (e.g., social influence) but also by their SNSs-related problematic behaviors that, in turn, influence their environment.

To our knowledge, the only model that includes the psychobiological mechanisms that are thought to underlie PSNSU is the Interaction of Person-Affect-Cognition-Execution (I-PACE) model of addictive behaviors (Brand, Wegmann, et al., 2019; Brand et al., 2016). Brand et al. (2019) have proposed that during the process of becoming addicted to a specific behavior, the association between exaggerated cue-reactivity/craving and diminished inhibitory control processes would lead to the development of habitual (addictive) behaviors. At the neural level, this would be reflected in the imbalance between the activity of fronto-striatal circuits (i.e., dorsolateral PFC, ventral striatum, and amygdala) during the early stages of problematic behavior, and the dominance of dorsal striatum activity during the later stages of addiction (Brand, Wegmann, et al., 2019; for further details on this model see *Current models and* *proposed mechanisms for problematic Internet use* of the *Characterizing problematic Internet use* subsection, Section 1).

Overall, it is generally accepted that a combination of biological, psychological, and social factors contributes to the etiology of PSNSU (Griffiths, 2013; 2005a; Kuss & Griffiths, 2017; Rosenberg & Feder, 2014; Shaffer et al., 2004). However, while several models of PSNSU have been proposed, many research gaps still exist, with relevant controversies about the need to discern people addicted *on* SNSs from those who are addicted *to* social networking (Griffiths, 2013), and large research gaps on the mechanisms underlying the development and maintenance of SNSs-related problematic behaviors.

Assessing problematic Social Networking Sites use

The critical issues in the development of diagnostic criteria for PSNSU are the same as those described in the context of PIU (see *Which diagnostic criteria for problematic Internet use?* of the *Characterizing problematic Internet use* subsection, Section 1). Overall, a general consensus regarding the diagnostic criteria for specific problematic online activities (i.e., pornography viewing, social networking sites use, online shopping, etc.) seems not to be possible to achieve currently (Kuss & Lopez-Fernandez, 2016). However, in the meanwhile, many different self-reports have been developed and used to assess PSNSU (Kuss & Griffiths, 2017). The following paragraph provides a brief description of the instruments that are most widely used at present.

The **Addictive Tendencies Scale** (ATS; Wilson, Fornasier, & White, 2010) is based on the addiction theory and includes three items taken from other scales assessing addictive tendencies in the use of text messages and instant messaging services (Ehrenberg, Juckes, White, & Walsh, 2008). Items are rated on a 7-point scale (1: Strongly disagree, 7: Strongly agree). Higher ratings indicate higher addictive tendencies. The three items measure salience ("One of the first things I do each morning is log onto a social networking internet site (e.g., MySpace or Facebook)"); loss of control ("I find it hard to control my use of a social networking site (e.g. MySpace or Facebook)"); and withdrawal ("I feel lost when I cannot access my social networking site (e.g., MySpace or Facebook)"). Although these three aspects have been central in the characterization of addiction, addiction has been more frequently described in the relevant literature as involving six core components: salience, mood modification, tolerance, withdrawal, conflict, and relapse (Andreassen et al., 2012; Griffiths, 2005a). Moreover, the psychometric qualities of the ATS for PSNSU are in need of further assessment.

The **Bergen Facebook Addiction Scale** (BFAS; Andreassen, TorbjØrn, Brunborg, & Pallesen, 2012) assesses the components of addiction proposed by Griffiths (Griffiths, 2005a). The BFAS includes 18 items, three for each of the six components of addiction (Griffiths, 2005a): salience, mood modification, tolerance, withdrawal, conflict, and relapse. Each item is scored on a 5-point scale (1: Very rarely and 5: Very often). Higher scores indicate a higher level of PSNSU. This questionnaire has been translated into several languages and is arguably the most psychometrically robust scale to assess PSNSU.

Both the ATS and the BFAS have been criticized because they examine the problematic use of one specific commercial SNS (i.e., Facebook), rather than the activity itself (i.e., social networking; Griffiths, 2012). The BFAS does not differentiate between addiction *on* Facebook (e.g., playing Farmville) from addiction *to* Facebook. Moreover, it has been argued that the fact that they are based on the diagnostic criteria of other behavioral addictions (i.e., problematic gaming or gambling disorder) can represent a weakness since PSNSU, and PFU in particular, are more similar to PIU than to gaming or gambling (Marino, Vieno, Altoè, & Spada, 2017; Ryan et al., 2014).

The **Bergen Social Media Addiction Scale** (BSMAS) is similar to the BFAS in that 'Facebook' is replaced with 'Social Media' (Andreassen, Pallesen, & Griffiths, 2017), with social media being defined as "Facebook, Twitter, Instagram and the like" in the instructions. This scale has been implemented as a consequence of the debate about considering addiction to one particular commercial company's service (i.e., Facebook) as representative of SNSs activity (i.e., social networking; Griffiths, 2012).

The **E-Communication Addiction Scale** (Latif, Uçkun, Gökkaya, & Demir, 2016) includes 22 items with four subscales scored on a five-point Likert scale. The scale provides a measure of four core components of PSNSU, i.e., lack of self-control (cognitive), e-communication use in extraordinary places, worries, and control difficulty (behavioral). The scale has a high internal consistency, and reliably assesses addiction to e-communication across different severity levels, ranging from very low to very high (Kuss & Griffiths, 2017; Latif et al., 2016).

The **Facebook Dependence Questionnaire** (FDQ; Wolniczak et al., 2013) consists in an adapted version of a questionnaire on Internet addiction (Echeburúa, 2009) to the context of Facebook addiction. The FDQ comprises 8 two-choice questions (yes/no) focused on worries, concerns, satisfaction, time of use and efforts to reduce it, and control. The endorsement of five out of eight questions indicates addiction to Facebook use (Wolniczak et al., 2013).

The **Social Networking Addiction Scale** (SNWAS, Turel & Serenko, 2012) is a five-item scale where respondents are asked to answer based on their experience with their most frequently used SNSs. It is adapted from short versions of Charlton and Danforth's engagement vs. addiction questionnaire (Charlton & Danforth, 2007, 2010). The original questionnaires (Charlton & Danforth, 2007, 2010) assessed computer-related addiction symptoms in the context of massive multiplayer gaming based on Brown's conceptualization of addictive behaviors (Brown, 1997). However, the Authors argued that both online games and SNSs share similar features like helping to fill social voids in people's lives, improving users' social visibility, and creating a feeling of immersion. Thus, the scale may be used to assess core components of different technology addictions, i.e., symptomatic conflict; relapse and reinstatement symptoms; and psychological salience symptoms (Turel & Serenko, 2012).

The **Problematic Facebook Use Scale** (PFUS; Marino et al., 2017) includes 15 items rated on a 8-point scale (1 = "definitely disagree", 8 = "definitely agree") adapted from the Generalized Problematic Internet Use Scale 2″ (GPIUS 2; Caplan, 2010). The PFUS is based on the assumption that a theory specifically developed for PIU can provide the basis for the development of a reliable measure to assess PFU. Since Caplan's (2010) model of Generalized Problematic Internet Use (GPIU) and the GPIUS2 have been described as the best option for conceptualizing and measuring PFU, in the PFUS the word "Internet" used in the GPIUS 2 has been replaced with the word "Facebook" where necessary. The PFUS includes five subscales, i.e., preference for online social interaction (POSI), mood regulation, cognitive preoccupation, compulsive use, and negative outcomes. POSI refers to beliefs that one is safer, more confident, and more comfortable with online than with face-to-face social interactions (e.g., "Online social interaction is more comfortable for me than face-to-face interaction"). Mood regulation refers to a cognitive symptom of PFU, reflecting the motivation to use Facebook for mood regulation purposes (e.g., "I have used Facebook to make myself feel better when I was down"). Cognitive preoccupation refers to obsessive thought patterns about the use of Facebook (e.g., "When I haven't been on Facebook for some time, I become preoccupied with the thought of going on Facebook"). Compulsive use refers to deficient self-regulation in Facebook use (e.g., "I have difficulty controlling the amount of time I spend on Facebook"). Negative outcomes refer to the extent to which an individual experiences personal and social problems resulting from Facebook use (e.g., "My Facebook use has made it difficult for me to manage my life"). Scores range from 15 to 120, with higher scores indicating higher levels of PFU. The scale has shown good psychometric proprieties (Assunção & Matos, 2017; Marino et al., 2017; Moretta & Buodo, 2018b).

The short description of some of the self-report instruments currently used to assess PSNSU highlights two critical features, i.e., the different theoretical frameworks that they are based on, and the inconsistencies in dimensional perspectives on PSNSU. These issues make cross-study comparisons difficult, and severely limit the reliability of current epidemiological research on SNSs-related problematic behavior. Taken together, the use of different conceptualizations and different assessment instruments questions the construct validity of PSNSU (Kuss & Griffiths, 2017).

"I want to use Facebook right now because

I would like to relax, feel calm and mind off"

Participant 214

Study 4: Mood regulation and preference for online social interaction in problematic Facebook use

Introduction

A validated theoretical model of Problematic Social Networking Sites Use (PSNSU), and of Problematic Facebook Use (PFU) in particular, is currently lacking in the literature. To increase our understanding of PSNSU, it is necessary to continue developing and refining a conceptual model of PSNSU, and model-driven instruments that accurately measure PSNSU (Griffiths, 2012).

As mentioned before, despite the current debate on **the conceptualization of PSNSU** as a behavioral addiction, the dominant perspective suggests that PSNSU shares core components of other behavioral and substance addictions (Andreassen, 2015; Andreassen et al., 2016, 2012; Griffiths, 2005a; Griffiths et al., 2014). In the case of PSNSU (e.g., PFU), however, the current criticism arise from the need to discern people **addicted *to* Facebook** (because of the rewards provided by social networking) from those **addicted *on* Facebook** (because of because of the rewards provided by other online activities that are made available on Facebook; Griffiths, 2012). Notably, a similar debate as that arisen over the conceptualization of PSNSU has been (and still is) unfolding about what scholars have variously termed problematic, pathological, compulsive, or addictive Internet use. Specific Pathological Internet use (PIU) would refer to the pathological use of the Internet for a specific purpose (e.g., online sex, online gambling; for further details see *Current models and proposed mechanisms for problematic Internet use* of the *Characterizing problematic Internet use* subsection, Section 1). This kind of overuse is content-specific and can occur even in the absence of Internet access. Generalized PIU, instead, would refer to wasting time online without a specific purpose, or spending vast amounts of time in activities that are not content-specific (Davis, 2001). Generalized and specific PIU can be viewed as addiction to the Internet itself and addiction on the Internet, respectively (Widyanto & Griffiths, 2006, 2007). The cognitive-behavioral model of generalized PIU proposed by Davis (2001) posits that generalized PIU results from a lack of social support and/or social isolation and low psychosocial well-being (e.g., mood disorders, substance dependence). The need for social contact and reinforcement obtained online would result in an increased desire to remain in a virtual social life (Davis, 2001). Existing psychopathology would act as a distal necessary cause of symptoms of PIU, predisposing individuals to develop maladaptive Internet-related cognitions, such as ruminating about one's overuse of the Internet, low self-efficacy, negative self-appraisal, and overgeneralization. Maladaptive Internet-related cognitions would act as proximal sufficient causes of behavioral and affective symptoms of both specific and generalized PIU, leading to difficulties with impulse control, that ultimately results in negative outcomes associated with Internet use (Davis, 2001). Aiming to update Davis' model, Caplan (2010) proposed a model of generalized PIU that incorporates some cognitive and behavioral variables that have been identified by more recent research as key constructs associated with negative outcomes of Internet use (Caplan, 2010). According to Caplan's model, individuals with a preference for online social interactions are more likely to use computer-mediated communication for alleviating the affective distress associated with face-to-face interactions. Using online interaction to regulate mood would be associated with deficient self-regulation, manifested as obsessive thought patterns related to Internet use and compulsive use of the Internet. In turn, deficient self-regulation would lead to negative outcomes in daily life.

Given the social focus of SNSs, it has been proposed that **Caplan's cognitive-behavioral** model of generalized PIU may provide a conceptual basis for understanding the problematic use of SNSs (Casale & Fioravanti, 2015, 2017; Ryan et al., 2014). However, the only study to our knowledge that has empirically tested this possibility has been conducted on a sample of

Portuguese adolescents (aged between 14 and 18 years; Assunção & Matos, 2017). The findings showed that Caplan's model of generalized PIU is indeed applicable to PFU, i.e., preference for online social interaction and the use of Facebook to regulate mood predict deficient self-regulation in Facebook use, which in turn predicts the negative outcomes associated with Facebook use (Assunção & Matos, 2017). With reference to the above findings, it has been shown that users' motivations for using Facebook is strongly influenced by culture (e.g., see Vasalou, Joinson, & Courvoisier, 2010, for differences between users from the United States, United Kingdom, Italy, Greece, and France) and by age (McAndrew & Jeong, 2012). Adolescence is associated with an imbalance caused by the different developmental trajectories of reward and regulatory brain circuitry (Bjork, 2004; Van Leijenhorst et al., 2010), resulting in heightened reward sensitivity associated with immature cognitive control (Somerville & Casey, 2010). Due to the mostly nonlinear and regionally specific development of the cerebral cortex during development (e.g., Tamnes et al., 2010) and to the relation of risk-tasking behavior and addiction with the imbalance between motivation and cognitive control (Gladwin, Figner, Crone, & Wiers, 2011), age may indeed play an important role in modulating the nature and strength of the relationships between the variables included in Caplan's cognitive-behavioral model. Thus, even though some studies have begun assessing whether Caplan's model of generalized PIU can be extended to PFU, the cross-cultural generalization of the model remains limited, and further tests on participants from other cultural and age groups are warranted (Anderson et al., 2017; McAndrew & Jeong, 2012; Vasalou et al., 2010). No study to our knowledge has yet investigated the validity of Caplan's model of generalized PIU in the context of PFU in a large sample of Italian young adults.

The present study aimed at building on and extending previous work about the conceptual aspects of PFU by testing whether the relationships among constructs proposed in Caplan's cognitive-behavioral model of generalized PIU are valid in the context of PFU. To this purpose, a representative sample of Italian young adult Facebook users was considered. The model was tested by administering participants the Problematic Facebook Use Scale (PFUS) (Marino et al., 2017). The PFUS is an adaptation to Facebook use of the Generalized Problematic Internet Use Scale 2 (GPIUS2), the self-report introduced by Caplan (2010) to measure cognitions, behaviors, and outcomes in generalized PIU. The PFUS allows to measure both users' overall levels of PFU and its specific dimensions. The results of the factor structure validation of the PFUS indicate that a five-factor structure, including preference for online social interaction, mood regulation, cognitive preoccupation, compulsive use, and negative outcomes, provide a good fit to the data.

Four research questions were formulated:

1) Does preference for online social interactions predict the use of Facebook for mood regulation?
2) Does preference for online social interactions predict deficient self-regulation of Facebook use?
3) Does using Facebook for mood regulation predict deficient self-regulation of Facebook use?
4) Does deficient self-regulation predict negative outcomes of Facebook use?

Also, we tested the indirect (mediated) effects (Holbert & Stephenson, 2003) and total effects (the sum of all the direct and indirect effects) among the constructs described in Caplan's model (Caplan, 2010). More specifically, three other research questions related to indirect effects were formulated:

5) Does using Facebook for mood regulation mediate the relationship between preference for online social interactions and deficient self-regulation?

6) Does deficient self-regulation mediate the relationship between preference for online social interactions and negative outcomes?

7) Does deficient self-regulation mediate the relationship between mood regulation and negative outcomes?

As an additional exploratory analysis, we examined whether the factor structure of the PFUS and the relationships among constructs proposed in Caplan's model are similar in females and males.

Methods

Participants

A convenience sample of 815 Italian young adults (406 girls, mean age = 23.2 ± 3.1 years, range = 18–30 years) recruited in different cities in the North (N = 393, 215 girls, mean age = 23.01 ± 3.4 years), Center (N = 206, 93 girls, mean age = 23.6 ± 3.4 years), and South (N = 216, 98 girls, mean age = 23.1 ± 3.2 years) of Italy was enrolled for this study. Our sample size met the recommended sample size for Structural Equation Modeling (Violato & Hecker, 2007).

Approval for the study was obtained from the Ethical Committee of Psychological Research, Area 17, University of Padova. The ethical principles of the Helsinki and its amendments or comparable ethical standards were followed.

Measures

Participants filled in the Italian version of the Problematic Facebook Use Scale (PFUS; Marino et al., 2017. See more details on the PFUS in *Assessing problematic Social Networking*

Sites use of the *Characterizing problematic Social Networking Sites use* subsection, Section 2). Participants are asked to rate the extent to which they agree with each of the 15 items on a 8-point scale (from 1 = "definitely disagree" to 8 = "definitely agree"). Scores range from 15 to 120, with higher scores indicating higher levels of PFU. The Italian version of the PFUS has shown a good construct and convergent validity (Marino et al., 2017).

Procedure

Potential participants were contacted informally at University facilities and through several open Facebook groups (where people come together around a common topic to organize, discuss issues, and share related content), and asked for participation in a survey on Facebook use among young people aged 18-30 years. Those who agreed to participate had to send an email to the first author and then received the URL they had to click to be connected to an anonymous on-line version of the PFUS.

Before accessing the PFUS, the URL led to a first web page that asked participants to read an informed consent and to click on the statement "I agree to the above consent form" or to log out by clicking on a "I don't agree to the above consent form". Then participants were required to indicate their gender, age and whether or not they had a Facebook account by clicking on the appropriate option. Only respondents who indicated an age between 18 and 30 years and had a Facebook account were given the possibility to continue to the questionnaire by clicking on a "Start the questionnaire" button, or to log out by clicking on a "I don't want to take the questionnaire" button. Otherwise, they were automatically logged out.

The online version of the PFUS was set in such a way that participants had to answer all questions before they were able to submit the questionnaire (by clicking on a "Submit" button), but they could quit the questionnaire at any time (by clicking on a "Quit" button). No participant quit before the end of the questionnaire. See raw data in Supplementary file.

Statistical analysis

Whereas in the factorial structure of the Italian version of the PFUS there are five first-order factors, i.e., preference for online social interaction (POSI), mood regulation, compulsive use, cognitive preoccupation, and negative outcomes (Marino et al., 2016), in the GPIUS2 "deficient self-regulation" is also included as a second-order factor, determining the two first-order factors "compulsive use" and "cognitive preoccupation" (Caplan, 2010). Because the aim of the present study was to test whether the factorial structure of Caplan's cognitive behavioral model of generalized PIU applies to Facebook use, the factorial structure of the GPIUS2 was considered.

The two-step approach (Anderson & Gerbing, 1988) adopted by Caplan (2010) for the development and testing of the theoretical model of PIU was employed. First, a confirmatory factor analysis (CFA) of the model was conducted, and then a confirmatory structural equation model (SEM) analysis was performed to test the hypothesized relationships between constructs. Because the data were strongly skewed and ordinal, the Weighted Least Squares Mean and Variance (WLSMV) robust estimator for ordinal items was employed (Rhemtulla, Brosseau-Liard, & Savalei, 2012). The delta method was employed to estimate the standard errors and statistical significance of total and indirect effects. Goodness-of-fit was evaluated using the following indices (Schermelleh-Engel, Moosbrugger, & Müller, 2003): Chi square ($\chi 2$), Comparative Fit Index (CFI; values greater than 0.97 were considered as indicating good fit), Tucker Lewis index (TLI; values greater than 0.95 were considered as indicating acceptable fit), and Root Mean Square Error of Approximation (RMSEA; values lower than 0.05 and between

0.05 and 0.08 were considered as indicating good and adequate fit, respectively). Internal consistencies of both the PFUS and its subscales were assessed by using Cronbach's α.

The factorial structure of the GPIUS2 was also tested separately in females and males to assess configural invariance. A multigroup CFA was employed to assess measurement invariance of the scale across genders. Then, a hierarchical approach was adopted to constrain model parameters and to compare changes in the model fit. Configural, metric and scalar models were estimated, and both the change in fit indices (i.e., ΔCFI larger than 0.01 and ΔRMSEA larger than 0.015; Cheung & Rensvold, 2002) and multigroup model fit indices were used to evaluate measurement invariance.

Lastly, a multigroup SEM was performed to test gender differences in the structural model. Testing for group invariance involved comparing a baseline model where no constraints were specified with a model where all regressions were constrained to be invariant across genders. Both changes in fit indices (i.e., ΔCFI larger than 0.01 and ΔRMSEA larger than 0.015; Cheung & Rensvold, 2002) and multigroup model fit indices were used to evaluate measurement invariance.

All analyses were performed using R software (R Development Core Team, 2016) and the Lavaan package (Rosseel, 2012).

Results

Descriptive statistics including gender differences are reported in Table 9. The linear model analysis revealed gender differences only in the POSI subscale of the PFUS, with significantly higher scores among males than among females. Percentiles of the PFUS total score and of its subscales are shown in Table 10.

Confirmatory factor analysis

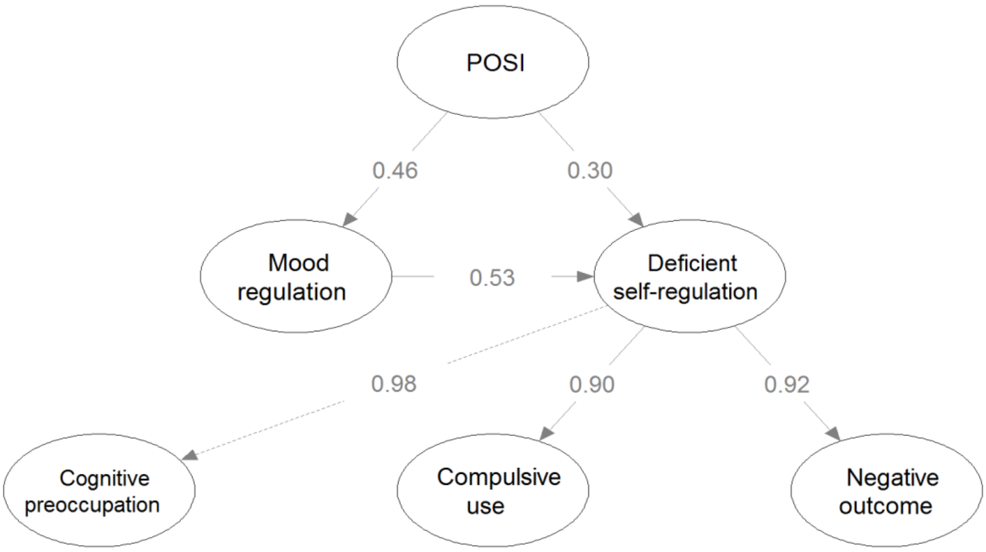
The measurement model for the CFA was specified considering deficient self-regulation as a second-order factor, and compulsive use and cognitive preoccupation as first-order factors. The other first-order factors are POSI, mood regulation, and negative outcome.

The CFA provided a good fit to the observed data ($\chi^2(82) = 381.27$, $p < .001$; CFI = 0.98; TLI = 0.97; RMSEA = 0.067 90%CI = 0.06, 0.07). Good internal consistencies were observed for the whole PFUS ($\alpha = 0.93$) and its subscales, i.e., POSI ($\alpha = 0.89$), mood regulation ($\alpha = 0.82$), cognitive preoccupation ($\alpha = 0.86$), compulsive Facebook use ($\alpha = 0.91$), and negative outcome ($\alpha = 0.85$). All factor loadings were significant ($p < .001$) and ranged between 0.64 and 0.97 (see Table 11. Furthermore, the model fit was adequate for both males ($\chi^2(82) = 314.279$, $p < .001$; CFI = 0.97; TLI = 0.97; RMSEA = 0.083 90%CI = 0.07, 0.09) and females ($\chi^2(82) = 196.655$, $p < .001$; CFI = 0.99; TLI = 0.98; RMSEA = 0.059 90%CI = 0.05, 0.07). The fit indices of the unconstrained multigroup model indicated configural invariance of the factor structure across genders ($\chi^2(164) = 509.585$, $p < .001$; CFI = 0.98; RMSEA = 0.072 90%CI = 0.07, 0.08). Next, metric invariance was tested by constraining all item loadings to be equal across gender groups, and no significant reduction in model fit was found (ΔCFI = 0.001; ΔRMSEA = 0.004; fit indices: $\chi^2(175) = 504.429$, $p < .001$; CFI = 0.98; RMSEA=. 068 90%CI = 0.06, 0.08). Lastly, by constraining all item intercepts to be equal across gender groups scalar invariance was found (ΔCFI = 0.001; ΔRMSEA = 0.013; fit indices: $\chi^2(259) = 572.591$, $p < .001$; CFI = 0.98; RMSEA=. 055 90%CI = 0.05, 0.06).

Structural equation modeling

The factorial structure including both the five first-order factors and the second-order factor provided a good fit to the data. Thus, the original Caplan's model including five first-order factors and one second-order factor was tested. To examine the hypothesized relationships among the latent constructs, the SEM was tested by using WLSMV robust estimator. The tested model and the estimated standardized beta coefficients (β) are shown in Figure 10.

Figure 10. Standardized estimates resulting from the structural model.



The structural model showed a good fit of the data ($\chi^2(84) = 375.5$, $p < .001$; CFI = 0.98; TLI = 0.98; RMSEA = 0.06 90%CI = 0.06, 0.07). The total effect (direct plus indirect effects) resulted to be significant ($\beta = 3.22$, $p < .001$). A good fit of the data was also found when testing males and females separately (males: $\chi^2(84) = 301.686$, $p < .001$; CFI = 0.98; TLI = 0.97; RMSEA = 0.080 90%CI = 0.07, 0.09; females: $\chi^2(84) = 199.742$, $p < .001$; CFI = 0.99; TLI = 0.98; RMSEA = 0.058 90%CI = 0.05, 0.07). The fit indices of the unconstrained multigroup SEM model indicated invariance across genders ($\chi^2(168) = 500.008$, $p < .001$; CFI = 0.98; RMSEA = 0.070 90%CI = 0.06, 0.08). Next, invariance was tested by constraining regressions to be equal across genders, and no significant reduction in model fit was found (ΔCFI = 0.002; ΔRMSEA = 0.004; fit indices: $\chi^2(172) = 478.399$, $p < .001$; CFI = 0.98; RMSEA=. 066 90%CI = 0.06, 0.07).

Table 9. Descriptive statistics and gender differences

		Age	POSI	Mood regulation	Cognitive preoccupation	Compulsive use	Negative outcomes	PFUS total score
Female (n=406)	mean±sd skew kurtosis	23.26±2.9 0.42 -0.73	5.88±3.8 1.39 1.53	9.29±5.1 0.66 -0.43	5.88±3.8 1.83 4.25	8.05±4.9 1.01 0.07	4.47±2.8 2.40 7.42	33.57±15.3 1.11 0.83
Male (n=409)	mean±sd skew kurtosis	23.20±3.3 0.51 -0.23	6.94±4.6 1.53 1.88	9.17±5.1 0.64 -0.49	5.69±3.1 1.76 3.70	8.13±5.0 0.99 0.14	4.78±2.9 3.23 13.78	34.71±15.4 1.27 2.02
Test Statistic		$-0.31^{\text{t test}}$ p = .75 BF = 0.08	$3.58^{\text{t test}}$ p < .001 BF = 40.8	$-0.34^{\text{t test}}$ p = .73 BF = 0.08	$-0.85^{\text{t test}}$ p = .4 BF = 0.11	$0.25^{\text{t test}}$ p = .8 BF = 0.08	1.56^{test} p = .12 BF = 0.26	$1.06^{\text{t test}}$ p = .29 BF = 0.14
Total sample (n=815)	mean±sd skew kurtosis	23.23±3.1 0.46 -0.50	6.41±4.2 1.49 1.91	9.23±5.1 0.65 -0.46	5.78±3.3 1.81 4.02	8.09±5.0 1.00 0.11	4.62±2.8 2.80 10.35	34.14±15.4 1.19 1.42

The results of linear model analysis considering gender as predictor are shown for age, subscales and total scores of the PFUS. To quantify the predictive success of linear models with gender as predictor relative to an intercept-only model, Bayes factor (BF) are also reported

Table 10. Percentiles of PFUS scores for females, males and total sample.

	Percentiles	POSI	Mood regulation	Cognitive preoccupation	Compulsive use	Negative outcomes	PFUS total score
Females	5th	3	3	3	3	3	16
	10th	3	3	3	3	3	18
	25th	3	5	3	4	3	22
	50th	4	8	5	7	3	30
	75th	8	13	7	11	5	41
	90th	11	17	10	16	7	55
	95th	14	19	13	18	10	60.75
Males	5th	3	3	3	3	3	16
	10th	3	3	3	3	3	19
	25th	3	5	3	4	3	23
	50th	5	8	5	7	3	31
	75th	9	13	7	11	6	42
	90th	14	16.2	9.2	17	8.2	59
	95th	17	19	12	19	11	66.6
Total sample	5th	3	3	3	3	3	16
	10th	3	3	3	3	3	18
	25th	3	5	3	4	3	23
	50th	5	8	5	7	3	30
	75th	8	13	7	11	5	41
	90th	12.6	17	10	16	8	56
	95th	15	19	12.3	19	10.3	65

Table 11. Standardized factor loadings for the PFUS; N = 815.

Items	POSI	Mood regulation	Cognitive preoccupation	Compulsive use	Negative outcomes
Deficient Self-regulation			0.99	0.90	
I prefer online social interaction over face-to-face communication	0.78				
Online social interaction is more comfortable for me than face-to-face interaction	0.81				
I prefer communicating with people online rather than face-to-face	0.97				
I have used Facebook to talk with others when I was feeling isolated		0.64			
I have used Facebook to make myself feel better when I was down		0.81			
I have used Facebook to make myself feel better when I've felt upset		0.89			
When I haven't been on Facebook for some time, I become preoccupied with the thought of going on Facebook			0.73		
I would fell lost if I was unable to go on Facebook			0.87		
I think obsessively about going on Facebook when I am offline			0.89		
I have difficulty controlling the amount of time I spend on Facebook				0.86	
I find it difficult to control my Facebook use				0.87	
When offline, I have a hard time trying to resist the urge to go on Facebook				0.90	
My Facebook use has made it difficult for me to manage my life					0.91
I have missed social engagements or activities because of my Facebook use					0.79
My Facebook use has created problems for me in my life					0.75

Direct effects

As shown in Figure 10, POSI resulted to be a significant positive predictor of Facebook use for mood regulation ($p < .001$; $\beta_{males} = 0.45$, $p < .001$; $\beta_{females} = 0.50$, $p < .001$) and of deficient self-regulation ($p < .001$; $\beta_{males} = 0.30$, $p < .001$; $\beta_{females} = 0.29$, $p < .001$). Moreover, using Facebook for mood regulation was a significant positive predictor of deficient self-regulation ($p < .001$; $\beta_{males} = 0.51$, $p < .001$; $\beta_{females} = 0.55$, $p < .001$). Lastly, deficient self-regulation resulted to be a significant positive predictor of negative outcomes of Facebook use ($p < .001$; $\beta_{males} = 0.92$, $p < .001$; $\beta_{females} = 0.93$, $p < .001$).

Indirect effects

A significant positive relationship was found between POSI and deficient self-regulation, mediated by mood regulation ($\beta_{total} = 0.24$, $p < .001$; $\beta_{males} = 0.23$, $p < .001$; $\beta_{females} = 0.28$, $p < .001$). A significant positive relationship was also found between POSI and negative outcomes, mediated by deficient self-regulation ($\beta_{total} = 0.28$, $p < .001$; $\beta_{males} = 0.28$, $p < .001$; $\beta_{females} = 0.27$, $p < .001$). Lastly, a significant positive relationship was found between mood regulation and negative outcomes, mediated by deficient self-regulation ($\beta_{total} = 0.49$, $p < .001$; $\beta_{males} = 0.47$, $p < .001$; $\beta_{females} = 0.51$, $p < .001$).

Overall, the tested model resulted to account for 21% of the variance in mood regulation, 52% of the variance in deficient self-regulation, and 86% of the variance in negative outcomes.

Discussion

The present study was aimed at testing the cognitive-behavioral model of generalized PIU (Caplan, 2010) in the context of PFU, in a sample of Italian young adults.

The confirmatory factor analysis (CFA) supported the original model by Caplan (2010), that includes a second-order factor, “deficient self-regulation”, determining the two first-order factors “cognitive preoccupation” and “compulsive use”. The structural equation model (SEM) supported all the hypothesized direct and indirect relationships among the latent constructs. Specifically, we found that preference for online social interaction (POSI) has a significant role in influencing both the extent to which people use Facebook for regulating their mood, and the capacity to self-regulate one's use of Facebook. The degree to which people self-regulate their use of Facebook resulted to be significantly predicted by how much they use Facebook for mood regulation. Lastly, the inability to self-regulate one's use of Facebook was found to have a significantly role in predicting the negative outcomes of Facebook use.

Furthermore, the significant relationship between POSI and inability to self-regulate one's use of Facebook was mediated by the use of Facebook for regulating mood. We also found that the difficulty in self-regulating Facebook use mediates the significant links that POSI and mood regulation have with the negative outcomes of Facebook use.

As for the observed direct effect of using Facebook to regulate mood on difficulties in self-regulating Facebook use, we found that difficulties in self-regulating Facebook use is more strongly related to using Facebook for mood regulation than to POSI. This result, suggesting that difficulty in mood regulation may be a key factor involved in pathological Facebook use, replicates that of Assunção & Matos (2017) in the context of PFU among Portuguese adolescents. Also, it is in accordance with the results of a recent meta-analysis (Marino, Gini, Vieno, & Spada, 2018a), in which a positive correlation between neuroticism and PFU was found, suggesting that Facebook can serve as a means to regulate mood and to seek for support for people with poor emotional stability. Furthermore, students with low emotional stability have been found to be more likely to use Facebook in a problematic way, suggesting that less emotionally stable adolescents tend to use Facebook to regulate their mood (Marino et al., 2016).

The indirect effect of using Facebook to regulate mood on negative outcomes of Facebook usage, is worth noting. Differently from what reported by both Caplan (2010) for generalized PIU and by Assunção and Matos (2017) for PFU among Portuguese adolescents, we found that the effect of using Facebook to regulate mood on negative outcomes, mediated by deficient self-regulation, was stronger than that of POSI. This finding suggests that among Italian young adults, using Facebook for mood regulation has a greater impact than POSI on negative outcomes of PFU, that is, the more Facebook is used to regulate mood, the more the negative outcomes of Facebook use. In support of this result, it has been recently reported that PFU is positively correlated with signs of psychological distress, including anxiety and depression, and also has a negative impact on general wellbeing. Moreover, this relationship appears to be stronger than others reported in the literature on PIU and psychological distress (Marino, Gini, Vieno, & Spada, 2018b). The conflicting results obtained on Italian young adults and on Portuguese adolescents (Assunção & Matos, 2017) suggest that during adolescence POSI plays a more central role than mood regulation in determining the negative outcomes of Facebook use, whilst mood regulation becomes a major goal of Facebook use later during development. Future studies should further examine the relationships of POSI and mood regulation with negative outcomes in PFU, considering participants with different age ranges and from different cultural contexts.

Similarly to findings reported by both Caplan (2010) for generalized PIU and Assunção and Matos (2017) for PFU, we found that POSI is strongly related with using Facebook for mood regulation. It might be hypothesized that preferring online social interaction favors the use of Facebook for mood regulation purposes. But, in a different perspective, Facebook usage for mood regulation may be a vulnerability factor that underlies POSI and difficulty in self-regulation of Facebook use. In order to establish causal links, future research using longitudinal studies should investigate whether using Facebook for mood regulation represents a risk factor or a consequence of both POSI and compulsive Facebook use.

Concerning the variance accounted for by the model, the strongest relationship was found between deficient self-regulation and the negative outcomes of Facebook use (86% of explained variance). This result is similar to that reported by Assunção & Matos (2017) in their study of PFU among Portuguese adolescents, and substantially higher than that reported by Caplan (2010), where the model explained 61% of the variance in negative outcomes. Considering that in Caplan's study the participants' age ranged between 18 and 70 years, whereas participants in the current study aged 18 to 30 years, a possible explanation of the above inconsistency may be related to the fact that self-regulatory capacity increases with age (Lawton, Kleban, Rajagopal, & Dean, 1992), and this could influence both self-regulatory capacity and the related direct and indirect effects. Future studies considering a wider age range would be needed in order to clarify how and why findings vary across different age ranges. As an alternative explanation, Assunção and Matos (2017) suggested that, unlike the Internet in general, Facebook might be a context where the user is most likely to engage in addictive behavior leading to problematic consequences, possibly because Facebook offers several different features that might make its use addictive (e.g., online games). In contrast with this explanation, and in line with Brand, Young, & Laier (2014), we believe that the Internet includes, as much as Facebook does, many features that people can become “addicted” to. Depending on predisposing factors, i.e. neurobiological characteristics, coping styles, affective and cognitive responses to situational triggers in combination with reduced executive functioning (Brand et al., 2016), both generalized and specific Internet use may become problematic, as much as Facebook use may. In line with this view, it has been argued that

Facebook addiction and Internet addiction are the same phenomenon, and they are positively associated with each other (Błachnio, Przepiorka, Senol-Durak, Durak, & Sherstyuk, 2017). The discrepancy between studies on PFU and those on generalized PIU may be explained by considering some differences between individuals who use the Internet and those who use Facebook, related to factors that directly and indirectly influence negative outcome, such as self-regulation skills, degree of POSI, and mood regulation capacity. Specifically, the fact that we found POSI to be an important positive predictor of Facebook use for mood regulation suggests that preferring online social interactions favors the use of Facebook for mood regulation purposes. Such relationship between POSI, the use of Facebook for mood regulation, and negative outcomes may characterize the problematic use of SNSs such as Facebook, rather than disordered Internet use, because PIU includes addiction to applications that do not provide online social interaction (e.g. online gaming, online shopping, etc.). Indeed, it has been argued that the social focus in Caplan's cognitive-behavioral model, evidenced by the inclusion of POSI, makes it a good model to study the use and abuse of SNSs applications (Ryan et al., 2014).

Overall, the factor structure of the PFUS did not differ as a function of gender. Also, no significant gender differences were found in the direct and indirect relationships among the latent constructs in the model. Therefore, the conceptual model of PFU does not seem to change according to gender. However, research on gender differences in Facebook use is still rather limited (e.g., Thompson & Lougheed, 2012), and therefore additional studies on PFU and its consequences should include gender as a key variable.

Overall, our results are in accordance with those previously reported by Assunção & Matos (2017) relative to a sample of Portuguese adolescents. By taking a different cultural background and a different age range into consideration, our findings provide a novel contribution supporting the generalizability of Caplan's cognitive-behavioral model to PFU.

Future studies aimed at further testing the generalizability of these results should consider other European and non-European cultural contexts.

Our findings should be interpreted in light of four main methodological limitations. First, although this is one of the firsts studies that tested the cognitive-behavioral model of PFU, the study was implemented using a cross-sectional design. This makes it difficult to infer cause-effect relationships between variables. Longitudinal studies on Facebook users are needed in order to better test the model and the causal relations between the constructs. Second, only self-report data were collected. Future studies including objective measures of Facebook use, mood regulation and negative outcomes would improve measure validity. Third, we did not assess the participants' main Facebook use, that could help to clarify the specific individual Facebook “function”. Further studies aimed at further contributing to the discussion about the conceptual aspects of PFU should include this aspect. Lastly, we did not collect measures of psychopathology (e.g, anxiety, depression, impulsivity, etc.). Future research should take the presence of psychopathology into account to control its possible influence on the variables included in the model.

Concluding, in Italian young adults, using Facebook to regulate mood and preference for online social interactions appear to predict difficulties in regulating Facebook use, which in turn predicts negative outcomes of Facebook usage. Of note, among Italian young adults, difficulties in self-regulating Facebook use is related more strongly to using Facebook for mood regulation than to preference for online social interaction. Similarly, using Facebook for mood regulation appears to have a greater impact than preference for online social interaction on negative outcomes of PFU. These findings suggest that mood regulation abilities may be a potential target for prevention and treatment of PFU.

“Out of habit, I stay by my smartphone.

As a consequence, I use Facebook out of boredom”

Participant 213

Study 5: Cue-reactivity to Facebook-related and affective pictures: an ERP study

Introduction

Recent research argues that social networking sites (SNSs) are potentially addictive and their problematic use (i.e., Problematic Social Network Sites Use, PSNSU) shares core components with substance use disorders (SUDs) and behavioral addictions, including tolerance, withdrawal, conflict, salience, relapse, and mood modification (Griffiths et al., 2014; Hormes et al., 2014). However there is not yet an agreement in the definition of PSNU as an addictive behavior (LaRose, Kim, & Peng, 2010), and its underlying mechanisms remain to be clarified (Andreassen, 2015; Kuss & Griffiths, 2017). Specifically, a comprehensive characterization of PSNSU in neurobiological and psychophysiological terms is currently lacking, whereas psychobiological mechanisms are often addressed when describing other problematic and addictive behaviors (Cerniglia et al., 2017; Grant et al., 2010; Horseman & Meyer, 2019; Kwako, Bickel, & Goldman, 2018; Potenza et al., 2019; Sussman, Harper, Stahl, & Weigle, 2018).

Only few studies have investigated the **psychobiological mechanisms involved in PSNSU** (He, Turel, & Bechara, 2017; Turel, He, Xue, Xiao, & Bechara, 2014) and only one theoretical model explicitly includes psychobiological factors implicated in PSNSU as a specific type of Internet-use disorder (Brand et al., 2016). This model suggests that, similarly to SUDs and behavioral addictions, other potential addictive behaviors like PSNSU **involve an interaction of sensitized reward processing and cue-reactivity** with defective prefrontal inhibitory control (Brand et al., 2016). Studies on PSNSU show that the activation of the amygdala-striatal neural pathway seems to be positively associated with PSNSU severity, while the negative association between PSNSU severity and prefrontal cortex activity (inhibition system) has not been supported (He et al., 2017; Turel et al., 2014). Furthermore, individuals with PSNSU seem to be characterized by significant structural modifications in subcortical brain systems, as indicated by reduced grey matter volumes in the amygdala bilaterally, suggesting that PSNSU is characterized by structural brain changes that are similar to those highlighted in other addictions (substance, gambling etc.) (He et al., 2017). It has also been showed that, in contrast to other addictions in which the anterior-/mid- cingulate cortex has reduced grey matter volume and fails to inhibit behavior properly, this region does not show structural changes in PSNSU and, surprisingly, its grey matter volume is positively correlated with PSNSU severity (He et al., 2017). It has been speculated that the positive relationship between PSNSU severity and increased volume of the anterior-/mid- cingulate cortex may reflect a compensation process, which is operated in response to functional changes in the amygdala (He et al., 2017). Despite these findings, it remains to be clarified whether functional neural changes in PSNSU include sensitized reward processing and cue-reactivity in conjunction with poor inhibitory control capacity (Brand, Wegmann, et al., 2019; Brand et al., 2016).

Cue-reactivity refers to the specific pattern of subjective, peripheral physiological, and neural responses shown by individuals who are addicted to substances when they are confronted with substance- relevant cues. Cue-reactivity depends on learning mechanisms, i.e., in the case of SUDs various cues (e.g., drug-related paraphernalia) become associated with the rewarding properties of the drug (Hyman, Malenka, & Nestler, 2006); in the case of gambling, gaming, and buying disorders addiction-relevant cues become associated with the addictive behavior (Starcke et al., 2018).

Cue-reactivity paradigms are largely employed to investigate the motivational relevance of addiction-related cues at the basis of craving and relapse in both human and animal models

(Drummond, 2000). One commonly used paradigm consists in the exposure to addiction-related and neutral cues while psychophysiological responses are recorded. The reactivity to addiction-related cues is quantified as increased responses to addiction-related than to neutral cues (Jasinska, Stein, Kaiser, Naumer, & Yalachkov, 2014).

In individuals with SUDs, the exposure to substance-related cues has been found to elicit increased subjective arousal, increased HR and skin conductance, and decreased skin temperature (Carter & Tiffany, 1999). Craving is strongly connected to cue-reactivity. In the context of SUDs, craving has been described as a difficult-to-resist urge to consume a substance, resulting from the repeated exposure to conditioned addiction-related stimuli that trigger cue-reactivity (Carter & Tiffany, 1999), and representing the underlying basis for addictive behavior (Robinson & Berridge, 1993).

In preclinical studies, it has been showed that neutral stimuli closely associated in time and space with the effects of self-administered drugs gain incentive salience through the process of Pavlovian conditioning. These conditioned stimuli motivate compulsive drug seeking behaviors. Pavlovian conditioning is thought to be the most important mechanism characterizing drug dependence also in humans (Everitt & Robbins, 2005). More recently, it has been proposed that drug use can alter reward processes by both increasing the motivational salience of drugs and drug-related cues, and reducing the motivational salience of non-drug-related rewards (Koob & Volkow, 2010; Versace et al., 2017). Thus, the difference between reactivity to addiction-related and neutral cues seems to not be sufficient to conclude that psychophysiological responses to addiction-related cues are exaggerated. A further comparison with motivationally relevant, non-addiction-related stimuli that would engage the activity of appetitive and aversive motivational systems is necessary, as it would provide a stronger test of whether addiction-related cues hijack human brain motivational systems and motivate drug seeking over alternative behaviors (Versace et al., 2017). Moreover, comparing reactivity to natural rewards vs. unpleasant vs. neutral cues is necessary to assess whether and how addiction affects appetitive and aversive responding in general (Versace et al., 2017, 2011).

The concepts of cue-reactivity and craving have been transferred from SUDs to behavioral addictions, showing several similarities between these two groups of disorders (Starcke et al., 2018). Specifically, the processing of addiction-related cues in behavioral addictions has been recently reviewed in a meta-analysis that showed higher reactivity (as indicated by both peripheral and central psychophysiological measures) to addiction-related cues in individuals with gambling, gaming, and buying disorders compared with healthy controls (Starcke et al., 2018). At the neural level, significant activations were observed in the caudate nucleus, inferior frontal gyrus, angular gyrus, precuneus, and inferior network, suggesting that cue-reactivity occurs not only in SUDs but also in behavioral addictions (Noori, Cosa Linan, & Spanagel, 2016; Starcke et al., 2018). Despite the similarities between PSNSU and addictive behaviors (Griffiths et al., 2014), and theoretical hypothesis on cue-reactivity inducing craving in specific types of problematic Internet use (e.g., PSNSU, Brand et al., 2016), no study to our knowledge has yet investigated cue-reactivity in individuals with PSNSU.

The **Event-Related Potentials** (ERPs) have been largely used to study human attentional and motivational processes in real time during exposure to addiction-related and emotional stimuli (Brand, Rumpf, et al., 2019; Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000; Hajcak, MacNamara, & Olvet, 2010; Littel, Euser, Munafò, & Franken, 2012; Versace et al., 2017, 2011). Long-latency positive ERP components, the P3 and the Late Positive Potential (LPP), reflect sustained attention, representation of stimuli in short-term memory or meaning evaluation (Hajcak et al., 2010; Schupp, Flaisch, Stockburger, & Junghöfer, 2006). In emotion research, larger parietal positivity following emotional compared to neutral stimuli has been taken to reflect “motivated attention”, i.e., emotion automatically directs attention, and thereby facilitates subsequent processing (Bradley et al., 2003; Ferrari, Codispoti, Cardinale, & Bradley, 2008; Hajcak, Dunning, & Foti, 2009; Morris et al., 1998; Sabatinelli, Bradley, Fitzsimmons, & Lang, 2005).

The P3 component of the ERPs (peaking around 300 ms after stimulus onset) is larger in response to pleasant and unpleasant relative to neutral pictures, with the most arousing pictures eliciting the largest P3 amplitudes (Hajcak et al., 2010). ERP studies on addictions have measured the P3 amplitude in response to different stimulus types. For instance, a study on both IGD and alcohol use disorder (AUD) using an auditory oddball task showed that both individuals with IGD and with AUD had reduced centro-parietal P3 amplitudes compared with healthy controls (Park, Kim, Kim, & Choi, 2017). Moreover, in methamphetamine (MA) dependent patients the ERPs have been recorded during a Stroop color-matching task, using MA-related and neutral words. The findings showed larger P3 amplitudes elicited by MA-related words over left-anterior electrode sites (Haifeng et al., 2015). It has been showed that the amplitude of the P3 component in response to rewards is reduced in patients with Internet Gaming Disorder (IGD) in comparison to healthy controls, supporting the hypothesis of tolerance effects in this kind of patients (Duven, Müller, Beutel, & Wölfling, 2015).

The LPP is a positive, sustained shift reaching its maximum amplitude about 1 s after the presentation of motivationally relevant stimuli (Cuthbert et al., 2000; Hajcak et al., 2010). Similarly to the P3, the LPP over central and parietal sites is larger in response to motivationally relevant stimuli, both pleasant and unpleasant, as compared with neutral stimuli (Cuthbert et al., 2000; Hajcak et al., 2010; Schupp et al., 2000). This effect is more pronounced for highly arousing pictures (Schupp et al., 2004) and is characterized by temporal stability and resistant to manipulations affecting perceptual composition (Codispoti, Ferrari, & Bradley, 2007; De Cesarei & Codispoti, 2006).

Cue-reactivity research on individuals with SUDs showed enhanced P3 and LPP amplitudes in response to addiction-related than to neutral pictorial stimuli (Littel, Euser, et al., 2012). However, no study to our knowledge has yet investigated these two ERPs components during a cue-reactivity task in PSNSU.

The present study aims at investigating cue-reactivity to Facebook-related visual cues in individuals classified as problematic vs. non-problematic Facebook users.

We hypothesized that in problematic Facebook users, Facebook-related pictures, a category of stimuli that may have acquired motivational significance by being repeatedly associated with the rewarding proprieties of using Facebook, would elicit larger P3 and LPP amplitudes than neutral pictures, and larger than in non-problematic Facebook users. Possibly, Facebook-related stimuli may have acquired as much rewarding properties as to elicit comparable neural responses to those elicited by high arousal pleasant stimuli.

We also expected in problematic Facebook users to endorse higher craving ratings for Facebook usage than non-problematic Facebook users, and to rate Facebook-related pictures as more pleasant and arousing than neutral pictures, and than non-problematic Facebook users. Possibly, problematic Facebook users may rate Facebook-related and high-arousal pleasant stimuli as comparably pleasant and arousing.

Method

Participants

Students of the University of Padua, Italy, were contacted informally at university facilities and asked to fill in an online version of the PFUS (Marino et al., 2017; see more details on the PFUS in *Assessing problematic Social Networking Sites use* of the *Characterizing problematic Social Networking Sites use* subsection, Section 2). Based on the Italian percentiles of the PFUS scores distribution (Moretta & Buodo, 2018b), 27 participants who scored equal to or higher than 41 (i.e., the 75th percentile) were included in the problematic Facebook users (PFUs) group. Twenty-seven participants who scored equal to or lower than 23 (i.e., the 25th percentile) were included in the non-PFUs group. One participant in the non-PFUs group was excluded because of technical problems (see below). The final non-PFUs group was thus composed of 26 participants.

We chose to adopt the extreme-groups approach, because it provides clear advantages in terms of cost-efficiency and statistical power (Preacher, Rucker, MacCallum, & Nicewander, 2005), and because our focus was on comparing individuals with high vs. low problematic Facebook use, rather than on considering individuals with scores close to the median of the distribution. If we did test the same number of participants without performing any selection, chances were that the greatest part of the sample would have scored close to the median of the distribution and, thus, we would not have been able to observe the extremes. However, as the extreme-groups approach has the limit of treating individuals assigned to a group as identical on the categorizing variable, thus losing information about more subtle individual differences (Preacher et al., 2005), we also performed correlational analyses between P3 and LPP amplitudes and subjective ratings of Arousal and Valence for each emotional category in PFU and non-PFU.

As reported in Table 12, the two groups significantly differed on PFUS scores and were comparable for sex distribution, age, and sleep hours.

All participants read and signed an informed consent. The study was conducted in compliance with the declaration of Helsinki on research on human subjects and was approved by the Ethical Committee of Psychological Research, Area 17, University of Padova.

Craving measure

To assess craving for Facebook use, participants were asked to respond to a question ("How much would you like to use Facebook now?") using a Likert scale (range 1-5; 1 = not at all, 5 = very much).

The passive picture viewing task

Ninety six digitized color pictures (600 × 800 pixel) were presented, divided into Facebook-related, and unpleasant (attacking humans), pleasant (erotic couples), and neutral (people) taken from the International Affective Picture System, IAPS; Lang, Bradley, & Cuthbert, 2008)[1]. Only highly arousing pleasant and unpleasant pictures were selected, since these have been observed to induce the most remarkable psychophysiological changes (e.g., Bradley, Codispoti, Cuthbert, & Lang, 2001). Pleasant and unpleasant pictures were matched for normative arousal ratings (unpleasant = 6.25 ± 0.61; pleasant = 6.41 ± 0.33; p = .47), which were significantly higher than for neutral pictures (neutral = 3.29 ± 0.46; all ps < .001). Pleasant

[1] **The IAPS picture numbers were as follows: Pleasant: 4611. 4647, 4650, 4651, 4652, 4656, 4658, 4659, 4660, 4664, 4666, 4669, 4670, 4672, 4676, 4680, 4681, 4683, 4687, 4690, 4694, 4695, 4800, 4810. Unpleasant: 2683, 2691, 3500, 6211, 6212, 6213, 6242, 6243, 6244, 6250, 6260, 6312, 6313, 6315, 6350, 6510, 6540, 6550, 6560, 6561, 6571, 6821, 6836, 9425. Neutral: 2038, 2102, 2104, 2190, 2191, 2210, 2214, 2215, 2372, 2381, 2383, 2393, 2396, 2480, 2485, 2493, 2495, 2514, 2570, 2575, 2580, 2593, 2850, 8010**

and unpleasant pictures different significantly for mean normative valence ratings (pleasant = 6.63±0.38; unpleasant = 2.61±0.45, $p < .001$), which were significantly higher and lower, respectively, than for neutral pictures (neutral = 5.04±0.41; all $ps < .001$). Facebook-related pictures were copyright-free pictures downloaded from websites and depicted one or more persons using Facebook (see Figure 11).

Figure 11. Example of Facebook-related pictures

Each picture was presented for 4 seconds and was followed by a variable intertrial interval (ITI) of 4–5 seconds, during which a black background with a white fixation cross was presented. The order of picture presentation was pseudo-randomized, so that no two pictures of the same category were presented in succession. The pictures were presented three times each, for a total of 288 trials. The entire experimental session was divided into three blocks, that were counterbalanced between participants. The participants were allowed to rest between blocks. The entire picture presentation lasted approximately 30 minutes.

During picture viewing and during ITIs a startle probe (a burst of 100 dB white noise, 50 ms duration) was delivered binaurally at one of three intervals (i.e., 300, 1500, and 3500 ms after picture onset). Since the P3 and the LPP develop between 400 and 1000 ms after picture onset, for ERP analysis trials where the startle probe was presented at 300 ms (1/3 of the trials) were not included.

Pictures were presented on a 19-inch computer screen through a Core i5-4440 computer running E-prime presentation software (version 2.0, Psychology Software Tools, Pittsburgh, PA, USA), at a viewing distance of 1 m.

After picture presentation, participants were asked to rate 12 pictures for each category used for the viewing task, using a computerized version of the 1-9 point scales of Valence and Arousal of the Self-Assessment Manikin (SAM; Bradley & Lang, 1994).

Physiological recording

The electroencephalogram (EEG) was recorded using an elastic cap with 32 tin electrodes (ANT Neuro Company) arranged according to the 10–20 System (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2, and M1 and M2 [mastoids]), referenced online to Cz.

Both vertical and horizontal electrooculograms (EOGs) were recorded using a bipolar montage to monitor eye movements and eye-blinks. The electrode pairs were placed at the supra- and suborbit of the right eye and at the external canthi of the eyes, respectively.

All electrophysiological signals were amplified with EEGO amplifier (ANT Neuro Company, https://www.ant-neuro.com/products/eego_mylab). All electrode impedances were kept below 5 kΩ. The EEG signal was bandpass filtered online (EEG filter = 0.1-40 Hz) and digitized at 1000 Hz. Offline, the EEG was re-referenced to linked mastoids, corrected for eyeblink artifacts using independent component analysis, and low-pass filtered at 30 Hz. Filtering and further EEG processing were run using Brain Vision Analyzer 2.1 software. The EEG was segmented off-line into 1100-msec epochs, from 100 ms before to 1000 ms after stimulus onset. The EEG epochs were baseline-corrected against the mean voltage during the 100-ms prestimulus period. All EEG epochs were visually scored for eye movements and other artifacts, and each portion of data containing artifacts greater than ±70 uV in any channel was rejected for all the recorded channels prior to further analysis. One participant was removed from the study sample due to technical problem during data recording. On the basis of inspection of grand-average ERPs waveforms at frontal, central and parietal electrodes (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4), where the P3 and the LPP amplitudes reach their maximum on passive viewing task (Cuthbert et al., 2000), the mean amplitude of the P3 was calculated in the 280-400 ms time window, and the mean amplitude of the LPP in three consecutive time windows, i.e., 400-600 ms (LPP1), 600-800 ms (LPP2), and 800-1000 ms (LPP3).

The eyeblink component of the startle response was measured by recording the electromyographic activity from the orbicularis oculi muscle, using two Ag/AgCl miniature electrodes beneath the left eye. The sampling rate was 1000 Hz. The startle data will not be reported here.

Procedure

After participants provided a written informed consent, they were asked to report information about their demographic characteristics, health status, daily time spent on Facebook, sleep ours, and daily cigarette consumption. Moreover, they were asked to rate their Facebook craving using a Likert scale (see below). Then, they were seated on a comfortable chair in a dimly lit, sound-attenuated room. After electrode attachment, they were instructed that a series of pictures would be shown, and that each picture should be viewed the entire duration it was on the screen. They were also told to ignore occasional noises heard on the headphones, to avoid blinking during picture presentation and maintain fixation. The pictures presentation began after a 10-minute adaptation period and the presentation of six trials with neutral pictures and startle probes that served as practice before the task. The entire procedure took about 60 min.

Statistical analysis

All analyses were performed using R software (R Development Core Team, 2016).

As the groups differed significantly with regard to time spent daily on Facebook (*Cohen d* = 1.1), with PFUs spending more time on Facebook than non-PFUs (see Table 12), the "time spent daily on Facebook" was included as covariate in all analyses. Given the ordinal nature of the Self-reported craving level and data skewness (i.e., 2.44), a cumulative link generalized linear model (Christensen, 2015) considering group (PFUs, non-PFUs) as predictor was performed to compare self-reported craving for Facebook usage between groups.

Prior to running the other analyses, all data were examined for skewness, kurtosis, outliers, and normalcy by both exploratory analyses and graphs, i.e., violin plots and boxplots (Pastore et al., 2017). The normal Probability-Probability (P-P) plot of the standardized residuals showed points that were not completely on the line, but close, and the scatterplot of the standardized residuals showed that the data met the assumptions of homogeneity of variance and linearity for all dependent variables.

Separate linear mixed-effect models (LMMs) with individual random intercept (R package: lme4, Bates, Maechler, Bolker, & Walker, 2014) were conducted on mean P3 and LPP1, LPP2, and LPP3 amplitudes, with Category (i.e., Facebook-related, Pleasant, Unpleasant, and Neutral), Group (PFUs and non-PFUs), Area (frontal [F3, Fz, F4], central [C3, Cz, C4], and parietal [P3, Pz, P4]), and Laterality (left [F3, C3, P3], midline [Fz, Cz, Pz], right [F4, C4, P4]) as fixed factors.

Valence and Arousal ratings were submitted to separate LMMs, with participants and pictures as random terms, and Category (i.e., Facebook-related, Pleasant, Unpleasant, and Neutral) and Group (PFUs and non-PFUs) as fixed factors. The strength of parameters evidence within the models was estimated as the difference in the Akaike information criterion (AIC) between the model without and the model with the parameter (ΔAIC, Burnham & Anderson, 2002). Denominator degrees of freedom for F-tests were estimated by Satterthwaite and Kenward-Roger methods (Alnosaier, 2007; Kuznetsova, Brockhoff, & Christensen, 2017). Bonferroni HSD post-hoc tests were employed to further examine significant effects (using a $p < .05$ criterion for significance).

Lastly, Pearson's correlation coefficients were calculated between P3 and LPP amplitudes at frontal, central, and parietal midline sites (Fz, Cz, Pz), and SAM ratings, separately for PFUs and non-PFUs. Only meaningful effects have been commented on (see below).

Results

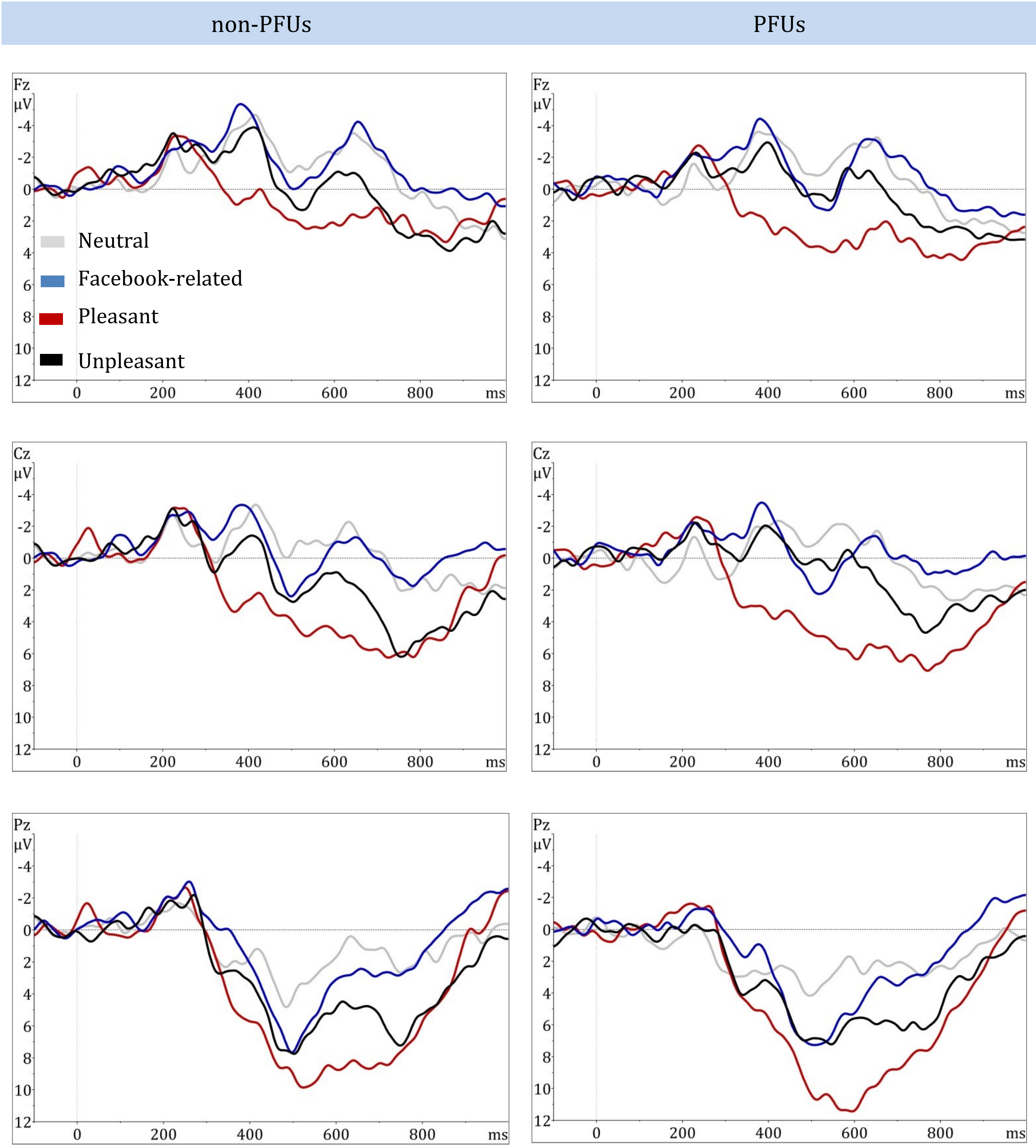
Self-reported Craving ratings for Facebook usage

As shown in Table 12, cumulative link generalized linear model showed that PFUs were more likely to endorse higher self-reported craving for Facebook usage as compared with non-PFUs (OR = 5.16).

ERPs

Grand-average ERPs waveforms over Fz, Cz, and Pz in PFUs and non-PFUs are shown in Figure 12.

Figure 12. Grand-average ERPs waveforms recorded at Fz, Cz, and Pz to Neutral, Facebook-related, Pleasant, and Unpleasant pictures in non-PFUs and PFUs



P3

A significant main effect of Category (F [3, 1610] = 88.45, p < .001, ΔAIC = 249) was found, highlighting greater positivity for Pleasant than for all other picture categories (all ps < .001). Larger relative positivity for Unpleasant and Neutral than for Facebook-related pictures was also found (all ps < .001). The amplitude for Unpleasant pictures was comparable to that for Neutral pictures.

A significant main effect of Area (F [2, 1610] = 299.35, p < .001, ΔAIC = 525) was found. Larger P3 amplitude was observed in the parietal than the central and frontal areas (all ps < .001), with lower amplitude in the frontal than the central and parietal areas (all ps < .001).

The significant main effect of Laterality (F [2, 1610] = 5.55, p = .004, ΔAIC = 3.42) showed larger P3 amplitude on the right side than on the midline (p = .003), however this effect showed low strength evidence as indicated by ΔAIC.

Lastly, a significant Group × Area interaction (F [2, 1610] = 2.77, p = .04, ΔAIC = 12.9) was found, showing that both PFUs and non-PFUs showed larger positivity in the parietal than the central and frontal areas (all ps < .05), with lower positivity in the frontal than the central and parietal areas (all ps < .05). No between group differences were found.

LPP1 (400–600 ms time window)

The significant main effect of Category (F [3, 1610] = 173.59, p < .001, ΔAIC = 463) highlighted larger relative positivity for Facebook-related, Pleasant, and Unpleasant than for Neutral pictures (ps < .001). The LPP1 amplitude was larger for pleasant than for all other picture categories (ps < .001). LPP1 amplitude for Facebook-related pictures was comparable to that for Unpleasant pictures.

A significant main effect of Area ($F [2, 1610] = 578.65$, $p < .001$, $\Delta AIC = 895$) was also found, with larger positivity in the parietal than the central and frontal areas (all ps < .001), and in the central than the frontal area (all ps < .001).

The significant main effect of Laterality ($F [2, 1610] = 578.65$, $p < .001$, $\Delta AIC = 895$) showed larger positivity on the right side than on the midline and the left side (all ps < .001).

A significant Group × Category interaction ($F [3, 1610] = 2.77$, $p = .04$, $\Delta AIC = 20.1$) also emerged. Larger LPP1 amplitude was observed for Pleasant pictures in PFUs than non-PFUs (uncorrected $p = .02$), however this difference did not survive Bonferroni correction. Within groups, the differences between picture categories were the same as reported for the main effect of Category and were comparable between groups.

The significant Group × Area interaction ($F [2, 1610] = 2.77$, $p = .04$, $\Delta AIC = 15.6$) showed larger LPP1 amplitude in the frontal area in PFUs than non-PFUs ($p = .03$). Within groups, the differences between Areas were the same as reported for the main effect of Area and were comparable between groups.

LPP2 (600–800 ms time window)

The significant main effect of Category ($F [3, 1610] = 241.12$, $p < .001$, $\Delta AIC = 620$) highlighted larger positivity for Pleasant and Unpleasant than for Facebook-related and Neutral pictures (all ps < .001). The amplitude was larger for Pleasant than for Unpleasant pictures ($p < .001$). No significant difference between Facebook-related and Neutral pictures was observed in this time window.

A significant main effect of Area ($F [2, 1610] = 271.81$, $p < .001$, $\Delta AIC = 490$) was also found, with larger LPP2 amplitude in the parietal than in the central and frontal areas (all ps < .001), and lower amplitude in the frontal than the central and parietal areas (all ps < .001).

The significant Group × Category interaction ($F [3, 1610] = 5.22$, $p = .001$, $\Delta AIC = 25.7$) showed larger positivity for Neutral pictures in PFUs than in non-PFUs (uncorrected $p = .03$), however this difference did not survive Bonferroni correction. Within groups, the differences between picture categories were the same as reported for the main effect of Category and were comparable between groups.

LPP3 (800–1000 ms time window)

The significant main effect of Category ($F [3, 1610] = 80.27$, $p < .001$, $\Delta AIC = 236$) highlighted larger relative positivity for Pleasant and Unpleasant than for Facebook-related and Neutral pictures (all $ps < .001$). LPP3 amplitude was lower for Facebook-related than for Neutral pictures ($p < .001$). The amplitude for Pleasant pictures was comparable to that for Unpleasant pictures.

A significant main effect of Area ($F [2, 1610] = 38.65$, $p < .001$, $\Delta AIC = 78$) was also found. Lower LPP3 amplitude was observed in the parietal than in the central and frontal areas (all $ps < .001$). The amplitudes in the central and in the frontal area did not differ from each other.

Lastly, a significant Group × Category interaction ($F [3, 1610] = 8.97$, $p < .001$, $\Delta AIC = 23$) emerged. Larger LPP3 amplitude was observed for Pleasant pictures in PFUs than in non-PFUs (uncorrected $p = .02$), however this difference did not survive Bonferroni correction. Both PFUs and non-PFUs showed larger positivity for Pleasant than for Facebook-related and Neutral pictures (all $ps < .05$), and lower positivity for Facebook-related than for Neutral pictures ($p < .001$). However, PFUs showed larger positivity for Pleasant than for Unpleasant pictures ($p = .002$), whereas non-PFUs showed comparable LPP3 amplitudes for Pleasant and Unpleasant pictures.

Table 12. Descriptive statistics and differences between Problematic (PFUs) and non-problematic (non-PFUs) Facebook users

	Non-PFUs (n=26)	PFUs (n=27)	Test-statistic	p-value
PFUS total score	19.2 (±2.5)	46.9 (±9.1)	15.0 t test	<.001
Sex (F/M)	21/5	18/9	1.15 Glm, z test	.24
Age	23.4 (±3.2)	23.5 (±2.5)	0.12 t test	.91
Sleep hours	7.3 (±0.7)	7.1 (±0.8)	1.14 t test	.26
Cigarette consumption	2.3 (±3.8)	1.3 (±3.3)	-1.1 t test	.30
Minutes on Facebook	45.9 (±29.3)	85.8 (±43.8)	3.42 t test	.001
Self-reported craving	0.2 (±0.37)	0.7 (±2)	5.84 χ^2 test	.02

Glm = generalized linear model with binomial error distribution. Sleep hours, cigarette consumption, and minutes on Facebook = quantities per day

Valence and Arousal ratings

The Group main effect was significant only for Valence ratings ($F[1,51] = 4.6$, $p = .04$, $\Delta AIC = 108$). Regardless of emotional category, pictures elicited greater pleasantness in PFUs than in non-PFUs.

For both Valence and Arousal ratings, the Category main effect was significant (Arousal: $F[3,44] = 151.28$, $p < .001$, $\Delta AIC = 1264$; Valence: $F[3,44] = 157.1$, $p < .001$, $\Delta AIC = 1642$). Unpleasant pictures were rated as significantly more arousing and unpleasant than Pleasant (Arousal: $p = .04$; Valence = $p < .001$), Neutral, and Facebook-related pictures ($ps < .001$). Moreover, Pleasant pictures were rated as significantly more arousing and pleasant than Neutral and Facebook-related pictures ($ps < .001$). No differences between Neutral and Facebook-related pictures were found for Valence and Arousal ratings.

These effects were specified by the significant Group × Category interactions (Arousal: $F[3, 2441] = 5.81$, $p < .001$, $\Delta AIC = 60$; Valence: $F[3, 2441] = 9$, $p < .001$, $\Delta AIC = 109$). As shown in Figure 13, in both groups Pleasant and Unpleasant pictures elicited significantly greater pleasantness and unpleasantness, respectively, and higher arousal than Neutral and Facebook-related pictures (all ps < .001). No difference between Neutral and Facebook-related pictures were found for Valence ratings. Only non-PFUs rated Facebook-related pictures as significantly less arousing than Neutral pictures ($p = .02$), and Unpleasant pictures as significantly more arousing than Pleasant pictures ($p = .03$). As for between group differences, PFUs rated Facebook-related pictures as significantly more arousing and pleasant than non-PFUs ($p < .001$). No between-groups differences were found for the other emotional categories.

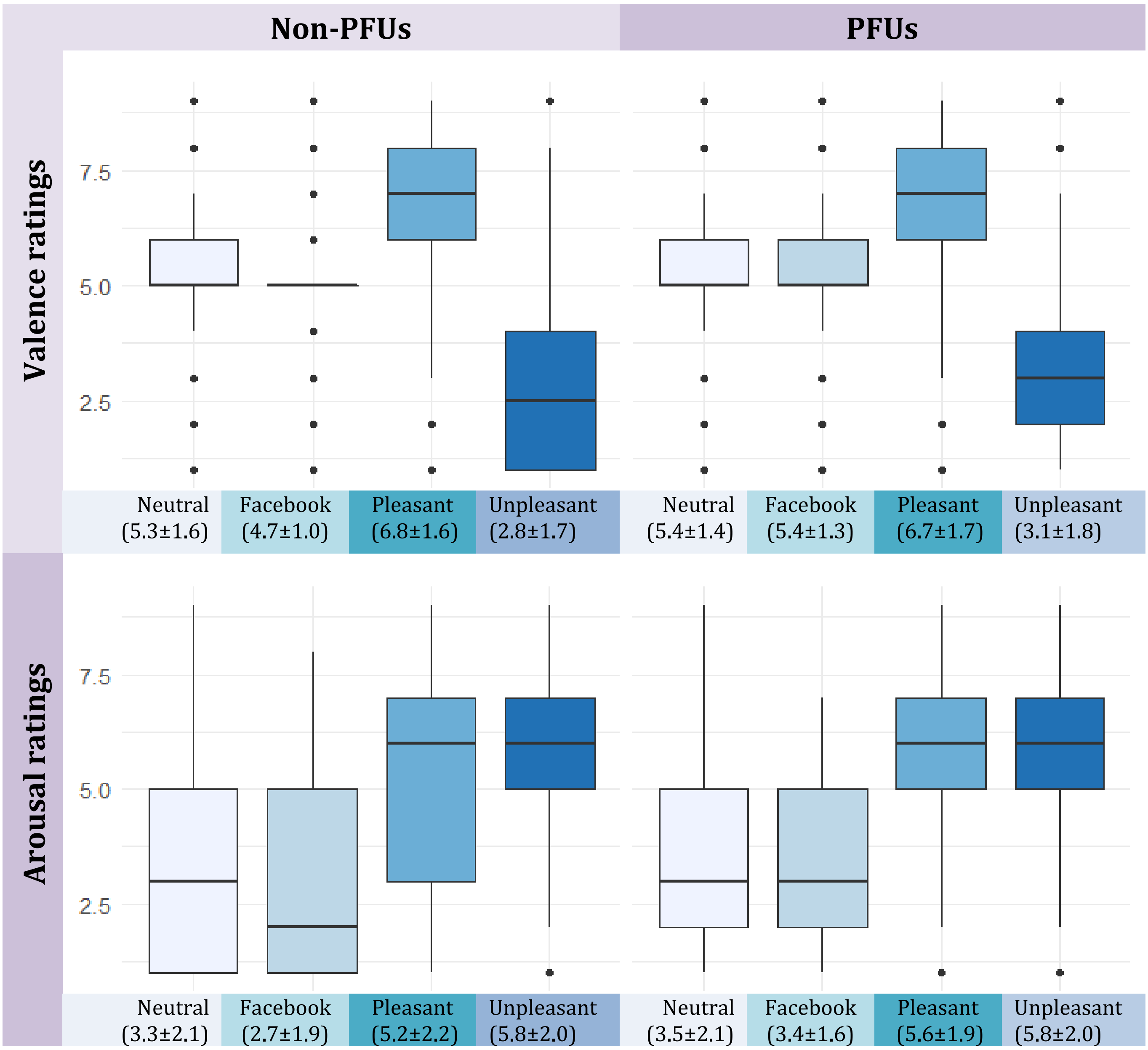
Pearson's correlations between Valence and Arousal ratings and ERPs in PFUs and non-PFUs

As reported in Table 13, in PFUs, Arousal ratings for Facebook-related and Neutral pictures were inversely correlated with LPP1 amplitude recorded in Pz, and with P3 amplitudes in Fz and Cz, respectively. Moreover, in this group, Arousal ratings for Pleasant pictures were positively correlated with LPP3 amplitude in Pz.

In non-PFUs, only Arousal ratings for Unpleasant pictures were positively correlated with LPP3 amplitude in Pz.

As reported in Table 13, in PFUs, only Valence ratings for Facebook-related pictures were positively correlated with LPP2 amplitude in Fz. Differently, in non-PFUs, Valence ratings for both Facebook-related and Unpleasant pictures were inversely correlated with LPP (all time windows) amplitude in Cz. Also, an inverse correlation was observed between Valence ratings and LPP2 amplitude in Fz and LPP3 amplitudes in Pz for Facebook-related pictures, and between Valence ratings and LPP2 and LPP3 amplitudes in Fz, Cz, and Pz for Unpleasant pictures.

Figure 13. Valence and Arousal ratings in non-PFUs and PFUs



***(Mean ± Standard deviation)**

*Table **13**. Pearson's (r) correlation coefficients between frontal, central, and parietal midline (Fz, Cz, Pz) P3 and LPP amplitudes and subjective ratings (Arousal and Valence) for each emotional category in problematic (PFUs) and non-problematic Facebook users (non-PFUs). Red color indicates significant correlations (p < .05)*

		PFUs							
		Facebook-related		Neutral		Pleasant		Unpleasant	
		Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence
LPP1 (400-600 ms)	Fz	-0.11	0.25	-0.26	-0.08	0.06	0.21	-0.10	-0.20
	Cz	-0.30	0.24	-0.31	0.01	0.26	0.33	-0.05	-0.02
	Pz	-0.45	0.02	-0.40	-0.24	0.21	0.06	0.01	-0.07
LPP2 (600-800 ms)	Fz	-0.02	0.46	-0.23	0.12	-0.04	0.15	0.09	-0.33
	Cz	-0.27	0.35	-0.15	0.20	0.27	0.12	0.21	-0.16
	Pz	-0.35	0.03	-0.32	-0.05	0.36	-0.27	0.32	-0.08
LPP3 (800-100 ms)	Fz	-0.15	0.05	-0.19	0.12	0.10	-0.07	0.26	-0.19
	Cz	-0.35	-0.11	-0.20	0.16	0.36	-0.11	0.31	-0.15
	Pz	-0.24	-0.17	-0.25	0.05	0.39	-0.33	0.38	-0.18
P3	Fz	-0.17	0.04	-0.50	-0.15	-0.25	-0.05	-0.24	-0.02
	Cz	-0.25	0.04	-0.48	-0.03	-0.19	0.14	-0.24	0.05
	Pz	-0.30	0.01	-0.37	-0.14	0.06	0.11	-0.24	-0.02

		non-PFUs							
		Facebook-related		Neutral		Pleasant		Unpleasant	
		Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence
LPP (400-600 ms)	Fz	0.17	-0.39	0.03	0.25	-0.12	0.11	-0.06	-0.27
	Cz	0.16	-0.46	0.08	0.22	-0.14	0.10	-0.02	-0.34
	Pz	-0.02	-0.22	0.02	0.11	-0.12	-0.17	0.01	-0.21
LPP (600-800 ms)	Fz	0.08	-0.47	0.12	0.29	-0.06	0.17	0.15	-0.42
	Cz	0.13	-0.46	0.15	0.24	0.08	0.27	0.26	-0.50
	Pz	0.19	-0.30	0.04	0.28	0.13	0.08	0.27	-0.40
LPP (800-100 ms)	Fz	0.16	-0.43	0.39	0.27	0.09	-0.14	0.26	-0.43
	Cz	0.17	-0.48	0.28	0.29	0.26	-0.01	0.37	-0.49
	Pz	0.19	-0.48	0.19	0.33	0.34	0.08	0.40	-0.43
P3	Fz	-0.06	-0.11	-0.01	0.00	-0.14	-0.07	-0.10	-0.11
	Cz	-0.07	-0.18	-0.05	0.03	-0.18	-0.12	-0.04	-0.06
	Pz	-0.20	0.06	-0.10	0.03	-0.18	-0.17	-0.14	0.18

Discussion

The results of our study do not provide evidence for cue reactivity in problematic Facebook users when exposed with Facebook-related pictures. Rather, we found cue reactivity in the 400-600 ms time window (i.e., LPP1) after the onset Facebook-related cues in both problematic and non-problematic Facebook users.

To the best of our knowledge, this is the first study investigating cue-reactivity in problematic Facebook users by means of ERPs recording. For none of the considered late ERP components (i.e., the P3 and LPP1,2, and 3) elicited by Facebook-related pictures did the amplitudes in problematic Facebook users differ significantly from those in non-problematic users. Therefore, individuals with and without problematic Facebook usage allocated similar amounts of attentional resources toward Facebook-related stimuli throughout emotional processing (up to 1000 ms). These findings contrast with previous research in the field of SUDs and behavioral addictions, demonstrating cue-reactivity toward addiction-relevant cues in individuals with SUDs, gambling, gaming, and buying disorders compared with healthy control participants (Jasinska et al., 2014; Starcke et al., 2018). However, in the present study, participants were classified as problematic Facebook users on the basis of PFUS scores and, unlike participants who received a diagnosis in SUDs and behavioral addiction studies, they may not be fully representative of severe, clinically relevant Facebook-related behaviors. Indeed, high scores on the PFUS may reflect at-risk problematic Facebook use, i.e., a condition not severe enough to be associated with functional changes at the neural level. Indeed, the higher self-reported craving for Facebook usage in problematic than in non-problematic Facebook users suggests that when behavioral problems related to Facebook use are not severe, a more intense craving experience for Facebook usage is not associated with altered neural processing. To be noted, despite problematic Facebook users reported higher craving ratings than non-problematic users, the mean craving ratings in problematic Facebook users were quite low, suggesting that in the present study, the pattern of problematic Facebook-related behaviors in problematic users was not severe enough to engage a strong subjective urge of using Facebook.

As expected, PFU rated Facebook-related pictures as more pleasant and arousing than non-PFU. These results are consistent with those of previous studies that compared valence and arousal ratings to addiction-related pictures in excessive users/addicted individuals and controls (e.g., Engelmann, Gewirtz, & Cuthbert, 2011; Littel & Franken, 2007; Lubman et al., 2009; Wölfling et al., 2011), and support the hypothesis that when problematic Facebook use is not severe, this condition is reflected in subjective ratings of higher pleasantness and arousal to Facebook-related cues, but not yet in the neural activity during the viewing of such contents.

Of note, a group difference emerged for the processing of pleasant contents, with only PFU showing larger LPP amplitude to pleasant than unpleasant pictures up to 1000 ms post-stimulus, suggesting sustained attention to, and, possibly, delayed disengagement from, pleasant contents in these individuals. This finding fits with those obtained by some studies that suggested exaggerated, rather than blunted, reward responsiveness (i.e., larger P3 amplitude to pleasant pictures) to predict the onset of SUDs. Enhanced and sustained reward reactivity has been found to increase the likelihood of risky behavior (including substance use) through its effects on the relative attribution of benefit vs. cost to different behaviors (Garfield, Allen, Cheetham, Simmons, & Lubman, 2015; Spear, 2011; Stice, Yokum, & Burger, 2013). Moreover, increased attentional deployment to non-addiction relevant pleasant stimuli has been suggested as a potential psychophysiological marker of reward and affective response that reflects vulnerability to harmful alcohol use (Garfield et al., 2015). Future studies should further explore the processing of non-addiction relevant pleasant contents and its timing in problematic Facebook users, in order to clarify whether it may be a potential risk factor for developing Facebook-related addictive behaviors.

In both problematic and non-problematic Facebook users, Facebook-related pictures triggered greater "motivated" attention/cue-reactivity, as indicated by larger LPP1 amplitude than neutral pictures, and comparable to unpleasant contents. The amplitude of the LPP increases in response to stimuli with high motivational value (Bradley, 2009; Bradley, Hamby, Löw, & Lang, 2007; Schupp et al., 2006). Enhancement of the LPP would reflect the mobilization of processing resources to facilitate rapid and appropriate responses to stimuli holding evolutionary significance (Löw, Lang, Smith, & Bradley, 2008). Taken together, our LPP1 findings seem to suggest that regardless of whether Facebook usage is problematic or non-problematic, Facebook-related cues are motivationally relevant stimuli that capture attentional resources in the earlier stages of "motivated" attentional allocation and engage the same resources involved in the processing of unpleasant stimuli (Hajcak et al., 2009, 2010; Schupp et al., 2000, 2006). Although Facebook-related cues do not hold intrinsic motivational significance, they acquired it by repeated pairing with the cascade of neurophysiological events associated with Facebook usage.

Interestingly, in both problematic and non-problematic Facebook users, fewer attentional resources were allocated to Facebook-related than to neutral pictures during earlier (280-400 ms post-stimulus, i.e., the P3) and late processing stages (800-1000 ms post-stimulus, i.e., the LPP3). These findings suggest that independent of problematic use, repeated exposure to Facebook-related stimuli would facilitate associative learning processes leading to overlearned Stimulus-Stimulus associations (S-S). This kind of overlearning process may be generalized to pictures depicting Facebook, that would be perceived as "less new" than neutral ones, affecting both earlier and late attentional deployment. Indeed, both P3 and LPP3 have been described to be sensitive to stimulus novelty (Bradley, 2009; Courchesne, Hillyard, & Galambos, 1975; van Peer, Grandjean, & Scherer, 2014).

It could be hypothesized that the LPP1 modulation by Facebook-related stimulus significance may be fairly resistant to the overlearned S-S, as indicated by larger amplitude to Facebook-related than neutral pictures (i.e., cue-reactivity) during the central stages of affective processing, i.e., in the LPP1 time window. Moreover, cue-reactivity as measured by LPP1 was found to be inversely related to subjective ratings of arousal for the same picture category only in problematic Facebook users. In other words, the more problematic Facebook users rated Facebook-related pictures as relaxing and calming, the larger their LPP to Facebook-related pictures, suggesting that motivated attention to Facebook-related stimuli is related to the relaxing and calming proprieties that these stimuli would acquire for problematic users. This finding seems to support the view that Facebook usage would serve as a way of coping with stress and worry, suggesting problematic Facebook use to be maintained via negative reinforcement (Hormes et al., 2014). A similar hypothesis has been argued in the context of addiction, i.e., the development of addiction-related behaviors would be driven by negative reinforcement processes (i.e., the removal of an aversive state increases the probability of the response, e.g., drug seeking and drug taking, that removes it; George, Koob, & Vendruscolo, 2014). These processes have been described to reflect the activity of the brain anti-reward neurotransmitter/neuromodulator systems, such as corticotropin-releasing factor, norepinephrine, and dynorphin, that trigger negative emotional states (Koob, 2015; Koob et al., 2014; Koob & Volkow, 2010) and thus drive behavior to remove those states. Future studies should further explore the role of negative reinforcement as one of the possible core mechanisms underlying the development and maintenance of PFU.

In addition to the above-mentioned limitations related to the criteria employed for sample selection, a further limitation of the current study is represented by the fact that we employed a single-item scale to collect Internet craving ratings (Cano et al., 2014; Dawkins et al., 2016). Although this is considered as a sensitive method to measure craving, the combination with a questionnaire that explores the construct of craving through multiple items would improve the accuracy of the measure (Davey et al., 2007). Lastly, our interpretation of ERPs results requires caution as, to the best of our knowledge, there are no published EEG/ERPs studies on cue-reactivity comparing Facebook-related and affective, pleasant and unpleasant, stimuli in problematic and non-problematic Facebook users. Further research should be conducted to support our findings.

“I want to use Facebook right now because

over time my curiosity is increasing”

Participant 201

Study 5: Tangled up in blue: response inhibition in Problematic Facebook Use

Introduction

Although using social networking sites (SNSs) has been described as a potentially addictive behavior (Griffiths et al., 2014; Hormes et al., 2014), the mechanisms underlying Problematic Social Networking Sites Use (PSNSU) remain unclear. One of key features that has been hypothesized to be at the basis of specific Problematic Internet Use (PIU), including PSNSU, is reduced response-inhibition capacity (Brand et al., 2016; Luijten et al., 2014). Specifically, in the context of addictive behaviors, it has been argued that compulsivity in engaging in a specific behavior (e.g., using SNSs, gaming, pornography) may arise from craving symptoms triggered not only by reactivity to addiction-related stimuli, but also by defective inhibitory control processes (Brand, Wegmann, et al., 2019; Brand et al., 2016; Potenza, 2006). In particular, inhibitory control appears to be adversely impacted by exposure to disorder-related stimuli or highly arousing pleasant and unpleasant stimuli (Bechara, 2003; Moretta, Sarlo, & Buodo, 2019). However, while inhibitory control processes in an emotional context are relatively well-studied in gambling disorder and gaming disorder, much less research has been conducted on other types of behaviors that potentially may become addictive (e.g., social-networking; Brand, Wegmann, et al., 2019).

Inhibitory control in emotional contexts can be investigated using the emotional Go/Nogo task, where affective stimuli (e.g., emotionally salient words or pictures) are used in place of standard neutral stimuli, thereby providing a reliable measure of the emotional modulation of behavioral response (Schulz et al., 2007). Two components of the event-related potentials (ERPs), i.e., the Nogo-N2 and the Nogo-P3 (Eimer, 1993; Kiefer, Marzinzik, Weisbrod, Scherg, & Spitzer, 1998), specifically reflect different aspects of response inhibition. The Nogo-

N2 is a negative deflection occurring 250-350 ms following Nogo stimuli, with maximum amplitude over frontocentral scalp locations. This component has been suggested to reflect early cognitive control processes necessary to implement inhibitory control, the most important being the detection of conflict between response execution and inhibition (Donkers & van Boxtel, 2004; Luijten et al., 2014; Nieuwenhuis, Yeung, van den Wildenberg, & Ridderinkhof, 2003). The Nogo-P3 is a positive deflection occurring 300-600 ms following Nogo stimuli, with maximum amplitude over frontocentral scalp sites (Kiefer et al., 1998). The Nogo-P3 is thought to reflect successful motor response suppression and/or the evaluation of the outcome of inhibition, and its neural source has been found to be close to motor and premotor cortices (Bruin, Wijers, & van Staveren, 2001).

In healthy individuals, reaction times (RTs) have been showed to be faster in response to pleasant and unpleasant than neutral Go stimuli, whereas RTs to pleasant and unpleasant Go stimuli were found to be comparable (e.g., Chiu, Holmes, & Pizzagalli, 2008) or faster to pleasant than unpleasant Go stimuli (e.g., Albert, López-Martín, & Carretié, 2010). There is also evidence that accuracy to Go trials (correct hits) is higher in response to pleasant and unpleasant than neutral conditions (e.g., Zhang & Lu, 2012). As for the ERP components, the amplitude of the Nogo-N2 appears not to be modulated by the emotional valence of stimuli. Specifically, no differences in Nogo-N2 amplitudes between emotional and neutral stimuli have been observed (Zhang & Lu, 2012). In contrast, the Nogo-P3 has been shown to be larger in response to emotionally arousing than neutral stimuli, suggesting that the more prepotent the tendency to respond induced by the emotion-laden stimuli, the greater the effort required to inhibit the response (Zhang & Lu, 2012).

In the context of problematic Internet use (PIU), ERP studies using the Go/Nogo task highlighted cognitive inefficiency and reduced response-inhibition capacity among individuals with PIU, as indicated by reduced and enhanced amplitudes of the Nogo-N2 and the Nogo-P3, respectively, among individuals with PIU compared with controls (Dong et al., 2010; Zhou et al., 2010). However, the ERPs findings of a study on excessive gaming contradict those of the other studies on general PIU by showing larger Nogo-N2 amplitudes in excessive gamers compared with controls (Littel, van den Berg, et al., 2012). To the best of our knowledge, the only study that investigated inhibitory control in PSNSU, in the context of emotionally salient stimuli, employed only disorder-related stimuli as emotionally salient cues (Gao, Jia, Zhao, & Zhang, 2019). In this study, inhibitory control processes were assessed by recording the ERPs during a Go/Nogo task including SNSs-related (i.e., WeChat and QQ logos) and neutral images. Despite behavioural measures (RTs to Go trials and/or accuracy) showed no differences between excessive users and controls, ERPs findings highlighted enhanced N2 (to Go and Nogo trials) and reduced Nogo-P3 amplitudes in excessive users as compared with controls, irrespective of stimulus content, suggesting a hyper-sensitive process of response selection and difficulty in motor inhibition, respectively (Gao et al., 2019). However, it would be important to investigate whether not only the processing of disorder-related stimuli, but also non-disorder-related, highly arousing pleasant and unpleasant stimuli modulates response inhibition in behavioral addictions, and in PSNSU in particular, as it does in substance addiction (Goldstein & Volkow, 2011). Given that a deficit in the modulation of emotional arousal and in the ability to act in desired ways, regardless of emotional state (Gratz & Roemer, 2004), is currently regarded as critically implicated in the development and maintenance of PSNSU (Casale et al., 2016; LaRose et al., 2003; Moretta & Buodo, 2018b; Spada & Marino, 2017; Yu et al., 2013), the investigation of inhibitory control in emotional contexts that are not only specifically related to SNSs use would contribute to a better understanding of emotional regulation abilities in PSNSU.

No study to our knowledge has yet investigated whether the processing of SNSs-related and highly arousing emotional stimuli modulates response inhibition in PSNSU (specifically, problematic Facebook use, PFU). In the present study, neural and behavioral measures allowed investigating whether individuals with vs. without PFU show greater difficulties in inhibiting prepotent motor responses during an emotional Go/Nogo task.

We expected individuals with PFU to be characterized by impaired inhibitory processes in an emotional context as indicated by faster RTs to Go trials, more commission errors (i.e., responses to Nogo trials) and by larger amplitude of the Nogo-N2 and/or reduced amplitude of the Nogo-P3 in the presence of Facebook-related and emotional vs. neutral pictures, and with respect to non-problematic Facebook users. Also, we hypothesized that individuals with PFU would rate Facebook-related pictures as more pleasant and arousing than neutral pictures and as compared with non-problematic Facebook users.

Method

Participants

Students of the University of Padua, Italy, were contacted informally at university facilities and asked to fill in an online version of the PFUS Marino et al., 2017. See more details on the PFUS in *Assessing problematic Social Networking Sites use* of the *Characterizing problematic Social Networking Sites use* subsection, Section 2).

Based on the scores obtained in the Italian study that validated the PFUS (Marino et al., 2017), 22 participants who scored equal to or higher than 30 (i.e., the 75th percentile, Marino et al., 2017) were included in the problematic Facebook users (PFUs) group. Twenty-three participants who scored equal to or lower than 23 (i.e., the 50th percentile) were included in the non-PFUs group. As reported in Table 14, the two groups differed significantly on PFUS scores and were comparable for sex distribution, age, and sleep hours. All participants read and signed an informed consent. The study was conducted in compliance with the declaration of

Helsinki on research on human subjects and was approved by the Ethical Committee of Psychological Research, Area 17, University of Padova.

Self-report measure

Given that trait impulsivity, which reflects inhibitory dyscontrol (Enticott et al., 2006; Logan et al., 1997), has been often found to be increased among individuals with problematic Internet use (Rothen et al., 2018), the participants' trait impulsivity was measured and controlled for in data analysis.

Trait impulsivity was assessed by the Barratt Impulsiveness Scale (BIS-11, Fossati et al., 2001; Patton, Stanford, & Barratt, 1995), see further details on the BIS-11 in *Method* of the *Study 1: Identifying Problematic Internet Users by their symptoms* subsection, Section 1.

The emotional Go/Nogo task

The task used in the present study consisted in the presentation of Facebook-related and affective pictures as Go and Nogo stimuli in an emotional Go/Nogo task. One hundred twenty pictures (538 × 720 pixel) were presented to each participant, divided into four categories: 30 Facebook-related (copyright-free pictures downloaded from websites, showing devices connected to Facebook; see Figure 14), and 30 pleasant (sport/adventure, erotic couples), 30 unpleasant (attacking humans and animals), and 30 neutral (neutral faces, household objects), selected from the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 2008)[2]. Pleasant and unpleasant pictures were matched for normative Arousal ratings

[2] The IAPS picture numbers were as follows: Pleasant: 4611, 4647, 4651, 4652, 4658, 4660, 4664, 4670, 4672, 4680, 4683, 4690, 4695, 4800, 4810, 8030, 8031, 8034, 8080, 8160, 8161, 8178, 8179, 8180, 8185, 8186, 8200, 8370, 8400, 8490. Unpleasant: 1050, 1051, 1114, 1120, 1300, 1301, 1302, 1321, 1930, 1932, 3500, 6200, 6210, 6230, 6242, 6243, 6244, 6250, 6260, 6300, 6312, 6313, 6370, 6510, 6540, 6550, 6560, 6571, 6821, 9425. Neutral: 7000, 7002, 7004, 7009, 7010, 7020, 7035, 7036, 7037, 7041, 7050, 7056, 7059, 7130, 7140, 7175, 7217,7224, 7233, 7235, 7242, 7491, 7500, 7546, 7547, 7560, 7590, 7595, 7700, 7950.

(pleasant = 6.45±2.07; unpleasant = 6.43±2.12; p = 1), which were significantly higher than for neutral pictures (neutral = 3.62±1.92; ps < .001). Pleasant and unpleasant pictures differed significantly for mean normative Valence ratings (pleasant = 6.77±1.82; unpleasant = 2.99±1.73, p < .001) which were significantly higher and lower, respectively, than for neutral pictures (5.35±1.27; ps < .001).

Figure 14. Example of Facebook-related pictures

Each picture had a pink or blue frame. The color of the frame cued the participant to either press a button (e.g., blue: Go cues) or withhold the response (e.g., pink: Nogo cues). The colors of the frame indicating Go and Nogo cues were counterbalanced across participants. The percentage of Go and Nogo cues was 70% and 30%, respectively, in order to increase the tendency to respond in participants. The 120 pictures were presented five times for a total of 600 trials (420 Go and 180 Nogo). These 600 stimuli were presented in two blocks of 300 trials. The Go and Nogo stimuli were presented for 600 ms in a semi-random sequence (i.e., no more than two Nogo stimulus had to be shown consecutively). Each picture (585 × 765 pixel) was preceded by a 500-ms black interval with a white fixation-cross; all the pictures and the fixation cross were placed centrally on the screen. The inter-stimulus interval was randomly varied between 500 and 800 ms.

The task was programmed using E-Prime software (version 2.0, Psychology Software Tools, Pittsburgh, PA, USA) and was presented by a Core i5-4440 computer on a 19-inch computer screen, at a viewing distance of 1 m.

Behavioral measures

RTs to Go trials and accuracy in Go and Nogo trials (i.e., key presses in Go trials and no responses in Nogo trials, respectively) were calculated for each emotional category. Given that RTs below 150 ms can be considered as anticipation errors, they were excluded from the analyses.

EEG recording

The electroencephalogram (EEG) was recorded using an elastic cap with tin electrodes (ANT Neuro Company), according to the 10–20 System, from 32 scalp positions (i.e., Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, POz, O1, Oz, O2 and M1 and M2 [mastoids]), referenced online to Cz.

Both vertical and horizontal electrooculograms (EOGs) were recorded using a bipolar montage to monitor eye movements and eyeblinks. The electrode pairs were placed at the supra- and suborbit of the right eye and at the external canthi of the eyes, respectively. All electrophysiological signals were amplified with a EEGO amplifier (ANT Neuro Company, https://www.ant-neuro.com/products/eego_mylab). All electrode impedances were kept below 5 kΩ. The EEG signal was bandpass filtered online (0.1–40 Hz) and digitized at 1000 Hz. Offline, the EEG was re-referenced to mastoids, corrected for eyeblink artifacts using independent component analysis, and low-pass filtered at 30 Hz. Filtering and further EEG processing were run in Brain Vision Analyzer 2.1 software. EEG epochs of -100 to 600 ms post-stimulus were baseline-corrected by subtracting the mean voltage during the 100-ms prestimulus period, and then averaged separately for each participant and experimental condition. Individual ERPs averages were derived for correct Go and Nogo trials (i.e., excluding Go trials with missed responses and Nogo trials with commission errors). On the basis of visual inspection of the grand-average ERPs waveforms at fronto-central electrodes (F3, Fz, F4, C3, Cz, C4), where N2 and P3 amplitudes reach their maximum on response inhibition tasks (Falkenstein, Hoormann, & Hohnsbein, 1999), the mean amplitudes of the following ERPs components were computed: N2, as the mean amplitude 220-280 ms after stimulus onset; P3, as the mean amplitude 340-420 ms after stimulus onset.

Procedure

Upon arrival at the laboratory, the participants read and signed an informed consent form and were seated in a comfortable armchair in a sound-attenuated, dimly-lit room. Then, each participant completed the BIS-11. After the electrodes were attached, the participants were instructed to press a key with the index finger of their right hand, as rapidly and accurately as possible, when a picture with the Go color frame (e.g., pink) was presented, and to withhold pressing the key upon the presentation of a picture with the Nogo color frame (e.g., blue). Before the beginning of the task, participants underwent a practice block of 10 trials (7 Go and 3 Nogo), to ensure they understood task instructions. The participants were also asked to maintain their gaze on the fixation-cross. Each participant was allowed to rest between the two experimental blocks. After the experimental session, the participants performed Valence and Arousal ratings for all pictures used in the emotional Go/Nogo task, using a computerized version of the 1–9 point scales of Valence and Arousal of the Self-Assessment Manikin (SAM; Bradley & Lang, 1994).

Statistical analysis

All analyses were performed using R software (R Development Core Team, 2016).

As the groups did not differ in BIS-11 total scores (*Cohen d* = 0.44, see Table 14), impulsivity was not included as covariate in the analyses.

To investigate whether the two groups differed in terms of response accuracy to Go and Nogo trials, we estimated a generalized linear mixed-effects model (GLMM) with binomial error distribution and individuals as random term. The GLMM included Condition (Go, Nogo), Category (Facebook-related, Pleasant, Unpleasant, and Neutral), Group (PFUs, non-PFUs), and their interactions as fixed factors.

Prior to running the other analyses, all data were examined for skewness, kurtosis, outliers, and normalcy by both exploratory analyses and graphs, i.e., violin plots and boxplots (Pastore et al., 2017). The normal Probability-Probability (P-P) plot of the standardized residuals showed points that were close on the line, and the scatterplot of the standardized residuals showed that the data met the assumptions of homogeneity of variance and linearity for all dependent variables. Thus, to compare RTs to Go trials between groups, a linear mixed-effect model (LMM) with individual random intercept (R package: lme4, Bates, Maechler, Bolker, & Walker, 2014) was conducted on RTs to Go trials with Category (i.e., Facebook-related, Pleasant, Unpleasant, and Neutral), and Group (PFUs, non-PFUs) as fixed factors.

As for analysis of ERP data, in a first step the effect of Condition (Go, Nogo) on both N2 and P3 amplitudes was checked by a linear mixed-effect models (LMM) with individual random intercept and Condition as fixed factor. Then, linear mixed-effect models (LMMs) with individual random intercept were conducted on the mean amplitudes of Nogo-N2 and Nogo-P3 components, with Group (PFU, non-PFU), Category (Facebook-related, Pleasant, Unpleasant, and Neutral), Area (frontal [F3, Fz, F4], and central [C3, Cz, C4]), and Laterality (left [F3, C3], midline [Fz, Cz], right [F4, C4]) as fixed factors. ERP analysis was focused on Nogo trials given that only Nogo-N2 and Nogo-P3 amplitudes reflect the inhibitory processes and therefore are directly relevant for the research question addressed in the present study.

Valence and Arousal ratings were submitted to separate LMMs, with individuals and pictures as random terms, and Category (Facebook-related, Pleasant, Unpleasant, and Neutral) and Group (PFUs, non-PFUs) as fixed factors.

Overall, the strength of parameters evidence within the models was estimated as the difference in the Akaike information criterion (AIC) between the model without and the model with the parameter (ΔAIC, Burnham & Anderson, 2002). Denominator degrees of freedom for F-tests were estimated by Satterthwaite and Kenward-Roger (Alnosaier, 2007; Kuznetsova et al., 2017) methods, and Bonferroni HSD post-hoc tests were employed to further examine significant effects (using a $p < .05$ criterion for significance).

Lastly, Pearson's correlation coefficients were calculated between Nogo-N2 and Nogo-P3 amplitudes at frontal and central midline sites (Fz, Cz), behavioral measures (RTs to Go trials, accuracy in Nogo trials) and SAM subjective ratings separately for PFUs and non-PFUs.

Only meaningful effects have been reported.

Results

Descriptive statistics are reported in Table 14.

Table 14. Descriptive statistics and differences between Problematic (PFUs) and non-problematic (non-PFUs) Facebook users

	Non-PFUs (n=23)	PFUs (n=22)	Test-statistic	p-value
PFUS total score	19.0 (±2.3)	49.1 (±15.7)	9.11 $^{t\ test}$	<.001
Sex (F/M)	20/3	19/3	0.06 $^{Glm,\ z\ test}$	.95
Age	22.3 (±1.5)	22.4 (±2.1)	0. 2 $^{t\ test}$	.85
Sleep hours per day	7.5 (±0.6)	7.6 (±0.7)	0.6 $^{t\ test}$	.55
Cigarette consumption per day	1.8 (±3.6)	0.8 (±2.3)	-1.15 $^{t\ test}$	0.26
BIS total score	57.8 (±8.7)	61.4 (±8.1)	1.45 $^{t\ test}$	0.16

Glm = generalized linear model with binomial error distribution

Behavioral data

Accuracy to Go and Nogo trials

A statistically significant effect of Condition was found ($\chi^2(1) = 632.23$, $p < .001$, $\Delta AIC = 14499$, OR = 31.7), indicating that accuracy was lower for Nogo (mean = 90.35%, sd = 8.34) than for Go trials (mean = 99.76 %, sd = 0.48).

A significant main effect of Category was also found ($\chi^2(3) = 17.86$, $p < .001$, $\Delta AIC = 4775$), however post-hoc comparisons did not reveal significant differences between emotional categories (Facebook-related: mean = 94.62%, sd = 8.33; Pleasant: mean = 94.40%, sd = 7.84; Unpleasant: mean = 96.16%, sd = 6.12; Neutral: mean = 95.04%, sd = 7.63).

The significant main effect of Group ($\chi^2(1) = 4.43$, $p = .03$, $\Delta AIC = 4674$, OR= 1.5) showed that PFU were likelier to be significantly less accurate (mean = 94.23, sd = 8.12) than non-PFU (mean = 95.84, sd = 6.87).

Reaction times (RTs) to Go trials

Only a significant main effect of Category was found ($\chi^2(3) = 27.29$, $p < .001$, $\Delta AIC = 37.5$). Overall, participants were slower in the presence of both Pleasant (mean = 347.16, sd = 30.58) and Facebook-related (mean = 346.65, sd = 29.63) than Neutral (mean = 339.82, sd = 28.55) and Unpleasant (mean = 340.85, sd = 27.62) pictures (ps < .01).

ERPs data

Grand-average ERPs waveforms over Fz, and Cz in PFUs and non-PFUs are shown in Figure 15.

A significant effect of Condition was found for both N2 ($F [1, 2114] = 299$, $p < .001$, $\Delta AIC = 275$) and P3 ($F [1, 2114] = 245$, $p < .001$, $\Delta AIC = 228$) amplitudes, indicating larger amplitudes for Nogo (N2: mean = -2.69, sd = 3.68; P3: mean = 10.41, sd = 5.09) than Go (N2: mean = -0.65, sd = 3.54; P3: mean = 8.52, sd = 4.09) trials.

Nogo-N2 amplitude

A significant main effect of Category ($F [3, 989] = 48.54$, $p < .001$, $\Delta AIC = 103$) was found, highlighting larger Nogo-N2 amplitude to Facebook-related (mean = -3.88 μV, sd = 3.92) than to Neutral (mean = -2.77 μV, sd = 3.38), Unpleasant (mean = -1.74 μV, sd = 3.50), and Pleasant pictures (mean = -2.36 μV, sd = 3.59, all ps < .001). Nogo-N2 amplitude was smaller to Unpleasant than to Facebook-related, Neutral (both ps < .001), and Pleasant stimuli (p = .005).

The Nogo-N2 amplitudes to Pleasant and Neutral stimuli did not differ significantly from each other.

The significant main effect of Area ($F [1, 989] = 424.92$, $p < .001$, $\Delta AIC = 342$) showed larger negativity in the frontal (mean = -4.02 μV, sd = 3.40) than the central (mean = -1.36 μV, sd = 3.46) area.

The significant main effect of Laterality ($F [2, 989] = 42.99$, $p < .001$, $\Delta AIC = 53.2$) showed larger negativity in the middle (mean = -3.30 μV, sd = 3.87) than the right (mean = -1.87 μV, sd = 3.55, $p < .001$), and the left (mean = -2.90 μV, sd =3.47. $p = .04$) sides. Negativity was larger in the left than the right side ($p < .001$).

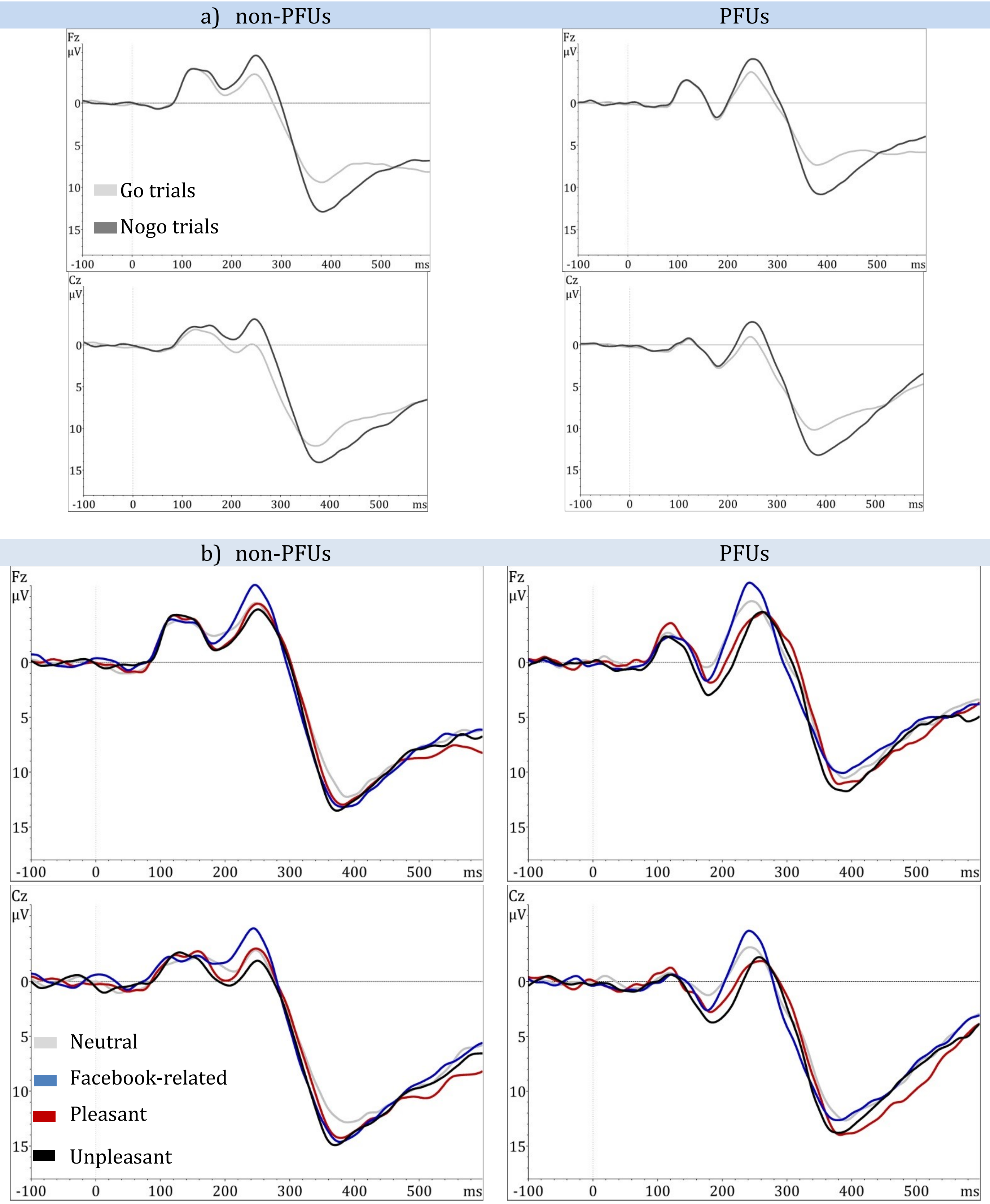
Nogo-P3 amplitude

A significant main effect of Category ($F [3, 989] = 16.40$, $p < .001$, $\Delta AIC = 31.2$) was found, highlighting larger Nogo-P3 amplitude to Facebook-related (mean = 10.50 μV, sd = 5.35), Unpleasant (mean = 11.06 μV, sd = 4.94), and Pleasant stimuli (mean = 10.52 μV, sd = 5.05) than to Neutral (mean= 9.57 μV, sd=4.92, all ps < .001) in both PFU and non-PFU. No significant differences emerged between the Nogo-P3 amplitudes to Facebook-related, Unpleasant, and Pleasant stimuli.

A significant main effect of Area ($F [1, 989] = 35.55$, $p < .001$, $\Delta AIC = 58.7$) was also found, showing larger positivity in the central (mean = 10.86 μV, sd = 5.44) than in the frontal (mean = 9.97 μV, sd = 4.68) area.

The significant main effect of Laterality ($F [2, 989] = 75.97$, $p < .001$, $\Delta AIC = 145$) showed larger positivity in the middle (mean = 11.73 μV, sd = 5.60) than the right (mean = 9.92 μV, sd = 4.58, $p < .001$), and the left (mean = 9.60 μV, sd = 4.79. Both ps < .001) sides. No difference between the Nogo-P3 amplitudes in the right and the left sides was observed.

Figure 15. Grand average ERP waveforms recorded at Fz, Cz, and Pz sites to a) Go and Nogo trials and b) to Nogo trials for Neutral, Facebook-related, Pleasant, and Unpleasant conditions in non-PFUs and PFUs



The significant Group × Category interaction ($F [3, 989] = 4.16$, $p = .006$, $\Delta AIC = 7.89$) showed that in non-PFU, the amplitude of the Nogo-P3 was larger for Facebook-related (mean = 11.54 μV, sd = 6.27), Unpleasant (mean = 11.59 μV, sd = 5.49), and Pleasant (mean = 11.07 μV, sd = 5.51) than Neutral (mean = 9.89 μV, sd = 5.48. All ps < .01) pictures. The Nogo-P3 amplitudes to Facebook-related, Pleasant, and Unpleasant pictures did not differ significantly from each other. Differently, in PFU, the Nogo-P3 amplitudes to Neutral (mean = 9.24 μV, sd = 4.25), Facebook-related (mean = 9.42 μV, sd = 3.92) and Pleasant (mean = 9.95 μV, sd = 4.46) pictures were comparable. The Nogo-P3 amplitude was larger to Unpleasant (mean = 10.51 μV, sd = 4.25) than to Facebook-related and Neutral pictures.

The significant Group × Area interaction ($F [1, 989] = 13.48$, $p < .001$, $\Delta AIC = - 6.69$) specified larger Nogo-P3 amplitude in the central (mean = 10.51 μV, sd = 4.48) than the frontal (mean = 9.05 μV, sd = 3.85, $p < .001$) area in PFU. However, the negative ΔAIC indicated no evidence for supporting this effect.

A significant Area × Laterality interaction ($F [2, 989] = 13.20$, $p < .001$, $\Delta AIC = 9.47$) was also found, showing larger Nogo-P3 amplitude in the central midline (mean = 12.71 μV, sd = 5.92) than the frontal midline (mean = 10.74 μV, sd = 5.08, $p < .001$) area. Within areas, the differences were the same as reported for the Laterality main effect.

Valence and Arousal ratings

The Group main effect was significant only for Arousal ratings ($F[1,43] = 6.78$, $p = .01$, $\Delta AIC = 198$). Regardless of their emotional category, pictures were rated as more arousing for PFU than non-PFU.

The Category main effect was significant for both Valence and Arousal ratings (Valence: $F[3,116] = 355.26$, $p < .001$, $\Delta AIC = 321$; Arousal: $F[3,116] = 518.74$, $p < .001$, $\Delta AIC = 496$).

Unpleasant pictures were rated as significantly more arousing and unpleasant than all other picture categories (all ps $< .001$). Moreover, pleasant pictures were rated as significantly more arousing than Facebook-related and Neutral pictures and more pleasant than all other picture categories (all ps $< .001$). Facebook-related pictures were rated as more arousing than Neutral pictures ($p = .001$). As for Valence ratings, no difference was found between Neutral and Facebook-related pictures.

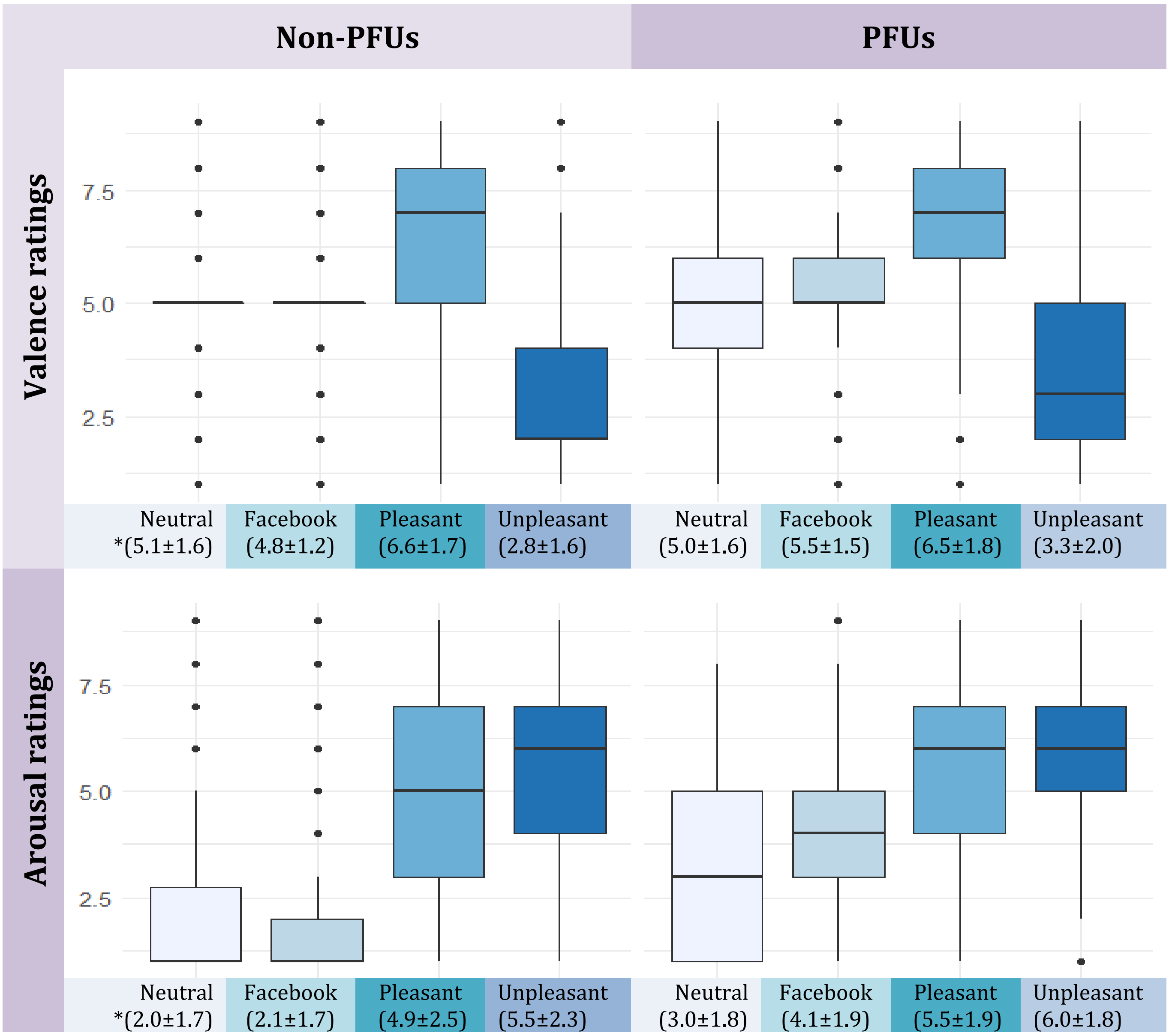
These effects were specified by the significant Group × Category interactions (arousal: $F[3, 5233] = 70.53$, $p < .001$, $\Delta AIC = 193$; valence: $F[3, 5233] = 24.57$, $p < .001$, $\Delta AIC = 58.8$). As shown in Figure 16, in both groups Unpleasant pictures elicited significantly greater unpleasantness and arousal than all other picture categories (all ps $< .01$), and Pleasant pictures elicited significantly greater pleasantness and greater arousal than Neutral and Facebook-related pictures (all ps $< .001$). In non-PFUs, no differences between Neutral and Facebook-related pictures were found for Arousal and Valence ratings. Conversely, PFUs rated Facebook-related pictures as significantly more pleasant and arousing than Neutral pictures ($p < .001$). As for between group differences, PFUs rated Facebook-related pictures as significantly more arousing and pleasant than non-PFUs (both ps $< .05$). No between-groups differences were found for the other emotional categories.

Correlations between Nogo-ERPs, behavioral data, and subjective ratings

As reported in Table 15, in non-PFUs, the amplitudes of the Nogo-N2 for Facebook-related (in Fz and Cz), Pleasant (in Cz) and Unpleasant pictures (in Cz) were positively correlated with Arousal ratings. Moreover, in these individuals, the frontocentral Nogo-N2 to Facebook-related and Pleasant pictures were positively correlated with Valence ratings. Lastly, the Nogo-P3 amplitude to Pleasant pictures was inversely correlated with Nogo accuracy.

In PFUs, no meaningful correlations were found between Nogo-ERPs, behavioral data, and subjective ratings.

Figure 16. Valence and Arousal ratings in non-PFUs and PFUs.



***(Mean ± Standard deviation)**

*Table **15**. Pearson's (r) correlation coefficients between frontal and central (Fz, Cz) Nogo-N2 and Nogo-P3 amplitudes, behavioral data (RTs to Go trials and accuracy in Nogo trials) and subjective ratings (Arousal and Valence) for each emotional category in problematic (PFUs) and non-problematic (non-PFUs) Facebook users. Red color indicates significant correlations (p < .05)*

PFUs	Facebook-related				Neutral				Pleasant				Unpleasant			
	Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3	
	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz
RTs (ms)*	.11	.04	-.08	-.20	-.32	-.35	-.34	-.41	-.29	-.17	-.16	-.11	-.01	-.00	-.25	-.34
Accuracy (%)*	-.07	-.29	.27	-.01	-.03	-.17	-.24	-.08	-.23	-.39	-.10	-.20	-.03	-.17	-.04	-.07
Arousal*	.10	.01	.33	.30	-.13	-.11	-.31	-.20	-.31	-.35	-.12	-.02	-.19	-.13	.35	.34
Valence*	.08	.01	.24	.12	-.33	-.26	-.02	.01	-.05	-.06	.10	.08	.14	-.03	-.09	-.12

non-PFUs	Facebook-related				Neutral				Pleasant				Unpleasant			
	Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3		Nogo-N2		Nogo-P3	
	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz	Fz	Cz
RTs (ms)[a]	-.16	-.19	-.18	-.11	-.36	-.35	-.29	-.26	-.14	-.13	-.28	-.21	.04	-.06	-.27	-.24
Accuracy (%)[b]	.17	.32	.15	.16	.25	.34	.32	.22	-.14	-.07	-.43	-.42	.03	.20	-.15	-.10
Arousal	.56	.62	.43	.34	.19	.32	.15	.04	.35	.44	.09	.11	.18	.44	-.01	.05
Valence	.48	.55	.20	.24	.17	.33	.27	.20	.42	.42	-.10	-.17	.00	-.17	.08	.04

[a]Reaction times to Go trials; [b]Percentage of accuracy to Nogo trials

Discussion

The present study examined whether the processing of Facebook-related and highly arousing emotional stimuli modulates response inhibition in problematic Facebook users during an emotional Go/Nogo task. It was hypothesized that problematic relative to non-problematic users would show faster RTs to Go trials, more commission errors in Nogo trials, larger amplitude of the Nogo-N2 and/or reduced amplitude of the Nogo-P3 in the presence of Facebook-related and emotional vs. neutral pictures.

Some interesting differences emerged between problematic and non-problematic Facebook users on the behavioral and the neural level. On the behavioral level, accuracy was lower in problematic vs. non-problematic Facebook users, both when they had to respond to Go stimuli and when they had to withhold from responding to NoGo stimuli, irrespective of the pictures' content. This seems to suggest an overall greater difficulty with adjusting behavior to contextual demands. Our findings are consistent with those of Zhou et al. (2010) and Moretta et al. (2019), reporting both higher false alarm and higher miss rates in problematic vs. non-problematic Internet users. Other studies that used a standard Go/Nogo task to investigate inhibitory control in individuals with non-specific problematic Internet use (Ding et al., 2014; Dong et al., 2010; Sun et al., 2009) did not report reduced performance accuracy in either Go or NoGo trials in excessive vs. casual Internet users. No difference on the behavioral performance between excessive Social Networking Sites (SNSs) users and controls was also reported by Gao et al. (2019), who used an emotional Go/Nogo task including SNSs-related and neutral stimuli (Gao et al., 2019) to assess inhibitory control in excessive SNSs users. It may be hypothesized that that similarly to that reported for non-specific problematic Internet use (Moretta, Sarlo, & Buodo, 2019), difficulties in inhibitory control only emerge in PFU when the effort required to suppress inappropriate responses exceeds a certain threshold, i.e., when prepotent responses must be inhibited pursuant to complex rules (Zhou et al., 2010), or in an emotional context (Moretta, Sarlo, & Buodo, 2019).

On the neural level, only in non-problematic Facebook users the Nogo-P3 amplitude was modulated by emotional contents, i.e., it was larger to Facebook-related and emotional stimuli vs. neutral stimuli., suggesting that Facebook-related and highly arousing emotional stimuli activated similar (successful) inhibitory processes. Interestingly, in problematic Facebook users the Nogo-P3 amplitude was lower to Facebook-related, pleasant and neutral stimuli than to unpleasant stimuli, suggesting less efficient evaluation of the outcome of inhibition when it is required in the presence of both natural and secondary (Facebook-related) rewards. The Nogo-P3 is taken to reflect the closure of the inhibition process after the decision (Gajewski & Falkenstein, 2013), the evaluation of the inhibitory performance (Bruin et al., 2001; Roche, Garavan, Foxe, & O'Mara, 2005), or the effectiveness of motor inhibition engaged in or near the motor or premotor cortices (Kok, Ramautar, De Ruiter, Band, & Ridderinkhof, 2004; Ramautar, Kok, & Ridderinkhof, 2004). In this framework, in non-PFU, the negative correlation between NoGo-P3 amplitude and percentage of accuracy to Nogo trials, which was observed for pleasant pictures only, suggests that the underlying inhibitory process modulated by this emotional condition is mainly related to the evaluation of the inhibitory performance in case of failed stops (Bruin et al., 2001; Roche et al., 2005). In contrast, in problematic Facebook users the Nogo-P3 to pleasant, Facebook-related and neutral did not differ from each other and was significantly reduced as compared to the Nogo-P3 to unpleasant pictures. Reduced Nogo-P3 amplitude is considered a robust finding in SUDs (Cohen, Porjesz, Begleiter, & Wang, 1997; Colrain et al., 2011). Indeed, it has also been reported in nicotine use disorder (Evans, Park, Maxfield, & Drobes, 2009), alcoholism (Porjesz & Begleiter, 2003), and stimulant use disorder (Sokhadze, Stewart, Hollifield, & Tasman, 2008). Taken together, our findings suggest that similarly to SUDs, problematic Facebook use is characterized by under-engagement of response inhibition processes in the context of natural reward- and Facebook-related stimuli.

As expected, problematic users rated Facebook-related pictures as more pleasant and arousing as compared with non-problematic users, suggesting that, similarly to drug-related cues in SUDs (Engelmann et al., 2011; Littel & Franken, 2007; Lubman et al., 2009; Wölfling et al., 2011), positive reinforcement from Facebook use may be transferred to Facebook-related stimuli (Everitt et al., 1999; Grimm, 2000).

Of note, Facebook-related pictures were found to modulate inhibitory processes in both problematic and non-problematic users. Specifically, in the presence of both Facebook-related and pleasant Go trials ,RTs were slower as compared with unpleasant and neutral pictures, suggesting that in Facebook users, regardless of whether they engage in problematic Facebook-related behavior, Facebook-related stimuli capture attention as much as natural rewards (i.e., sex). Consistently, the Nogo-N2 amplitude was larger to Facebook-related than all other picture contents, suggesting that greater response conflict was generated when Nogo stimuli required to withhold responding in the context of Facebook-related stimuli. In the last decade, it has become increasingly clear that the Nogo-N2 does not properly reflect response inhibition, or only to a limited extent (Bruin et al., 2001; Donkers & van Boxtel, 2004). Instead, Nogo-N2 is now more commonly regarded as reflecting conflict monitoring performed by the anterior cingulate cortex (ACC; Bekker, Kenemans, & Verbaten, 2005; Donkers & Van Boxtel, 2004; Palermo, Stanziano, & Morese, 2018). In the present study, the lack of significant correlations between performance measures and Nogo-N2 amplitudes for all picture categories in both groups suggests that the neural representation of response conflict was not associated with both attentional and motivational aspects of responding (as indexed by RTs to Go trials) and motor inhibition (as indexed by accuracy to Nogo trials).

In the context of SUDs, the transition from flexible (goal directed) to reflexive (compulsive) behaviors has been described to be influenced by instrumental learning which is mainly modulated by interoceptive inputs from the insula. The insula would integrate information about the internal physiological state and would convey it to the ACC, ventral striatum and prefrontal cortex to initiate adaptive behaviors (Paulus, Tapert, & Schulteis, 2009). These processes have been described to lead at bridging changes in internal state and cognitive and affective processing (Volkow, Wang, Tomasi, & Baler, 2013). In particular, the ACC seems to have a fundamental role in craving symptoms. Craving has been linked to the learned associations between the addiction-related environment and a pleasurable or an intensely overpowering experience (Goldstein & Volkow, 2002). The consolidation of these associations is likely to mainly depend on activation of the thalamo-orbitofrontal circuit and the ACC (Goldstein & Volkow, 2002; Volkow et al., 1999). It may be speculated that in Facebook users, Facebook-related stimuli trigger higher conflict monitoring performed by the ACC than any other affective stimulus, possibly reflecting the potential addictive properties of Facebook. In this view, the positive correlation between NoGo-N2 amplitude and Valence and Arousal ratings for Facebook-related stimuli in non-PFU indicates that impared conflict monitoring is related to the pleasantness and salience of this kind of stimuli, and it is possible that this relationship underlies the initial stage of craving symptoms. Future studies are needed to further understand the relationship between the NoGo-N2 amplitude to Facebook (and other SNSs)-related cues and its possible role as a precursor /risk factor for the development of PFU.

The present results should be interpreted taking four main limitations into account. The first is the small sample size. The second is the criteria employed for sample selection. As participants were classified as problematic Facebook users on the basis of PFU scores, they may not be fully representative of problematic Facebook users. Third, previous studies showed gender differences in the use of the SNSs (e.g., Mazman & Usluel, 2011). Due to the difference in gender distribution in our samples of problematic and non-problematic Facebook users, we were unable to investigate gender differences. Further research including larger samples and equal gender distributions within group should be undertaken. Lastly, our interpretation of ERPs results requires caution as, to the best of our knowledge, there are no published ERPs studies that used the emotional Go/Nogo task to study inhibitory processes to Facebook-related and affective stimuli in problematic and non-problematic Facebook users.

SECTION 3: CONCLUSIONS

Dong-kyu, K. (2013). Sunday afternoon [based on: A sunday afternoon on the island of La Grande Jatte by Georges Seurat (1884–86)]. ART X SMART Project

“My computer thinks I'm gay, what's the difference anyway?

When all the people do all day it staring into a phone”

Placebo (2013). Too Many Friends. On Loud Like Love.

Conclusions

In the framework of the lively theoretical debate on whether it is appropriate to consider Problematic Internet Use (PIU) and Problematic Social Networking Sites Use (PSNSU) as addictive behaviors, the main aim of this work was to build on and extend previous findings about the psycho-physiological mechanisms underlying these problematic behaviors. Specifically, some psychophysiological mechanisms and psychological processes whose dysfunctions have already been highlighted in Substance Use Disorder (SUD) and behavioral addictions were investigated in the context of both PIU and PSNSU. Similarities and differences were highlighted and discussed.

The relevant literature reports that, similarly to individuals with SUD, individuals with PIU are more likely to have symptoms associated with substance addictions, mood and anxiety disorders, and obsessive-compulsive disorder, and to be characterized by highly impulsive behavior. In the first study, the assessment of these variables using self-report instruments in a cross-sectional design highlighted that PIU is characterized by a pattern of symptoms related to anxiety/mood disorders and Obsessive-Compulsive Disorder (OCD). Interestingly, we also found that only hoarding and obsessing symptoms significantly predicted the condition of problematic vs. non-problematic Internet use, with hoarding having greater accuracy than obsessing to discern problematic from non-problematic Internet users. Lastly, we found stronger and positive associations between stress, anxiety, and depression with some OCD dimensions in problematic vs. non-problematic Internet users. Such findings suggest an altered mechanism shared by OCD and PIU that may lie at the basis of PIU development and may consist in an aberrant activity in reward network/prefrontal-striatal/limbic circuits that leads to maladaptive emotional and behavioral patterns (Park et al., 2019; Spinella, 2005). Similarly to what has been argued for SUD, and considering that in this study individuals with PIU were classified as mild to moderate problematic Internet users (i.e., more likely to be in the earlier stages of PIU, rather than in later stages with severe PIU), it can be hypothesized that in the first stages, PIU and OCD overlap on different levels including phenomenology, comorbidity, neurocircuitry, etc. With progression and greater severity of OCD, the proportion of the OCD-related behaviors that are driven by impulsive 'rash' processes would increase as involvement of more ventral striatal circuits becomes prominent (Fontenelle et al., 2011). In contrast, as PIU progresses, the proportion of PIU-related behaviors that would be driven by compulsive ‘habitual’ processes could increase the involvement of more dorsal striatal circuits, which thus would become prominent. Therefore, in the earlier stages, PIU would share more similarities with OCD than with addiction; however, later in the process, similarities with addictive behaviors might become dominant. Future longitudinal studies are needed to test this hypothesis and further characterize problematic Internet-related behaviors and their similarities with both OCD and SUD.

Given the importance of stress-related mechanisms and craving symptoms in SUD (Sinha, 2008; Sinha et al., 2009, 2000), in the second study the relationship between autonomic reactivity during a stressful task and craving processes in PIU was investigated. Moreover, considering the relevant literature in the field and findings of Study 1, anxiety, depression, impulsivity, alexithymia, obsessive-compulsive symptoms and use of alcohol and cannabis in individuals with PIU vs. non-PIU were assessed. The findings showed lower resting heart rate variability (HRV) before the stressful task in individuals with PIU vs. non-PIU, suggesting that, in PIU, reduced autonomic flexibility may represent a stable condition, that is evidenced even in non-stressful conditions. Moreover, after the stressful task, higher craving ratings were related to lower HRV only in problematic users, suggesting that lower HRV in PIU may be related to reduced capacity for self-regulating craving for Internet usage. Of note, these results fit with previous research showing that lower resting HRV predicts higher craving in alcohol dependent outpatients (Quintana et al., 2013), and highlight similarities between PIU and SUD. Lastly, problematic users endorsed more mood, obsessive-compulsive, and alcohol-related problems, supporting previous findings on both PIU (e.g., Akin & Iskender, 2011; Ko et al., 2009; Stavropoulos, Gentile, & Motti-Stefanidi, 2016) and SUD (Blom et al., 2011; Merikangas et al., 1998).

When inhibitory processes in an emotional context, and their relationship with HRV were assessed by an emotional Go/Nogo task in PIU in the third study, we found significantly lower accuracy rates among problematic- than non-problematic Internet users, irrespective of pictures' emotional content. Moreover, only among individuals with PIU did lower resting HRV predict lower response accuracy in pleasant and unpleasant Go trials and less efficient task performance upon presentation of unpleasant stimuli, suggesting that reduced HRV is a potential indicator of defective inhibitory control in an emotional context in PIU. This pattern of findings in problematic Internet users provide support to results of previous research on resting HRV and inhibitory control in the context of addiction, highlighting further similarities between PIU and SUD. Indeed, despite the heterogeneity with respect to the experimental tasks and stimuli, and the disorder under investigation (e.g., substance and behavioral addictions), previous studies had reported autonomic imbalance at rest (Ingjaldsson et al., 2003; Kim et al., 2016; Lin et al., 2014; Yuksel et al., 2016) and impaired inhibitory control in individuals with addictions (Smith et al., 2014; Zhou et al., 2010).

As for the fourth study, the cognitive-behavioral model of generalized PIU (Caplan, 2010) in the context of PSNSU (i.e., Problematic Facebook Use, PFU) was tested on a sample of Italian young adults. The findings showed that using Facebook to regulate mood, and preference for online social interactions, are related to difficulties in regulating Facebook use, which in turn predicts negative outcomes of Facebook usage. Of note, difficulties in self-regulating Facebook use are related more strongly to using Facebook for mood regulation than to preference for online social interaction. Similarly, using Facebook for mood regulation appeared to have a greater impact than preference for online social interaction on negative outcomes of PFU. The findings of this study suggest that mood regulation abilities may be a core component of PFU and, thus, may represent a potential target for prevention and treatment of PFU. Furthermore, we found a substantially stronger relationship between deficient self-regulation and the negative outcomes of Facebook use than that reported by Caplan (2010) for the PIU context. Despite Facebook has been described as a context where the user is most likely to engage in addictive behavior leading to problematic consequences than the Internet does (Assunção & Matos, 2017), we are in line with the view that the Internet includes, as much as Facebook does, many features that people can become "addicted" to (Brand et al., 2014). Depending on predisposing factors, i.e., neurobiological characteristics, coping styles, affective and cognitive responses to situational triggers in combination with reduced executive functioning (Brand et al., 2016), Internet use may become problematic, as much as Facebook use may. The discrepancy between studies on PFU (including our forth study) and those on generalized PIU may be explained by considering some differences between individuals who use the Internet and those who use Facebook, related to factors that directly and indirectly influence negative outcome, such as self-regulation skills, degree of preference for online social interaction, and mood regulation abilities (Moretta & Buodo, 2018b).

An interaction of sensitized reward processing and cue-reactivity with defective prefrontal inhibitory control has been argued to characterize both addictive behaviors and potentially addictive behaviors, e.g., PSNSU (Brand, Wegmann, et al., 2019; Brand et al., 2016). However, only few studies to our knowledge have investigated psychobiological mechanisms in PSNSU (He et al., 2017; Turel et al., 2014). The aims of the fifth and the sixth studies were to investigate, respectively, cue-reactivity and response inhibition in the presence of Facebook-related and highly arousing emotional stimuli in individuals with vs. without PFU. Specifically, in the fifth study the Event-Related Potentials (ERPs) were recorded during the passive viewing of Facebook-related, pleasant, unpleasant and neutral pictures. Previous research has shown higher cue-reactivity to addiction-relevant cues in individuals with SUD, gambling, gaming, and buying disorders compared with healthy control participants (Jasinska et al., 2014; Starcke et al., 2018). However, the results of the fifth study did not provide evidence for cue reactivity to Facebook-related cues in problematic Facebook users. Rather, Facebook-related cues elicited larger ERP positivity than neutral, and comparable to unpleasant stimuli, 400-600 ms after picture onset in both problematic and non-problematic Facebook users. Interestingly, only in problematic Facebook users the ERP positivity elicited by Facebook-related cues was inversely related to subjective ratings of Arousal. Since in this study individuals classified as problematic users may be in the first stages of PFU/at risk to develop PFU, it can be speculated that similarly to addiction (George et al., 2014), negative reinforcement processes (the reduction of arousal associated with Facebook-related stimuli) might characterize PFU as a behavioral addiction (Brand, Wegmann, et al., 2019; Griffiths, 2012; Griffiths et al., 2014). Moreover, similarly to risk-taking behaviors and SUD, in which enhanced and sustained reward reactivity would increase the likelihood of risky behavior (Garfield, Allen, Cheetham, Simmons, & Lubman, 2015; Spear, 2011; Stice, Yokum, & Burger, 2013), we found long-lasting larger ERP positivity to pleasant than unpleasant pictures (up to 1000 ms post-stimulus) only in problematic Facebook users. Indeed, in non-problematic users larger positivity to pleasant vs. unpleasant pictures was less sustained (i.e., up to 800 ms). Lastly, consistently with previous studies that compared ratings to addiction-related pictures between addicted individuals and controls (e.g., Engelmann, Gewirtz, & Cuthbert, 2011; Littel & Franken, 2007; Lubman et al., 2009; Wölfling et al., 2011) individuals with PFU rated Facebook-related pictures as more pleasant and arousing than controls did.

In the sixth study, neural (i.e., ERPs) and behavioral (Reaction Times [RTs] to Go trials and accuracy to Go and Nogo trials) measures allowed investigating whether individuals with vs. without PFU show greater difficulties in inhibiting prepotent motor responses during an emotional Go/Nogo task. Overall, our findings suggest that, similarly to SUD, problematic Facebook users are characterized by under-engagement of response inhibition processes in the context of natural reward- and Facebook-related stimuli, as indexed by reduced overall accuracy ratings and Nogo-P3 amplitude to Facebook-related, pleasant and neutral stimuli than to unpleasant stimuli. Moreover, problematic users rated Facebook-related pictures as more pleasant and arousing than controls, suggesting that, similarly to drug-related cues in SUD (Engelmann et al., 2011; Littel & Franken, 2007; Lubman et al., 2009; Wölfling et al., 2011), Facebook-related stimuli acquire positive reinforcement properties from Facebook use (Everitt et al., 1999; Grimm, 2000). Of note, all participants (problematic and non-problematic Facebook users) were slower to respond to both Facebook-related and pleasant Go trials as compared with unpleasant and neutral pictures. Consistently, the Nogo-N2 amplitude was larger to Facebook-related than all other picture contents, suggesting that greater response conflict was generated when Nogo stimuli required to withhold responding in the context of Facebook-related stimuli. The Nogo-N2 is commonly regarded as reflecting conflict monitoring performed by the anterior cingulate cortex (ACC; Bekker, Kenemans, & Verbaten, 2005; Donkers & Van Boxtel, 2004; Palermo, Stanziano, & Morese, 2018). In the context of SUD, ACC and the thalamo-orbitofrontal circuit seem to have a fundamental role in consolidating the associations between addiction-related environment and drug-related rewards, which underlie craving symptoms, a core mechanism for SUD development and maintenance (Goldstein & Volkow, 2002; Volkow et al., 1999). In this view, in non-PFU, the positive correlation between Nogo-N2 amplitude to Facebook-related pictures and Valence and Arousal ratings may suggest that conflict monitoring in the presence of Facebook-related stimuli is related to the pleasantness and salience of this kind of stimuli that, as a speculation, may underlie the initial stage of craving symptoms. Future studies should further investigate the neural correlates of inhibitory processes in the presence of SNSs-related cues, and their possible role as precursor sign/risk factor for future PFU.

Overall, the findings of our studies seem to suggest that PIU and PFU share similar affective and cognitive processes with addictions. However, PIU and PFU are also associated with a complex pattern of symptoms shared with other psychopathological conditions (e.g., OCD). In order to overcome some methodological problems that are mainly related to a reliable identification of severe generalized and specific PIU to be compared with addiction, identifying core symptomatology and consequential diagnostic criteria of PIU and PSNSU has become a priority. One could keep referring to PIU and specific types of PIU as sets of psychopathological symptoms that are too heterogeneous to be classified under the *Substance-related and addictive disorders* section of the DSM-5 (American Psychiatric Association, 2013). Indeed, in addition to the aforementioned limited scientific evidence and methodological problems (see the *Introduction* paragraphs of *Section 1 and 2*) that hinder the development of reliable diagnostic criteria, it has been argued that Internet-related addictive behaviors would hide the "real" psychopathology, consisting in a dissociative process that protects the self from reactivating traumatic states connected to childhood experience of emotional neglect or abuse (Schimmenti & Caretti, 2010). Such view supports the strong criticisms against the conceptualization of generalized and specific PIU as behavioral addictions (Schimmenti & Caretti, 2017).

In contrast with this view, it can be argued that all psychopathological conditions are complex and multidimensional in nature (Vella, Aragona, & Alliani, 2000), such that clinicians and researchers are aware about potential biases from the intrinsic characteristics of the classification system they use (Vella et al., 2000). Moreover, psychopathology in general has been related to *how* the person's self-coherence is maintained (Parnas & Bovet, 1995) and to attachment representations, including trauma-related representations (Chiesa, Cirasola, Williams, Nassisi, & Fonagy, 2017; De Coro & Williams, 2008; Williams, 2009) that have been also found to characterize SUD in particular (Zlotnick et al., 1997). An integrative framework for understanding cognitive and affective problems in psychopathology should be at the basis of clinical research and practice for any psychopathological condition, but it should not hinder the classification of problematic behaviors (e.g., PIU) into a diagnostic system that would inform research and improve diagnostic power. Moreover, it is acknowledged that a diagnostic manual cannot be used without applying clinical judgment, with the individual history and variability to be among the core elements of clinical work "overly strict adherence to the criteria can get in the way of appropriate clinical care, and clinicians must be mindful of each patient's needs, not the sometimes arbitrary requirements of a coding system" (Black & Grant, 2014).

In the light of the limitations related to sample selection and some improvable methodological aspects, this PhD dissertation tried to adding knowledge on, and further characterize, both PIU and PSNSU from a psycho-physiological perspective. Our findings mainly highlighted Internet- and social networking-related problematic behaviors to share core psycho-physiological mechanisms with addictive behaviors, although some peculiarities are to be noted and deserve further investigation. This research project should be of importance for the conceptualization of PIU and PSNSU, that is the first step for a standardized diagnosis. A standardized and reliable diagnosis is a prerequisite for implementing effective treatments and prevention programs.

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Appendix

Formulae of the mixed-effects models (by lmer {lme4})

M1 Model1: Formula = Index ~ Phase*Group + AUDIT + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M2 Model2: Formula = Index ~ Phase + AUDIT + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M3 Model3: Formula = Index ~ Group + AUDIT + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M4 Model4: Formula = Index ~ Phase + Group + AUDIT + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M5 Model5: Formula = Index ~ AUDIT + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M6 Model6: Formula = Index ~ Phase*Group + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M7 Model7: Formula = Index ~ Phase + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M8 Model8: Formula = Index ~ Group + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M9 Model9: Formula = Index ~ Phase + Group + DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M10 Model10: Formula = Index ~ DASS.D + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M11 Model11: Formula = Index ~ Phase*Group + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M12 Model12: Formula = Index ~ Phase + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M13 Model13: Formula = Index ~ Group + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M14 Model14: Formula = Index ~ Phase + Group + DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M15 Model15: Formula = Index ~ DASS.A + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M16 Model16: Formula = Index ~ Phase*Group + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M17 Model17: Formula = Index ~ Phase + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M18 Model18: Formula = Index ~ Group + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M19 Model19: Formula = Index ~ Phase + Group + DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M20 Model20: Formula = Index ~ DASS.S + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual), data=IAdata, REML=FALSE
M21 Model21: Formula = Index ~ Phase*Group + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M22 Model22: Formula = Index ~ Phase + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M23 Model23: Formula = Index ~ Group + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M24 Model24: Formula = Index ~ Phase + Group + DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M25 Model25: Formula = Index ~ DASS.T + LoPRE + LoPER + OCI + TAS +(1|Individual)
M26 Model26: Formula = Index ~ Phase*Group + LoPRE + LoPER + OCI + TAS +(1|Individual)
M27 Model27: Formula = Index ~ Phase + LoPRE + LoPER + OCI + TAS +(1|Individual)
M28 Model28: Formula = Index ~ Group + LoPRE + LoPER + OCI + TAS +(1|Individual)
M29 Model29: Formula = Index ~ Phase + Group + LoPRE + LoPER + OCI + TAS +(1|Individual)
M30 Model30: Formula = Index ~ LoPRE + LoPER + OCI + TAS +(1|Individual)
M31 Model31: Formula = Index ~ Phase*Group + LoPER + OCI + TAS +(1|Individual)
M32 Model32: Formula = Index ~ Phase + LoPER + OCI + TAS +(1|Individual)
M33 Model33: Formula = Index ~ Group + LoPER + OCI + TAS +(1|Individual)
M34 Model34: Formula = Index ~ Phase + Group + LoPER + OCI + TAS +(1|Individual)
M35 Model35: Formula = Index ~ LoPER + OCI + TAS +(1|Individual)
M36 Model36: Formula = Index ~ Phase*Group + OCI + TAS +(1|Individual)
M37 Model37: Formula = Index ~ Phase + OCI + TAS +(1|Individual)
M38 Model38: Formula = Index ~ Group + OCI + TAS +(1|Individual)
M39 Model39: Formula = Index ~ Phase + Group + OCI + TAS +(1|Individual)
M40 Model40: Formula = Index ~ OCI + TAS +(1|Individual)
M41 Model41: Formula = Index ~ Phase*Group + TAS +(1|Individual)
M42 Model42: Formula = Index ~ Phase + TAS +(1|Individual)
M43 Model43: Formula = Index ~ Group + TAS +(1|Individual)

M44 Model44: Formula = Index ~ Phase + Group + TAS +(1|Individual)
M45 Model45: Formula = Index ~ TAS +(1|Individual)
M46 **Model46: Formula = Index ~ Phase*Group + (1|Individual)**
M47 Model47: Formula = Index ~ Phase + Group + (1|Individual)
M48 Model48: Formula = Index ~ Phase + (1|Individual)
M49 Model49: Formula = Index ~ Group + (1|Individual)
M0 Model0: Formula = Index ~ (1|Individual)

Formulae of the ordinal logistic regression models (by polr {MASS})

L1 Model1: Formula = Craving ~ Time * Group

L2 Model2: Formula = Craving ~ Time + Group

L3 Model3: Formula = Craving ~ Time

L4 Model4: Formula = Craving ~ Group

L0 Model5: Formula = Craving ~ 1