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ORIGINAL PAPER

The Role of Mindfulness, Mind Wandering, Attentional Control, and Maladaptive Personality Traits in Problematic Gaming Behavior

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Abstract

Objectives Problematic gaming has become a phenomenon of growing clinical relevance due to its negative impact on life and mental health outcomes. Much research has been carried out on its complex aetiology, and some studies have suggested that dispositional mindfulness, mind wandering, attentional control, and maladaptive personality traits may play some role, but they have never been included in the same prediction model. This study used Gaussian graphical models and Bayesian networks to investigate the pattern of association of these constructs and of background and gaming-related variables with problematic gaming in a sample of adult gamers.

Method Participants ($n = 506$) were administered an online survey comprising a questionnaire on background and gaming-related variables and the Gaming Disorder Test, the Five Facet Mindfulness Questionnaire-15, the Mind Wandering-Spontaneous and Deliberate scales, the Attention Control-Distraction and Shifting scales, and the Personality Inventory for DSM-5-Brief Form.

Results Gaussian graphical models showed that problematic gaming was directly associated with Acting with Awareness, Disinhibition, Psychoticism, playing more than 30 hr a week, ability level, and playing strategy games. Bayesian networks indicated that the occurrence of high levels of problematic gaming directly depended on the presence of low scores on Acting with Awareness.

Conclusions The results suggest that one key feature of problematic gamers can be a high level of spontaneous thinking, either in the form of mind wandering or in the lack of Acting with Awareness, while maladaptive personality traits and attentional control seem to play a less central role.

Keywords Gaming addiction · Gaming disorder · Mindfulness · Mind wandering · Attentional control · Maladaptive personality traits

In the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM-5), internet gaming disorder (IGD) was included in Section III as a temporary and not unique disorder that requires further research before recognition can be achieved (American Psychiatric Association, 2013a), while gaming disorder has been provisionally defined by the World Health Organization (WHO) as a persistent or recurrent online and/or offline gaming behavior causing significant deficits in the personal, family, social, educational, professional, or other important areas of functioning in an individual's life over a period of at least 12 months. Three core diagnostic criteria have been proposed: impaired control over gaming (e.g., onset, frequency, intensity, duration, termination, context); increasing priority given to gaming to the extent that gaming takes precedence over other life interests and daily activities; and continuation or escalation of gaming despite the occurrence of negative consequences (World Health Organization, 2019). However, no gold-standard procedures are currently available for diagnosing

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this disorder. Therefore, in this paper, we will use the more general term “problematic gaming.”

According to previous research, problematic gamers tend to become moody and irritable, physically aggressive, refuse to go to school or work, and refuse to stop playing (van Rooij et al., 2012). In addition, they are at an increased risk of not meeting physical activity recommendations and of being obese (Arnaez et al., 2018). In the most severe cases, problematic gaming appears to coexist with other disorders such as depression (King et al., 2013), anxiety (Adams et al., 2019), substance abuse (Ko et al., 2008), and personality disorders (Şalvarlı & Griffiths, 2021; Schimmenti et al., 2017). As a result, the association of problematic gaming with functional impairment in mental health and many other areas of life can lead to potentially devastating long-term effects.

However, while previous research has consistently shown an association between gaming and mental health outcomes, the conclusions about its direction are mixed. As a leisure activity, playing video games can also have positive effects on mental health, such as reducing emotional disturbance and stress and enhancing socialisation, emotion regulation, cognitive functions, positive affect, and life satisfaction (e.g., Granic et al., 2014; Jones et al., 2014; Kowert et al., 2015; Uttal et al., 2013). This seems to be especially true for individuals with high gaming engagement, rather than those with problematic gaming (Charlton & Danforth, 2007, 2010). Furthermore, some studies ascribed to problematic gaming symptoms a causal effect on impaired mental health (e.g., Griffiths & Meredith, 2009; Kirby et al., 2014; Scott & Porter-Armstrong, 2013), whereas others indicated that aspects of lower psychological well-being, such as lower social competence, self-esteem, and happiness, can be predictors, rather than outcomes, of problematic gaming (e.g., Hull et al., 2013; Lemmens et al., 2011). As suggested by Mettler et al. (2020), the association between problematic gaming and psychological well-being could as well be considered reciprocal. More generally, recent research has suggested that psychological traits likely contribute to the development and maintenance of addictive disorders, although the degree to which different traits predispose to or are the result of abuse varies with the specific substances, and unique psychosocial prediction models are needed for each addictive disorder (Mitchell & Potenza, 2014; Zilberman et al., 2018, 2020).

One of the key features of problematic gaming is preoccupation with gaming, i.e., a state in which “the individual thinks about previous gaming activity or anticipates playing the next game; internet gaming becomes the dominant activity in daily life” (American Psychiatric Association, 2013a, p. 795). In other words, gamers think about gaming so intensely that other things appear to be less important or interesting. In this perspective, problematic gaming has been conceived as a compensatory behavior used to escape negative moods (e.g., anxiety or guilt) and to cope with psychological issues and avoid everyday problems (e.g., Hagström & Kaldo, 2014; Kardefelt-Winther, 2014). As a result, it is possible to hypothesize that traits and/or dispositions, such as mindfulness, i.e., the innate capacity of paying and maintaining attention to present-moment experiences with an open and nonjudgmental attitude (Brown & Ryan, 2003), which promote nonavoidant coping, subjective well-being, and adaptive functioning (Soysa & Wilcomb, 2015; Weinstein et al., 2009), can be protective factors against problematic gaming (Mettler et al., 2020). Conversely, traits and/or dispositions that make the individual’s mind shift away from the “here and now” and from ongoing tasks and/or emotional states, such as mind wandering (Smallwood & Schooler, 2015) can be risk factors (Zhang et al., 2021).

Mindfulness can be conceived either as a state (i.e., momentarily experiencing it) or as a disposition (i.e., having a general and stable tendency to be mindful), with the latter being a predictor of the former (Brown & Ryan, 2003). Dispositional mindfulness is thought to improve acceptance and help people let go of negative feelings and thoughts, which is thought to have a beneficial effect on emotional well-being (Bishop et al., 2004). Research has shown that individuals with higher dispositional mindfulness tend to experience better quality of life and psychological functioning as they tend to report less negative affect (e.g., Brown & Ryan, 2003), lower levels of ruminative thinking (Raes & Williams, 2010), and better emotion regulation (Chambers et al., 2009). The results of interventions aimed at increasing dispositional mindfulness include better mental health outcomes (e.g., Khoury et al., 2013; Shapiro et al., 2011) and it has been shown that training momentary mindfulness increases dispositional mindfulness over time, which, in its turn, can ultimately improve affective well-being (Kiken et al., 2015). Consistent with these findings and findings from studies that found a negative association between mindfulness and internet use (Calvete et al., 2017; Gámez-Guadix & Calvete, 2016; Lisle et al., 2012; Mazzoni et al., 2017), mindfulness-based therapy has been proposed as a candidate treatment for problematic gaming (Dong & Potenza, 2014; Li et al., 2018; Li, et al., 2017).

Since problematic gaming can be a compensatory coping behavior, dispositional mindfulness can promote self-regulation, flexibility, and the ability to redirect attention away from a potentially harmful activity. Mettler et al. (2020) found a weak negative bivariate association of problematic gaming with dispositional mindfulness and hypothesized that the association between problematic gaming and elements of subjective well-being could be at least partially explained or mediated by individuals’ reports of dispositional mindfulness. They found that, when controlling for gender and weekly hours of gaming, higher levels of dispositional mindfulness were associated with higher levels of positive affect and life satisfaction and lower levels of negative affect. Using structural equation modeling, Mettler et al. (2020) also found that dispositional mindfulness had a negative indirect effect on the association between problematic gaming and well-being measures (life satisfaction and positive affect) and a positive indirect effect on the relationship between problematic gaming and negative affectivity. However, they specified problematic gaming as a predictor of dispositional mindfulness, despite the fact that, as reported above, previous research seems to suggest that it should have been the opposite. From a methodological point of view, moreover, in a cross-sectional study such as Mettler et al. (2020), the issue cannot be addressed through a causal mediation model, as per the authors' comment in their discussion.

Furthermore, Mettler et al. (2020) considered mindfulness as a unitary trait, when it has been suggested that collapsing across different mindfulness facets (i.e., Observing, Describing, Acting with Awareness, Nonreactivity to Inner Experience, and Nonjudging of Inner Experience) might prevent a more accurate assessment of the association of specific facets of mindfulness with substance use behaviors (Karyadi et al., 2014). While many studies found a weak relationship between trait mindfulness and substance use behaviors, others reported that the five facets of mindfulness were differentially related to substance use behaviors. Acting with Awareness, Nonreactivity to Inner Experience, and Nonjudging of Inner Experience were the ones more consistently associated with reduced substance use behaviors (for a review, see Karyadi et al., 2014). As for behavioral addictions, Calvete et al. (2017) reported that Acting with Awareness and Nonjudging of Inner Experience were the facets of mindfulness that were more strongly associated with problematic internet use when using baseline, cross-sectional data, while longitudinal analyses revealed that Nonjudging of Inner Experience predicted a decrease in the preference for online social interactions over face-to-face relationships.

Mind wandering is defined as "a shift of attention away from a primary task toward internal information" (Smallwood & Schooler, 2006, p. 946) so that attention decouples from external reality toward internally generated information during task engagement. It is a component of a larger family of mental states called *spontaneous thought*, defined as "unintended, nonworking, noninstrumental mental content that comes to mind unbidden and effortlessly" (Christoff, 2012, p. 52; Klinger, 2009), which also encompasses involuntary autobiographical memories and daydreaming (see, e.g., Marchetti et al., 2016). Recent conceptualizations of mind wandering have identified it in terms of (1) the unintentional drifting of one's thoughts from a focal task to inner, task-unrelated thoughts (Smallwood & Schooler, 2006) and (2) failures in executive control (e.g., McVay & Kane, 2010), which led to considering mind wandering as an equivalent of mindlessness (or acting without awareness). However, Giambra (1995) noted that task-unrelated imagery and thoughts can absorb awareness because they capture attention (the actual *uncontrolled* shift) or because the individual deliberately shifts their attention to them (a *controlled* shift). Carriere et al. (2013) thus proposed two distinct, albeit correlated, forms of mind wandering: spontaneous and deliberate. Subsequent research showed that the two forms of mind wandering were uniquely associated with some facets of mindfulness and of affective dysfunction. Specifically, deliberate mind wandering was uniquely positively associated with the nonreactivity to inner experience facet of mindfulness, negatively associated with stress and anxiety, and had no association with depression; spontaneous mind wandering was uniquely negatively associated with nonreactivity to inner experience and uniquely positively associated with depression, anxiety, and stress (Seli et al., 2015, 2019).

It has been estimated that between a third and a half of our waking thoughts can be considered as mind wandering (Killingsworth & Gilbert, 2010), consistent with claims that mind wandering seems to be a default mode of operation of the human brain (Buckner et al., 2008). Early studies on the neural underpinnings of mind wandering have shown that the default mode network is more active at rest and during mind wandering (Mason et al., 2007) than during the processing of an external stimulus (Buckner et al., 2008; but see Fox et al., 2015, for a more comprehensive review), while the frontoparietal control network, a network associated with executive control, has been found to be associated with goal-directed (i.e., intentional) activity (Spreng et al., 2010).

Golchert et al. (2017) suggested that the intentionality of the mind wandering state is determined by the integration of the frontoparietal control network and default mode network, with higher integration being associated with more deliberation and substantial differences in cortical thickness and functional connectivity in individuals who reported higher levels of either deliberate or spontaneous mind wandering. Consistent with these results and relevant to this study, Ding et al. (2013) found that adolescents with internet gaming addiction showed different patterns of brain activity, similar to other addictions (see, e.g., Ko et al., 2013). Very recently, Zhang et al. (2021) reported that self-report measures of mind wandering and internet gaming disorder were positively associated, with a partial mediation effect of social anxiety.

Although mindfulness and mind wandering seem to be key predictors for problematic gaming, research has suggested that attentional issues (distractibility and difficulty in shifting between tasks, Carriere et al., 2013) and maladaptive personality traits may also play a role. Neurocognitive studies have shown that the executive system can facilitate cognitive and behavioral control of motivational drives and can enable individuals to inhibit desire and control the extent to which they engage in reward-seeking behavior (for reviews, see Dong & Potenza, 2014; Wei et al., 2017). Several studies have shown that individuals with internet addiction have lower response-inhibition and cognitive-control tendencies or abilities than those without (Dong et al., 2010, 2011, 2014) and these issues are influenced by internet-gaming-related stimuli, with a stronger attentional bias toward online-gaming stimuli in cognitive tasks in participants with problematic gaming (Jeromin et al., 2016; Kim et al., 2018; Zhou et al., 2012). This cognitive bias is similar to the one observed in other addictions (Potenza, 2014), and is consistent with set-shifting tendencies that are related to the compulsive aspects of addictions. The neural processes underlying attention, response inhibition, and behavioral flexibility in individuals with problematic gaming are associated with the severity of the disorder, although it is not clear whether they are predisposing factors or neural functions that arise during the phases of problematic gaming development (Dong & Potenza, 2014).

Along with cognitive functioning, current theoretical models about the psychological processes underlying the development and maintenance of problematic gaming also highlight the role of personality characteristics in the form of unspecific predisposing factors in the development of problematic gaming, albeit indirect and in interaction with other biological, psychological, social, or cognitive factors (e.g., the Interaction of Person-Affect-Cognition-Execution model, Brand et al., 2016). Several studies have shown the association of problematic gaming with a wide range of personality characteristics that includes the Big Five, "dark" traits such as aggression and narcissism, sensation seeking and risk-taking, and affective dysfunctional traits (see Gervasi, La Marca, Costanzo, et al., 2017a and Şalvarlı & Griffiths, 2021, for a more comprehensive list). The inclusion of all these traits is unfeasible in practice, but recently Laier et al. (2018) have shown that problematic gaming was positively associated with all the five maladaptive personality traits of the DSM-5 that can be broadly considered as maladaptive variants of the Big Five, namely, negative affectivity, detachment, antagonism, disinhibition, and psychoticism (Krueger et al., 2011; Trull, 2012), consistent with the finding that such dysfunctional traits have been shown to be associated with internet-use disorder (Gervasi, La Marca, Lombardo, et al., 2017b) and psychological disorders (e.g., Hopwood et al., 2013).

In a scenario in which an outcome could be associated with several possible predictors, a common statistical approach to investigating the relative importance of each predictor while controlling for the others and background and gaming-related variables would be to specify a multiple regression model. However, such a model cannot map out multicollinearity and predictive mediation (Epskamp & Fried, 2018).

Multiple regression assumes that each predictor can potentially add to the prediction of the criterion. However, as one or more predictors are predicted, in their turn, by the other predictors in the model, they will have less and less unique information that can potentially contribute to the prediction of criterion. This issue, referred to as *multicollinearity*, becomes increasingly problematic when the multiple correlation of one or more predictors with the set of other predictors is very high. The estimates of single regression coefficients can change substantially in magnitude and even in sign, making them difficult to interpret and unreliable. This issue can be common in cross-sectional studies when multiple measures of the same or similar constructs are used as predictors in the model (Cohen et al., 2003), as is the case here. Although some remedies have been proposed (see, e.g., Cohen et al., 2003, Sect. 10.6), they do not directly provide insight into predictive mediation, i.e., a network in which two variables are not directly connected but are indirectly connected (e.g., X—Z—Y). This indicates that X and Y may be correlated, but any predictive effect from X to Y (or vice versa) is mediated by Z (Epskamp & Fried, 2018). Since previous studies on predictors of problematic gaming relied on causal mediation models (e.g., Mettler et al., 2020; Zhang et al., 2021), a statistical model that could map out both multicollinearity and predictive mediation would provide valuable insight into the network of associations of potential predictors of problematic gaming.

In the last decade, a viable solution to this issue has been offered by Gaussian graphical models (GGMs, Epskamp et al., 2018a, 2018b), which use pairwise Markov random fields to estimate a network of partial correlation coefficients, i.e., the correlation between two variables after conditioning on all other variables included in the analysis (Epskamp et al., 2018a, 2018b). Such models graphically describe interactions between a potentially large number of variables. Each variable is represented as a dot (node), and associations between nodes are represented by lines (edges) connecting them. The strength of these edges are the partial correlation coefficients that correspond to multiple regression coefficients, i.e., an estimate of the strength of the association of one variable with another after controlling for all other variables in the network. In their basic applications (see, e.g., Epskamp & Fried, 2018), GGMs allow the investigation of the *structure* of the network, but it is also possible to compute an equivalent of the R^2 index in multiple regression when one adds the computation of *predictability*, that is, how much variance of a variable is accounted for by the variables connected to it (Haslbeck & Waldorp, 2018). Very recently, it has been pointed out that, although GGMs can be indicative of potential causal effects (Epskamp & Fried, 2018), their causal interpretation is limited. As their edges are undirected, it is not possible to tell whether a variable is more likely to cause or be caused by another, since edges have no direction and thus do not encode this information. Moreover, assuming a partial correlation network when the underlying model contains directed edges can lead to spurious causal connections (Briganti et al., 2021). This issue can be overcome using Bayesian networks (BNs), which can determine both the direction and the magnitude of causal effects (see, e.g., Maathuis et al., 2018). BNs are defined by a directed acyclic graph (DAG) and by the joint probability distribution of the variables in the network. A DAG allows the expression of the conditional independence relationships between the variables (nodes) by using graphical separation (Scutari & Denis, 2021). In other words, if two variables are separated in the DAG by some other variables, they are independent in probability conditional on (that is, after controlling for) those other variables. As a result, the probability distribution expresses the magnitude of the causal effects connecting the variables that are not graphically separated. BNs contain only directed edges, and this allows the modelling of the admissible causal relationships in observational data, thus addressing the limitations of partial correlation networks. Research in psychopathology has already been using this method: a list of studies and an introduction to it are provided by Briganti et al. (2021).

In the present study, we use GGMs and BNs to investigate the network of associations of problematic gaming with facets of mindfulness and mind wandering, maladaptive personality traits, and background and gaming-related variables, with the aim of shedding light on the direct and indirect predictors and on the possible causes of problematic gaming. Mettler et al. (2020) and Zhang et al. (2021) considered mindfulness and mind wandering, respectively, as unitary constructs. As suggested by the authors themselves, investigating the association of the facets of these constructs with problematic gaming could help shed more light on its inner nature. Therefore, we used measures of the five mindfulness facets proposed by Baer et al. (2006) and of the two types of mind wandering (spontaneous and deliberate) operationalized in the scales developed by Carriere et al. (2013). We also included measures of distractibility and difficulty in shifting between tasks (as in Carriere et al., 2013) and of the five maladaptive trait dimensions of the Alternative Model of Personality Disorders provided in the DSM-5 (American Psychiatric Association, 2013a). Thus, with respect to previous studies that had similar aims (mainly Laier et al., 2018; Mettler et al., 2020; Zhang et al., 2021), this one includes in the same model more predictors and employs more advanced statistical methods that allow us to address the limitations of more "classical" methods and, despite using cross-sectional data, provide information about plausible causal effects. As a result, the expected outcome of this work is a clearer understanding of characteristics that could be targeted in clinical prevention and interventions for problematic gaming.

Method

Participants

The final sample included 506 participants recruited from the Italian general population between September 2020 and September 2021. The descriptive statistics of the background variables are reported in Table 1.

Procedure

Participants were recruited online by posting the link to a LimeSurvey platform on several online sources, such as social media and gaming websites and forums, and sending email invitations to the authors' contacts. In either case, recipients were asked to recruit participants among their contacts, too, as in a snowball-like sampling strategy. Figure 1 shows the flow diagram of participants' enrolment. The questions referred to in the figure can be found in the Appendix A of the Supplementary Materials (SM).

Measures

Background Questionnaire

Participants initially completed a schedule comprising questions about age, gender they identified with, highest achieved educational level, relationship status, occupational status, socioeconomic status (participants were asked to place themselves on the ladder proposed by Kilpatrick and Cantril (1960), anchored at the top [10] by those in Italian society who are best off in terms of income, education, and occupation, and at the bottom [1] by those who are worst off), whether they were taking psychotropic drugs, whether they were in therapy, whether they have ever been diagnosed with a mental disorder by a mental health professional, level of gaming ability, preferred type of gameplay, preferred gaming mode, frequency of physical activity, hours of weekly gameplay, preferred device for gaming, and preferred gaming genre. Videogame genre categories were adapted from Adams (2014) and "List of video game genres" (2019). Details are reported in Table 1 and in Appendix A of the SM.

Italian Gaming Disorder Test (I-GDT)

The GDT (Pontes et al., 2021) examines gaming activities that occur over a 12-month period using four items that operationalize the three core diagnostic criteria of

Table 1 Sample descriptive statistics of background variables — raw data ($n = 506$)

Variable	n (%) or $M \pm SD$ (range)
Gender identified with	
Female	44 (8.70%)
Male	462 (91.30%)
Trans	0 (0%)
Other	0 (0%)
Prefer not to answer	0 (0%)
Age (years)	27.15 ± 6.24 (18–55)
Educational level	
None	0 (0%)
Primary school	0 (0%)
Secondary School	34 (6.72%)
Some high school	43 (8.50%)
High school degree	264 (52.17%)
Some college	8 (1.58%)
Bachelor's degree	82 (16.21%)
Master's degree	57 (11.26%)
PhD or equivalent	18 (3.56%)
Relationship status	
Single, no partner	268 (48.73%)
Stable relationship with a partner	122 (22.18%)
Living with partner	79 (14.36%)
Married	33 (6.00%)
Divorced/separated	3 (0.55%)
Widow/widower	1 (0.18%)
Occupational status	
Working	253 (50.00%)
Studying	127 (25.10%)
Working and studying	61 (12.06%)
Nor working or studying	65 (12.85%)
Socioeconomic status	5.97 ± 1.45 (2–10)
Psychotropic drugs	11 (2.17%)
Psychotherapy	116 (22.92%)
Mental disorder diagnosis	29 (5.73%)
Ability level	
Very low	2 (0.36%)
Low	21 (3.82%)
Intermediate	245 (44.55%)
High	219 (39.82%)
Very high	19 (3.45%)

Table 1 Sample descriptive statistics of background variables — raw data ($n = 506$)

Variable	n (%) or $M \pm$ SD (range)
Preferred type of gameplay	
Mostly online	73 (14.43%)
Both online and offline	160 (31.62%)
Mostly offline	273 (53.95%)
Preferred gaming mode	
Singleplayer	324 (64.03%)
Multiplayer	33 (6.52%)
Both single- and multiplayer	149 (29.45%)
Frequency of physical activity	
Never	197 (38.93%)
Occasionally	150 (29.64%)
Regularly	159 (31.42%)
Weekly hours of gameplay	
1–10	166 (32.81%)
11–20	169 (33.40%)
21–30	111 (21.94%)
31–40	40 (7.91%)
41–50	12 (2.37%)
51–60	5 (0.99%)
60+	3 (0.59%)
Preferred device for gaming	
Console	325 (64.23%)
PC	158 (31.23%)
Smartphone/tablet	23 (4.55%)
Preferred gaming genre	
Action	191 (37.75%)
Action/Adventure	57 (11.26%)
Adventure	24 (4.74%)
Role playing	172 (33.99%)
Simulation	11 (2.17%)
Strategy	27 (5.34%)
Sports	17 (3.36%)
Other	7 (1.38%)

problematic gaming proposed by the WHO described above as well as an additional item reflecting the experience of significant problems in life. Since at high levels of this latter variable problematic gaming is of sufficient severity to result in significant impairment in all areas of functioning, its inclusion helps to ensure that the scale is able to effectively capture problematic gaming at different levels of severity rather than simply identifying excessive or hazardous gaming (Pontes et al., 2021). All four items are rated on a 5-point, Likert-type, frequency scale (from "never" to "very often"). A total score is obtained by summing up the gamer's responses, with higher scores reflecting higher degrees of severity and of detrimental effects of disordered gaming on the gamer's life. We developed an Italian version of the GDT (I-GDT) and investigated its psychometric properties in a preliminary study. The results are reported in Sect. 1 of the SM and support the reliability and validity of the I-GDT. In this study, Cronbach's α was 0.81 [0.78, 0.84] and McDonald's ω was 0.74 [0.70, 0.79].

Mind Wandering-Spontaneous and Mind Wandering-Deliberate (MW-S and MW-D, respectively, Carriere et al., 2013)

The MW-S and the MW-D are two 4-item, self-report measures of spontaneous (i.e., inadvertent and/or uncontrolled) and deliberate (i.e., intentional and controlled) MW, respectively. For both scales, items are scored using a 7-point, Likert-type scale, with higher scores

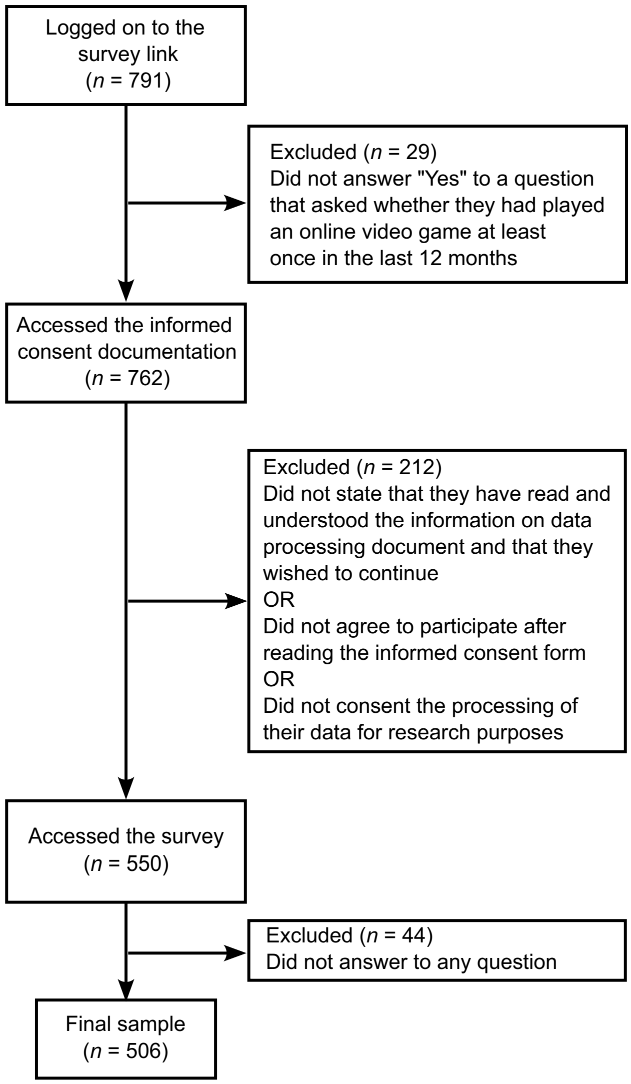

Fig. 1 Flow diagram of participants' enrolment

reflecting a higher frequency of mind wandering. The Italian versions of the scales (Chiorri & Vannucci, 2019) have shown adequate psychometric properties. In this study, Cronbach's α was 0.88 [0.86, 0.89] and McDonald's ω was 0.85 [0.83, 0.87] for MW-S, while for MW-D, Cronbach's α was 0.89 [0.88, 0.91] and McDonald's ω was 0.88 [0.85, 0.90].

Attention Control-Distraction (AC-D) and Attentional Control-Shifting (AC-S)

The AC-D and the AC-S (Carriere et al., 2013) are two 4-item, self-report measures of attentional distraction and difficulties with attentional shifting, respectively. For both scales, items are scored using a 5-point, Likert-type scale, with higher scores reflecting a higher frequency of attentional issues. The Italian versions of the scales (Chiorri & Vannucci, 2019) have shown adequate psychometric properties. In this study, Cronbach's α was 0.79 [0.76, 0.82] and McDonald's ω was 0.76 [0.73, 0.80] for AC-D, while for AC-S, Cronbach's α was 0.90 [0.89, 0.92] and McDonald's ω was 0.87 [0.84, 0.89].

Personality Inventory for DSM-5-Brief Form (PID-5-BF)

The PID-5-BF (American Psychiatric Association, 2013a) is a brief self-report, screening tool for personality pathology that assesses the five maladaptive trait dimensions of the Alternative Model of Personality Disorders provided in the DSM-5 (American Psychiatric Association, 2013b): Negative Affectivity (NA: emotional lability; anxiousness; separation insecurity; submissiveness; hostility; perseveration; depressivity; suspiciousness; restricted affectivity, see Waugh et al., 2017, p. 81), Detachment (De: withdrawal; intimacy avoidance; anhedonia; depressivity; restricted affectivity; suspiciousness), Antagonism (A: manipulativeness; deceitfulness; grandiosity; attention seeking; callousness; hostility), Disinhibition (Di: irresponsibility; impulsivity; distractibility; risk taking; rigid perfectionism), and Psychoticism (Ps: unusual beliefs and experiences; eccentricity; cognitive and perceptual dysregulation). Each scale comprises five items to be rated on a 4-point, Likert-type scale, with higher scores reflecting higher levels of the maladaptive trait. The Italian version of the scale (Fossati et al., 2017) has shown adequate psychometric properties. In this study, the reliability indices of the scales were as follows. Negative Affectivity: Cronbach's $\alpha = 0.80$ [0.77, 0.83], McDonald's $\omega = 0.78$ [0.75, 0.81]; Detachment: Cronbach's $\alpha = 0.78$ [0.75, 0.81], McDonald's $\omega = 0.74$ [0.70, 0.78]; Antagonism: Cronbach's $\alpha = 0.72$ [0.69, 0.76], McDonald's $\omega = 0.64$ [0.58, 0.70]; Disinhibition: Cronbach's $\alpha = 0.75$ [0.72, 0.79], McDonald's $\omega = 0.71$ [0.66, 0.75]; Psychoticism: Cronbach's $\alpha = 0.82$ [0.80, 0.85], McDonald's $\omega = 0.79$ [0.75, 0.83].

Five Facet Mindfulness Questionnaire-15 (FFMQ-15)

The FFMQ-15 (Gu et al., 2016) is a short version of the original 39-item FFMQ (Baer et al., 2006), a self-report measure of five facets of mindfulness: Observing (attending or noticing internal and external experiences such as thoughts, emotions or bodily sensations), Describing (ability to report on one's experiences), Acting with Awareness (attending to one's present moment activity, rather than behaving automatically, while attention is focused elsewhere), Nonjudging of Inner Experience (accepting and not evaluating thoughts and emotions in terms of "good" or "bad"), and Nonreactivity to Inner Experience (ability to detach from thoughts and emotions, allowing them to come and go without being overwhelmed by them). Each facet is operationalized by three items to be rated on a 5-point, Likert-type scale, with higher scores reflecting higher levels of the mindfulness dimension. The Italian version of the 39-item FFMQ (Giovannini et al., 2014) has shown adequate psychometric properties, but we could not find any Italian study about the 15-item version. Here we used the 15 items from the validated Italian 39-item version that corresponded to the Gu et al. (2016) items, and using the data collected for this study we tested whether the expected 5-factor measurement model and the reliability of the implied scales were supported. The results are reported in Sect. 2 of the SM and support the adequacy of the 5-correlated-factor measurement model and of the implied scales for the assessment of the facets of mindfulness. In this study, the reliability indices of the scales were as follows. Observing: Cronbach's $\alpha = 0.60$ [0.54, 0.66], McDonald's $\omega = 0.61$ [0.55, 0.76]; Describing: Cronbach's $\alpha = 0.84$ [0.82, 0.87], McDonald's $\omega = 0.81$ [0.78, 0.85]; Acting with Awareness: Cronbach's $\alpha = 0.73$ [0.69, 0.77], McDonald's $\omega = 0.69$ [0.64, 0.74]; Nonjudging of Inner Experience: Cronbach's $\alpha = 0.84$ [0.82, 0.86], McDonald's $\omega = 0.81$ [0.77, 0.84]; Nonreactivity to Inner Experience: Cronbach's $\alpha = 0.66$ [0.61, 0.71], McDonald's $\omega = 0.64$ [0.56, 0.70].

While the background questionnaire was always presented at the beginning, the order of the other measures was randomized for each participant to control for sequence and order effects. The complete materials are available at https://osf.io/4kcb2/

Data Analyses

To include categorical background variables in the model, before performing the analyses, we either recoded some variables by collapsing their categories (this also allowed us to address the issue of low frequencies for some categories) or dummy coded some other variables. When introducing binary variables, a GGM actually becomes a mixed graphical model (MGM; Haslbeck & Waldorp, 2020; Lee & Hastie, 2015). MGMs can be estimated with the *mgm* function in the *mgm* package (Haslbeck & Waldorp, 2020). When we performed the analyses using this function, the results did not substantially change.

Educational level was recoded as "degree" vs "no degree"; relationship status was recoded "with partner" (Stable relationship with a partner, Living with partner, and Married) vs "no partner"; occupational status was dummy coded with "Working" as reference; ability level was recoded as Low (Very low + Low), Intermediate, and High (High + Very High) and dummy coded with Low as reference; preferred type of gameplay was dummy coded with "Mostly offline" as reference; preferred gaming mode was dummy coded with "Singleplayer" as reference; frequency of physical activity was dummy coded with "Never" as reference; the categories "31–40", "41–50", "51–60", and "60 + " categories of weekly hours of gameplay were collapsed into one, and the resulting variable was dummy coded with the "1–10" category as reference; preferred device for gaming was dummy coded with "Console" as reference; the categories of preferred game genre "Simulation" and "Other" were collapsed into one and the resulting variable was dummy coded with "Action" as reference category.

Next, we modelled data using a GGM (Epskamp et al., 2018a, 2018b). A GGM estimates a network of partial correlation coefficients, namely, the correlation between two variables after conditioning on all other variables in the data set. In the last decade, network models have been increasingly employed in psychology, since psychological phenomena are often considered to depend on a large number of variables and interactions between them that are difficult to model with "traditional" methods such as multiple regression (Haslbeck & Waldorp, 2018). Relevant for this study, partial correlation coefficients from network models correspond to multiple regression coefficients, and a measure of how well a node can be predicted by all adjacent nodes in the network (*node predictability*) can be calculated (Haslbeck & Waldorp, 2018). As a result, a GGM provides the same information as a multiple regression model (the equivalent of regression coefficients and R^2) while additionally (1) showing which variables predict not only the response variables, but also the predictors; (2) taking into account *all* the interactions of the variables in the model; (3) mapping out multicollinearity; and (4) allowing for insight into predictive mediation, since a network in which two variables are not directly connected but are indirectly connected (e.g., X—Z—Y) indicates that X and Y may be correlated, but any predictive effect from X to Y (or vice versa) is mediated by Z. For technical details, see Epskamp and Fried (2018) and Epskamp et al., (2018a, 2018b).

We then followed the strategy used by McNally et al. (2022). We first estimated the GGM using the R package *bootnet* (Epskamp et al., 2018a, 2018b), which allows regularization of the network model via the graphical least absolute shrinkage and selection operator (LASSO; Friedman et al., 2008, 2019) to avoid spurious, false-positive edges that can occur when many parameters are estimated. However, more recently, Williams and colleagues (Williams & Rast, 2020; Williams et al., 2019) developed nonregularized methods of network estimation that address some issues related to the performance of the graphical LASSO when the number of cases largely exceeds the number of variables and sparsity (i.e., there are many fewer links than the possible maximum number of links within the network) is not warranted, as is the case here. We then used the method developed by Williams et al. (2019) and implemented in the R package *GGMnonreg*, by using the Bayesian information criterion (BIC) and the forward selection method. Bootstrap procedures (10,000 samples) were used to identify edges that could be considered as reliably different from zero; that is, their 95% confidence interval did not contain zero.

We also used the R package *qgraph* (Epskamp et al., 2012) to compute the centrality indices for the regularized and nonregularized networks, namely, strength centrality and expected influence. The former is the sum of the absolute values of its edges, while the latter is the sum of its edges, accounting for the sign of the edge (Robinaugh et al., 2016). The two indices overlap when all edges incident on a node are positive and diverge when there are negative edges. Other centrality measures are available (betweenness and closeness centrality), but research has advised against their use (see Bringmann et al., 2019; Epskamp et al., 2018a, 2018b).

Lastly, we performed BN analysis, in which an edge originating from one node and pointing toward another shows that the activation of the former predicts the activation of the latter. As a result, if a plausible directed causal system exists among the variables, then BN returns an estimate of the causal structure of the system. We computed DAGs using the algorithms provided in the R package *bnlearn* (Scutari, 2010). While previous studies chose only one algorithm (e.g., McNally et al., 2022, used only hill-climbing), we followed the recommendation by Briganti et al. (2021) to perform BN with different algorithms (those described in the paper by Briganti et al.) as a robustness check and to investigate whether and how edge directions could vary across algorithms.

For each algorithm, we first performed the BN to learn the structure of the network. We then obtained a stable network using the bootstrap function (10,000 samples), which distinguished the structural aspect of the network by adding edges, removing them, and reversing their direction to optimize a goodness-of-fit target score, namely, the BIC. We included in the final network the edges that appeared in at least 85% of the networks and whose direction appeared in more than 50% of the networks (Briganti et al., 2021). Finally, all networks were averaged to obtain the final network and plotted. The relevant R code for the GGMs and BNs is reported in Appendix B of the SM and at https://osf.io/4kcb2/

Results

Descriptive Statistics

The descriptive statistics (mean and standard deviation) and the zero-order correlations between the study variables are reported in Fig. 2. At a bivariate level, GDT showed negligible to weak correlations with background and gaming-related variables, and weak to moderate correlations with measures of mind wandering, attentional control, mindfulness, and maladaptive personality traits.

One of the assumption GGM is the multivariate normality of the data, which is usually addressed (see, e.g., Isvoranu et al., 2017; Richetin et al., 2017) using a nonparanormal transformation (Liu et al., 2009). We performed it and compared the resulting correlation matrix with the one computed on raw data using the test developed by Steiger (1980). The result was not statistically significant (χ^2(990, $n = 506) = 16.44$, $p > 0.999$), suggesting that the results would not have substantially changed had we used the transformed data.

Gaussian Graphical Models

Figure 3 shows the regularized and nonregularized GGM networks. We included in the graphs only those edges whose bootstrapped 95% confidence interval (limits: 97.5th and 2.5th percentile values) did not include zero.

In the regularized network, GDT had non-zero, direct edges with FFMQ-Acting with Awareness ($r_p = -0.13$), PID-5-Disinhibition ($r_p = 0.11$), PID-5-Psychoticism ($r_p = 0.11$), and with playing more than 30 hr weekly ($r_p = 0.21$). These variables, in their turn, were associated with the other maladaptive personality traits, mind wandering, and mindfulness measures, suggesting that at least some of them could have both a direct and an indirect association with GDT (e.g., PID-5-Disinhibition and PID-5-Psychoticism were associated, $r_p = 0.14$). The complete list of nonzero edges in the regularized network is provided in Sect. 3 of the SM. As shown by the centrality indices (Fig. 4), psychoticism stood out as one of the nodes with the highest strength and expected influence, together with playing online and playing more than 30 hr a week. In the regularized network, the correlation stability (CS) coefficients for strength centrality (CS = 0.52), expected influence centrality (CS = 0.75), and edges (CS = 0.75) exceeded the 0.50 recommended threshold (Epskamp & Fried, 2018).

In the non-regularized network, we again found a direct association with FFMQ-Acting with Awareness ($r_p = -0.14$), PID-5-Disinhibition ($r_p = 0.11$), and playing more than 30 hr weekly ($r_p = 0.23$), but also with having an intermediate ($r_p = 0.13$) and a high level of ability ($r_p = 0.15$), with playing 11–20 ($r_p = 0.11$) and 21–30 hr ($r_p = 0.12$) weekly, and with playing strategy games ($r_p = 0.15$). The pattern of indirect effects was substantially more complex than in the regularized network: it included the same psychological predictors, but more background variables. The complete list of nonzero edges in the non-regularized network is provided in Sect. 3 of the SM. This model also provided the predictability of the GDT score, that is, the equivalent of R^2 in multiple regression, which was 0.36 [0.37, 0.49]. The predictability measure for all nodes is provided in Sect. 4 of the SM.

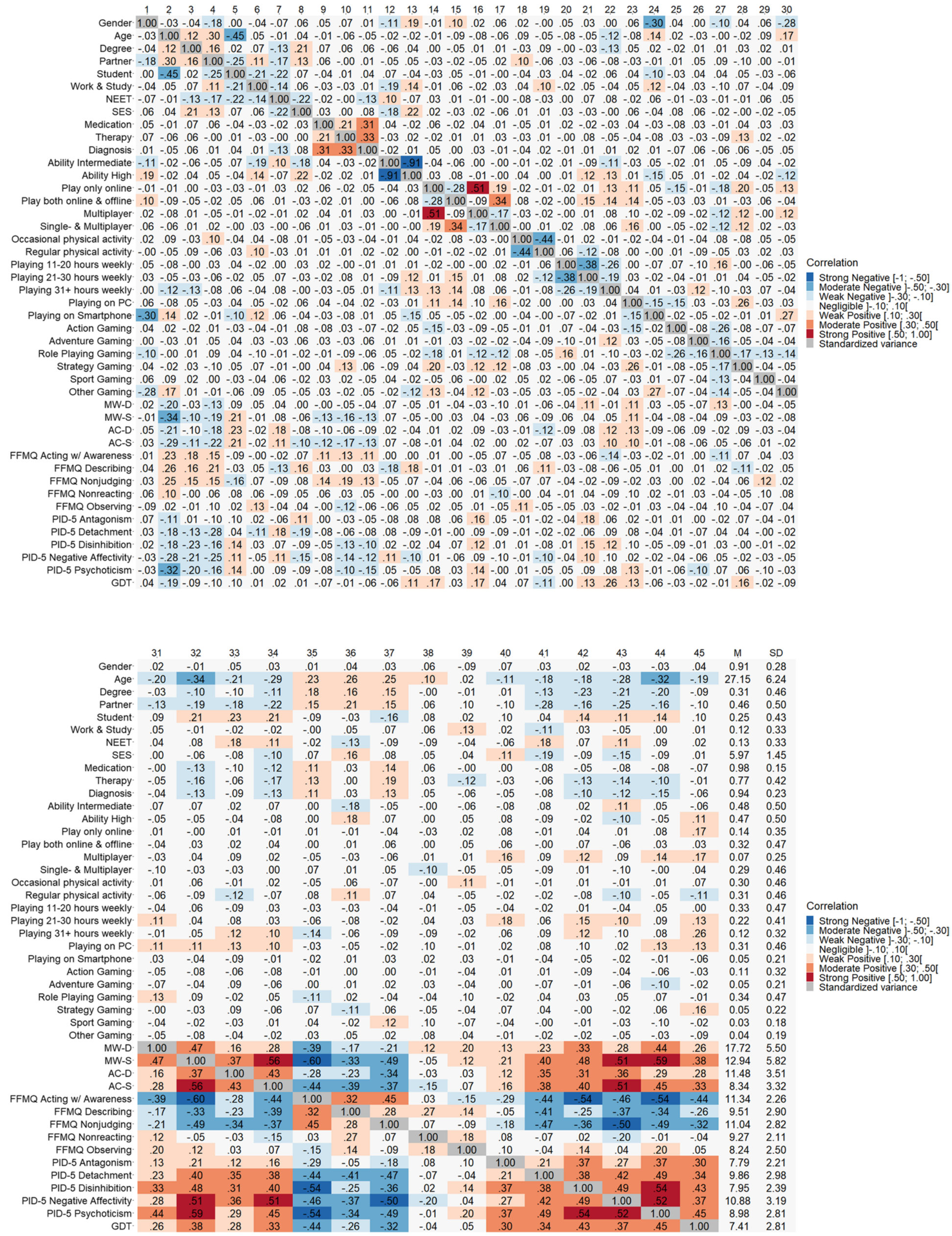

Fig. 2 Correlation matrix and descriptive statistics of the variables used in this study ($n = 506$). Statistical significance thresholds for correlation coefficients given the sample size are (absolute values): 0.146 ($p < 0.001$), 0.114 ($p < 0.01$), 0.087 ($p < 0.05$)

Directed Acyclic Graph

GGM models are useful for uncovering direct and indirect associations between variables, but they do not provide information on the direction of these associations, that is, on the plausible causal effects. For example, in the regularized GGM in Fig. 3, there is a chain of associations from GDT to FFMQ-Acting with Awareness to Mind Wandering-Spontaneous to PID-5 Psychoticism to PID-5 Detachment. The last variable could be the cause of the first, with the other variables being mediators, but the direction of these associations is unknown. As explained above, BNs are a principled alternative to address this issue. Figures 5, 6, and 7 show the networks resulting from the different algorithms implemented in the *bnlearn* package used in this study.

In four out of six solutions, GDT had no incoming edges (i.e., it was not predicted by any other variable), whereas it predicted playing more than 30 hr weekly. However, two algorithms, Hill climbing (Fig. 6, right) and Tabu Search (Fig. 7, left) suggested that GDT, while maintaining its predictor role with respect to a high gaming frequency, was predicted by FFMQ-Acting with awareness, which, in its turn, was predicted by spontaneous mind wandering, which, in its turn, was predicted by deliberate mind wandering. In other words, higher levels of GDT depended on lower levels of FFMQ-Acting with awareness, which depended on higher levels of spontaneous

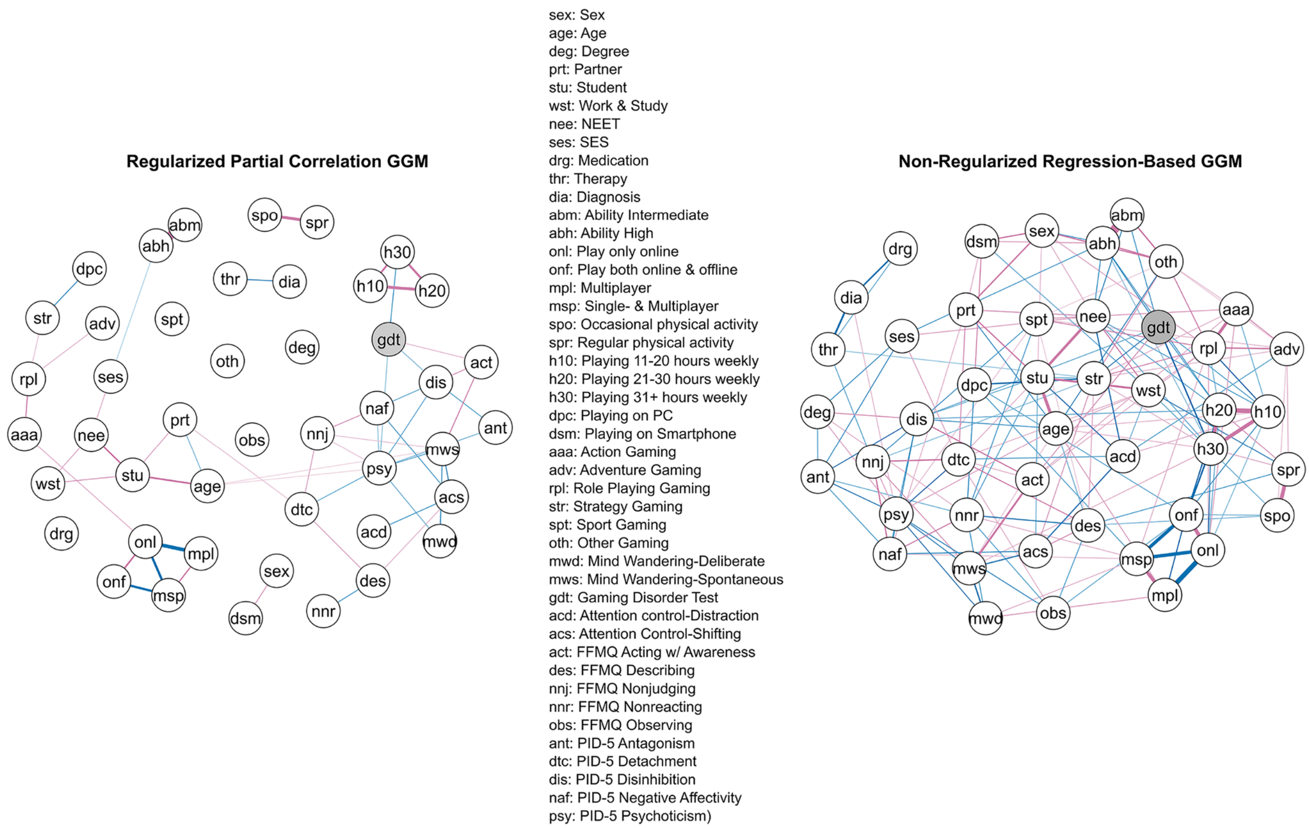

Fig. 3 Regularized and non-regularized Gaussian graphical models (GGM). Blue edges indicate positive associations. Purple edges indicate negative associations. Edge thickness signifies the magnitude of association connecting a pair of variables. The GDT node is greyed for ease of interpretation

mind wandering, which depended on higher levels of deliberate mind wandering.

Discussion

The present study is a substantive-methodological synergy (Marsh & Hau, 2007), bringing to bear new, principled, and evolving methodology (i.e., GGMs and BNs) to tackle a complex substantive issue such as the role of mindfulness, mind wandering, attention control, and maladaptive personality traits in problematic gaming. Previous studies investigated the potential predictors of problematic gaming separately and could not really provide convincing evidence of causal effects (Laier et al., 2018; Mettler et al., 2020; Zhang et al., 2021), since they used mediation models that make it possible to detect indirect relationships but not causal effects, as they used observational, cross-sectional data. In this study, we included all potential predictors in the same model and took advantage of modern statistical methods to gain a deeper understanding not only of the direct and indirect associations of the potential predictors with problematic gaming but also of plausible causal links despite the reliance on the same sort of data. It should be noted that this does not mean that we could empirically observe such causal effects, but BNs allowed us to model the *admissible* causal relationships in our data building upon the properties of DAGs, i.e., expressing the conditional independence relationships between variables by using graphical separation (Briganti et al., 2021).

Before reviewing the results, it is important to take into account that rigorous causal inference requires that there is actually a DAG underlying the data, that all causes of a given variable are measured, that all variables that are connected in a given way are probabilistically dependent, and that there are no bidirectional causal relations (i.e., X causes Y, and Y causes X) or causal loops (e.g., X causes Y, Y causes Z, and Z causes X) (Maathuis et al., 2018), all conditions that cannot be verified for this study. However, this study represents an advance over previous ones since GGMs and BNs allowed us (1) to show which variables predicted not only problematic gaming but also the other predictors, (2) to take into account *all* the interactions of the variables in the model, (3) to map out multicollinearity, and (4) to gain insight into predictive mediation.

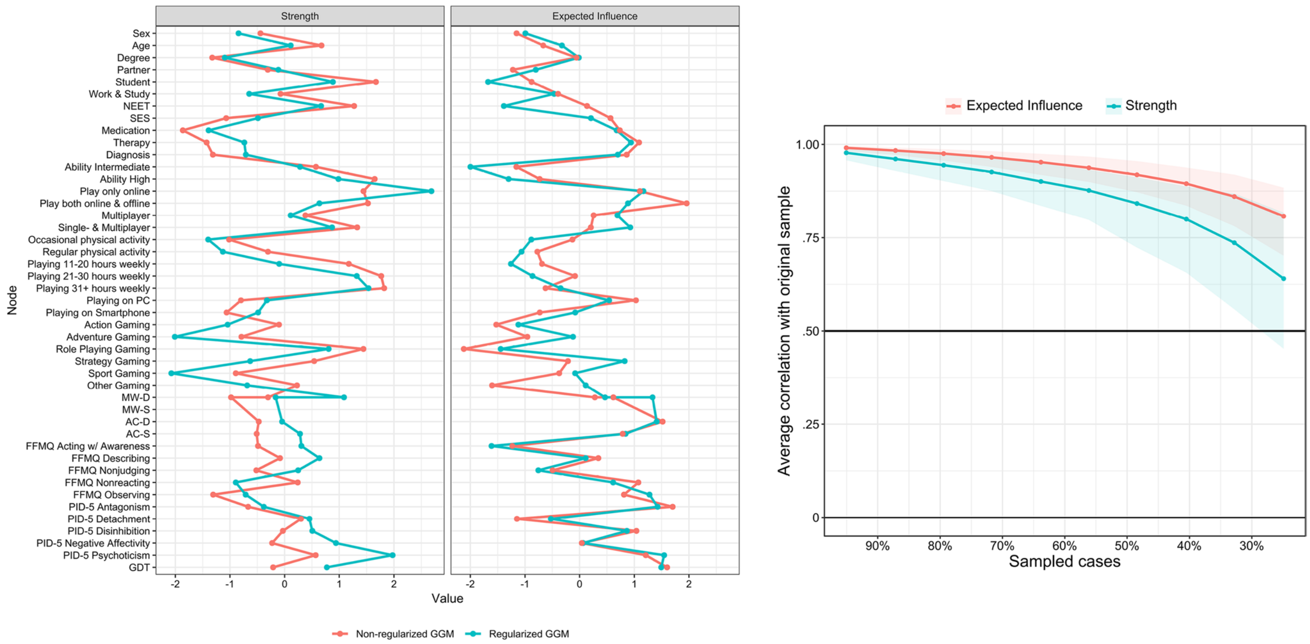

Fig. 4 Centrality (CPs, left) and correlation stability (CS, right) plots. CPs show the standardized node strength and expected influence for the regularized and non-regularized networks. CS represents the stability of strength and expected influence centrality indices in case-dropping analysis for the regularized GGM. CS plot shows the correlation between strength centrality values in the full sample with the centrality values from successively smaller subsets of the sample

The strength of zero-order correlations of problematic gaming with measures of mind wandering, mindfulness, attention control, and maladaptive personality traits was consistent with previous results, with values ranging from the 0.20 s to the 0.40 s. The strongest correlation of the problematic gaming measure with background and gaming-related variables was with playing more than 30 hr a week, but still in the 0.20 s.

GGMs showed a more complex pattern of direct and indirect associations. The regularized GGM revealed direct edges with FFMQ-Acting with Awareness, PID-5-Disinhibition, PID-5-Psychoticism, and with playing more than 30 hr a week. Similar results were obtained with the non-regularized GGM, which also indicated direct associations with the ability level and with playing strategy games. These variables with which problematic gaming had a direct link were, in their turn, directly associated with the other maladaptive personality traits and mind wandering and mindfulness measures, suggesting an even more entangled web of indirect associations. The direct associations with playing many hours a week, high levels of ability, and playing strategy games are somehow obvious. A distinctive feature of problematic gaming is spending an excessive amount of time playing, at the expense of other life activities, and this is likely to be associated with being (very) good at it, and an association of problematic gaming with playing strategy games has already been shown (e.g., Eichenbaum et al., 2015). It could be hypothesized that these sorts of games can become addictive because they challenge players to solve problems at a pace that can be set by the players themselves, and some players might have some traits, e.g., incompleteness feelings and not just right experiences (see Belloch et al., 2016) that might be predisposing factors.

The association with disinhibition is consistent with the known association of problematic gaming with impulsivity (e.g., Schiebener & Brand, 2017) and the way in which this construct is operationalized in PID-5-BF items (i.e., being seen as irresponsible, being described as reckless). As for psychoticism, i.e., having unusual beliefs and experiences as well as cognitive and perceptual dysregulation, its association with problematic gaming replicates previous studies that found that some problematic gamers seem to share their beliefs and pursue odd thinking without fear of judgement by identifying themselves with their avatar (Schimmenti et al., 2017).

However, when we used BNs to detect admissible causal effects, the only direct predictor (and thus possible direct cause) of problematic gaming was Acting with Awareness. This effect should be interpreted as the occurrence of high scores on problematic gaming depended on the presence of low scores on Acting with Awareness. In its turn, the occurrence of low scores on Acting with Awareness depended on the presence of high scores on spontaneous mind wandering, and the occurrence of high scores on spontaneous

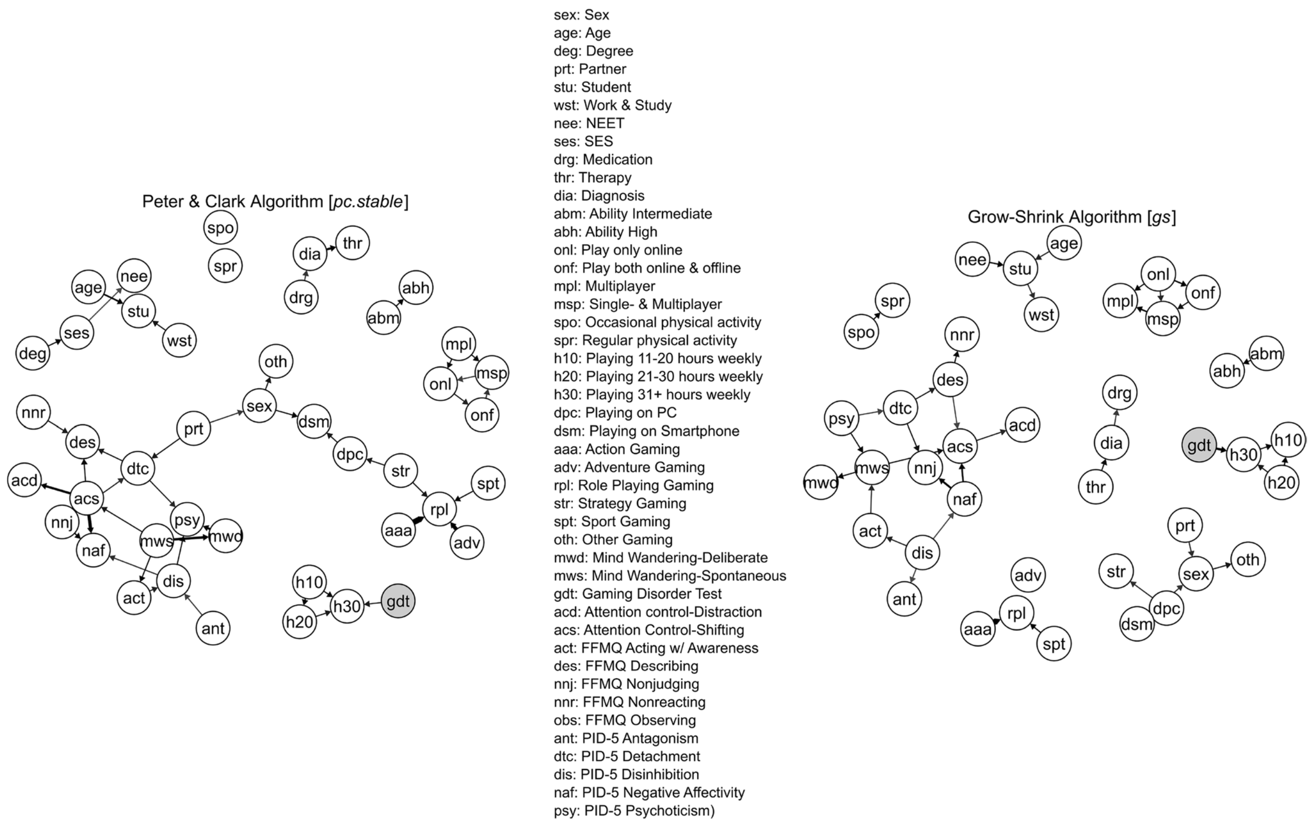

Fig. 5 Directed acyclic graphs (DAGs) using the Peter and Clark algorithm (left) and the grow-shrink algorithm (right). Edge thickness indicates confidence in the direction of prediction shown. The GDT node is greyed for ease of interpretation

mind wandering depended on the presence of high scores on deliberate mind wandering. Acting with Awareness consists in fully engaging in activities in the present moment, paying attention to them without distractions or thinking about something else, i.e., avoiding mind wandering. It has been shown that Acting with Awareness can inhibit the development of craving from negative affect in addictions (Enkema et al., 2020) and predicts better self-regulation and therefore fewer negative outcomes for problematic internet use (Calvete et al., 2017). As suggested by Mettler et al. (2020), problematic gamers might not be aware that gaming is a means to avoid or escape from adverse life events and/or negative affect, and a reason why mindfulness training can be beneficial in these cases is to enable individuals to cope without engaging in avoidance tendencies. For instance, Hagström and Kaldo (2014) reported that higher levels of negative escapism (i.e., escaping from or avoiding real-life problems or worries) predict problematic gaming and lower life satisfaction when taking into account gaming motivations for achievement or socialisation. In a similar vein, Laier et al. (2018) suggested that playing online might be used to avoid negative feelings such as separation insecurities, anxiety, emotional lability, intimacy avoidance, or anhedonia, thus potentially being a dysfunctional coping behavior with negatively reinforcing short-term effects and potentially negative effects in the long run.

The results of this study suggested that lower levels of Acting with Awareness are predicted (and possibly caused) by higher levels of spontaneous mind wandering, consistent with previous studies that found a direct link with behavioral addictions such as problematic smartphone use (Müller et al., 2021). Evidence from neuroimaging has suggested that mind wandering and, more generally, spontaneous thinking are associated with the activity of the default mode network (e.g., Mason et al., 2007), which has been suggested to be the "engine" of negative affect (Perkins et al., 2015). Spontaneous thought mostly focuses on unattained goals and evaluates the discrepancy between current and desired status (Marchetti et al., 2016), conditions that are likely to be experienced by problematic gamers, either in their life in general or in the game itself. In these individuals, spontaneous thought might promote severe cognitive vulnerabilities, such as rumination, hopelessness, low self-esteem, and cognitive reactivity.

Rumination can be in terms of reflective pondering, i.e., the extent to which gamers try to improve their mood by focusing on a problem, and of brooding, i.e., the passive

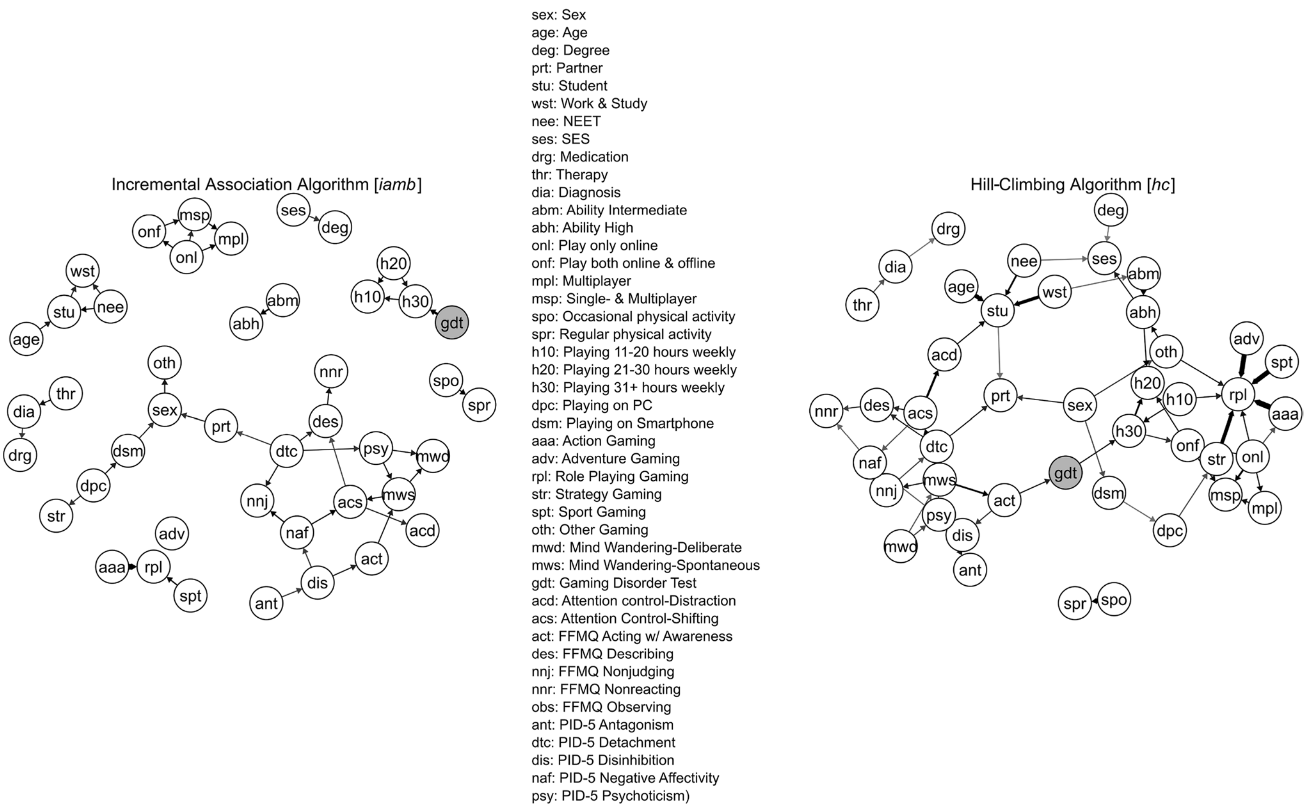

Fig. 6 Directed acyclic graphs (DAGs) using the incremental association algorithm (left) and the hill-climbing algorithm (right). Edge thickness indicates confidence in the direction of prediction shown. The GDT node is greyed for ease of interpretation

comparison of the gamer's current situation or with some unachieved standard (Kökönyei et al., 2019; Treynor et al., 2003). Hopelessness is commonly defined as "an expectation that highly desired outcomes will not occur or that highly aversive outcomes will occur, coupled with the expectation that no response in one's repertoire will change the likelihood of occurrence of these outcomes" (Abramson et al., 1989, p. 359). However, the non-occurrence of desirable scenarios can affect mental functioning and mood only to the extent to which the individual is committed to achieving those outcomes and thinks they are "in the realm of possibility." Thus, gamers can commit themselves to specific goals and remain concerned until either reaching or abandoning them (Abramson et al., 1989) and when a goal is self-central, it can lead to major consequences, similar to an actual stressful life event (Carver & Scheier, 1998).

Low self-esteem, i.e., a negative attitude toward the self (Rosenberg, 1965), is actively processed during spontaneous mind wandering, with the ideal self-representing a higher-order goal to which individuals are highly committed in their undirected thoughts. Individuals vulnerable to negative affect tend to dwell on and magnify previous mistakes and disappointments, which, in turn, leads to concurrent low self-esteem (Watson & Clark, 1984). Gamers that experience a large actual-ideal self-discrepancy may view their actual self as negative and unworthy, and the larger and more negative such discrepancy, the more pressing, more repetitive, and probably more abstract mind wandering can become (Marchetti et al., 2016). Cognitive reactivity represents the fluctuations of negative self-attitudes in reaction to stressors, even if these are mild (Butler et al., 1994). According to the cognitive schema theory (Beck, 1967), information processing depends on one's schemata, i.e., cognitive representations about the self, the world, and the future, that are thought to impact mental functioning if activated by relevant stimuli (Clark et al., 1999). Cognitive reactivity thus refers to the tightening of the associative network among the self, negative thinking, and negative mood following depressive episodes (Teasdale, 2008). Cognitive reactivity can be elicited by mind wandering through the narrowing of the associative network of spontaneous thinking (i.e., funneling effect).

According to the escaping hypothesis, all these issues could be coped with by gaming. A recent study on pathological slot playing (Kruger et al., 2020) found that problematic gamblers use deliberate mind wandering as a maladaptive strategy to cope with the negative affect induced by a highly repetitive and boring vigilance task, but not during slots play.

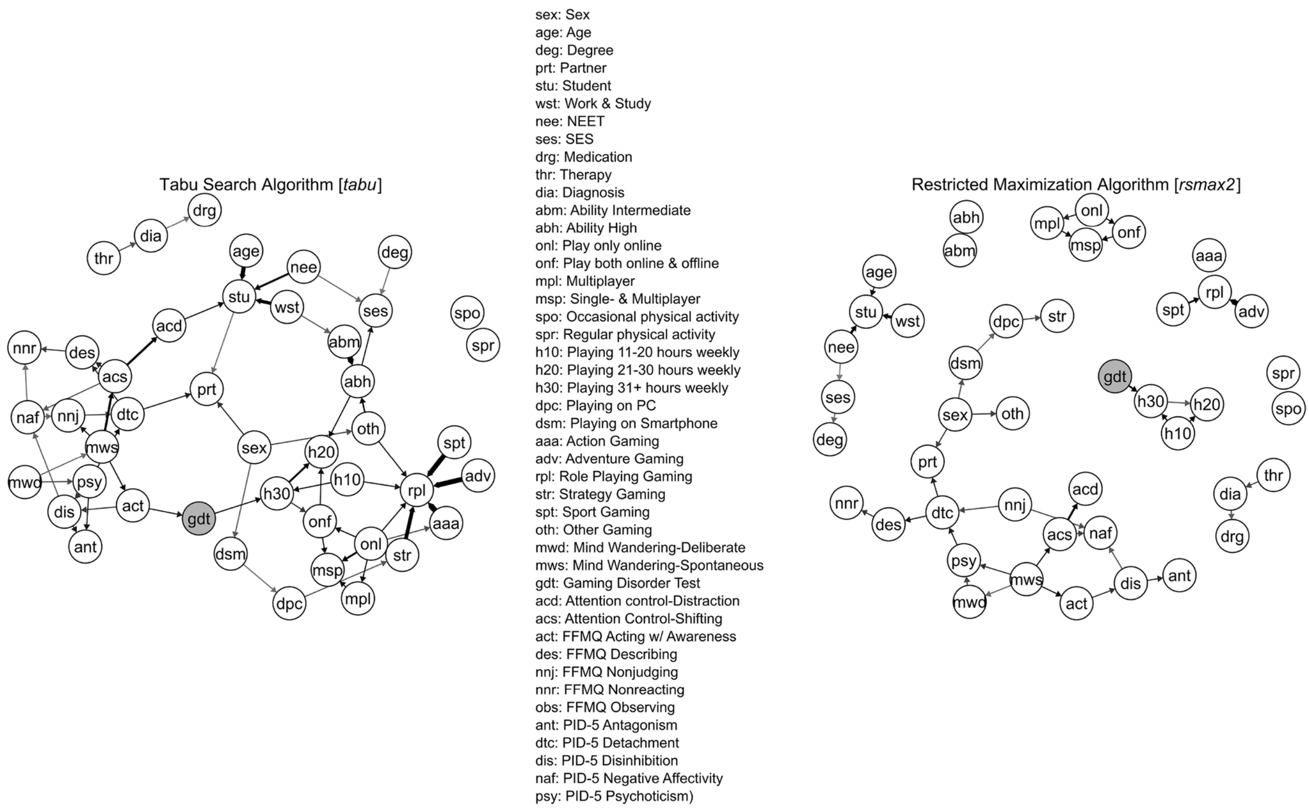

Fig. 7 Directed acyclic graphs (DAGs) using the Tabu search algorithm (left) and the restricted maximization algorithm (right). Edge thickness indicates confidence in the direction of prediction shown. The GDT node is greyed for ease of interpretation

The authors suggested that since slots play induces positive affect, deliberate mind wandering is no longer needed to escape negative affect. Our models did not provide evidence of a direct association of negative affect with deliberate mind wandering (Fig. 3 and Figs. 5, 6, and 7), although we found that deliberate mind wandering indirectly predicted problematic gaming (Fig. 4b right and Fig. 4c left), consistent with the result reported by Kruger et al. (2020) that deliberate mind wandering predicted unique variance in the severity of problematic gambling, while controlling for depression, mindfulness, and problem gambling.

Taken together, these results seem to indicate that mindfulness and mind wandering do play a role in problematic gaming. Although research has shown that they are contrasting constructs, with higher levels of one being associated with lower levels of the other (e.g., Mrazek et al., 2012), these two phenomena are not fully opposite as their correlation is only weak to moderate. Evans et al. (2009) suggested that such strength of association can be due to both phenomena partially relying on the same functions, such as self-awareness, but while mindful awareness is characterized by a non-judgmental attitude toward the self, problematic mind wandering seems to elicit a harmful tendency to process self-salient goal discrepancies, repetitively and abstractly, together with a reduced ability to stop it (Marchetti et al., 2016). The content of spontaneous thoughts of mindful individuals is focused on concrete processing, decreased personal significance, and positive valence, with reversed characteristics in individuals with high levels of rumination (Andrews-Hanna et al., 2013).

Although some studies (e.g., Enkema et al., 2020; Mettler et al., 2020) suggested a general "negative affect" as a potential primary cause for problematic gaming, the results of the current study (and especially BNs) seem to suggest that Acting with Awareness could be an ideal target for intervention. Mindfulness interventions have already shown some efficacy in the treatment of substance use and gambling disorders (e.g., ; Toneatto et al., 2014), and Mindfulness-Oriented Recovery Enhancement (MORE) has been found to be a promising treatment for internet gaming disorder (Li, et al., 2017). In general, the target of such interventions is the maladaptive aspects of spontaneous thinking, such as the content of spontaneous thoughts, the negative emotional reactivity elicited by the processing of concern-related cues that lead to a narrowing of undirected thought, the underlying motivational structure, and the extent of undirected thought. Mindfulness-based cognitive therapy (Ma & Teasdale, 2004) and acceptance and commitment therapy (Hayes et al., 1999) can effectively reduce self-criticism during spontaneous thinking, and there are specific trainings that can target individual processing styles, moving from abstract to more concrete (Watkins et al., 2012). In other words, interventions should help individuals to become able to stay with and adequately process the current negative emotional states without resorting to gaming to escape them.

Previous research had suggested that attentional control and maladaptive personality traits also seem to play an important role in the emergence and maintenance of the problematic gaming. In this study, BNs did not reveal compelling evidence of direct effects of attentional control and maladaptive personality traits on problematic gaming, although the results of GGMs and previous research suggest that their contribution might not be completely ruled out.

Limitations and Future Research

The results of this study should be considered in light of some limitations. As stated at the outset of this section, the results of BNs can reliably inform on causal links if certain conditions are met. As with any other correlation-based method (e.g., factor analysis), the inclusion of irrelevant variables and/or the exclusion of relevant ones can affect the whole pattern of association, and thus the results. For instance, participants' metacognitions (Spada et al., 2008) and motivational structure could have been assessed, too, since they can lead to either positive or negative outcomes. Both longing for unrealistic, overvalued, unattainable goals and reluctance to give up on them once failed are likely to produce emotional discomfort in individuals with excessive spontaneous thoughts (Marchetti et al., 2016). Unfortunately, at the time we designed the study, no validated Italian version of the Motivational Structure Questionnaire (Cox & Klinger, 2011) or of Yee's (2006) inventory of motivations for play in online games were available. As noted by one reviewer, motivations to play are conceptually close to Schwartz's (2012) values, Self-Determination Theory (Ryan & Deci, 2017), and also cover some aspects, such as escapism, in the realm of mindfulness and mind wandering.

Given the cross-sectional nature of this study, we could not test whether the relationships between Acting with Awareness and problematic gaming or between problematic gaming and hours of playing could actually be bidirectional or whether the two variables were involved in some causal loop that went undetected in the analyses. As pointed out by Briganti et al. (2021), the assumptions of BNs might be difficult to meet with psychological data.

Another limitation of this study is the complete reliance on self-report measures, which can be biased by, for example, social desirability and memory recall. As a result, there might have been inaccuracies in answers to psychological questionnaires and in reporting gaming time or having received a diagnosis or not, although the question explicitly specified that the diagnosis should have been obtained by a qualified professional. However, obtaining objective measures of mind wandering, of gaming time, and adequately screening for psychopathology (possibly recruiting a clinical sample fulfilling shared criteria) would have required a different study design.

This leads to another major limitation of this work, namely, the convenience sampling strategy. As in the preliminary study on the psychometric properties of our Italian version of the GDT, we searched for "gamers" through social media, gaming forums, and personal contacts. Despite the fact that the two samples were recruited independently, the vast majority (90%) of the participants identified themselves as males. Such self-selection bias is not new, likely because in Italy, too, there are common gender stereotypes around gaming and participants who identify as females are less likely to identify as gamers compared to participants who identify as males (Mettler et al., 2020; Shaw, 2012; Williams et al., 2008), while several reports indicate that the gender distribution of gamers is approximately equal between males and females (Elliott et al., 2012). On a related note, potential participants who identify as females could have been less willing to participate in a study focusing on video gaming, despite the fact that these participants tend to be more likely to participate in surveys (Mulder & Bruijne, 2019). The generalizability of these results is also limited by the cultural context in which the study was carried out, as cultural differences in who is a "gamer", what kinds of people are perceived to be "gamers", and who perceives themselves as gamer have been shown (Ćwil & Howe, 2020; Lee & Wohn, 2012).

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Author Contribution Carlo Chiorri: methodology, software, validation, formal analysis, data curation, writing — original draft, writing — review and editing, visualization, supervision, project administration.

Paolo Soraci: conceptualization, methodology, software, investigation, resources, writing — original draft, writing — review and editing, project administration.

Ambra Ferrari: conceptualization, methodology, software, investigation, resources, writing — original draft, writing — review and editing, project administration.

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Data Availability Due to the requirements of the consent form, participants of this study did not agree for their data to be shared publicly, so supporting data is not available. Materials that cannot be accessed otherwise and the R code for the Gaussian graphical models and the Bayesian network models are available in the Appendices of the Supplementary Materials file.

Declarations

Ethics Statement This study was performed in line with the principles of the Declaration of Helsinki, and with the Ethical Principles of Psychologists and Code of Conduct of the American Psychological Association and of the Italian Psychological Association. Approval was granted by the Ethics Committee of the Department of Educational Sciences of the University of Genova (Italy) [Comitato Etico per la Ricerca del Dipartimento di Scienze della Formazione (DISFOR) – Università degli Studi di Genova].

Informed Consent Potential participants were presented with a document that informed them on the treatment and processing of the data collected in this study, and to proceed they had to declare that they had read, understood, and agreed with it. Note that, according with the Italian law, in this document, it was explicitly stated that the data from this study would have been published only in aggregate form, and that no individual data would have been disclosed. Next, they were presented with the informed consent form, which described the aim of the study, the materials used, the estimated completion time, and the possible risks and benefits, including the absence of compensation. Participants had to declare that they were at least 18 years of age, that they had understood the content of the informed consent form, and that they were willing to participate and aware that they could quit the survey at any moment without consequences. Lastly, participants had to confirm that they consented to the processing of their data for the purposes of research within the limits and with the modalities presented in the former forms.

Competing Interests The authors declare no competing interests.

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