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The neurocognitive correlates of non-substance addictive behaviors

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ABSTRACT

Neurocognitive deficits have been implicated as transdiagnostic risk markers of substance use disorders. However, these have yet to be comprehensively evaluated in other, non-substance addictions. In a large, general community sample (N = 475) the present study evaluated the neurocognitive correlates of problem alcohol use and three non-substance-related addictive behaviors: addictive eating (AE), problematic pornography use (PPU), and problematic use of the internet (PUI), to identify potential shared and distinct neurocognitive correlates. A sample of Australian residents (54.4 % female M[SD] age = 32.4[11.9] years) completed a comprehensive online assessment of neurocognitive tasks tapping into eight distinct expert-endorsed domains purportedly associated with addiction. Multiple linear regressions with bootstrapping were used to examine associations among each addictive behavior of interest and neurocognition, trait impulsivity, and compulsivity, as well as key covariates. Neurocognition was differentially associated with each addictive behavior. None of the neurocognitive domains were significantly associated with problematic alcohol use or AE (p >.05), poorer performance monitoring was significantly associated with higher levels of PPU and PUI ($\beta = -0.10$, p =.049; $\beta = -0.09$, p =.028), and a preference for delayed gratification was associated with more severe PUI ($\beta = -0.10$, p =.025). Our findings have theoretical implications for how we understand non-substance addiction and suggest the need for a more nuanced approach to studying addictive behaviors that take into account the underlying neurocognitive mechanisms associated with each type of addiction.

1. Introduction

Addiction is a complex condition characterized by repeated engagement in substance use or other behavior despite negative consequences (Diagnostic Statistical Manual of Mental Disorders [DSM-5]: American Psychiatric Association, 2013). The literature has predominantly centered on substance use disorders, such as alcohol use disorder (AUD), whereas there has been an increasing focus on non-substance (behavioral) addictions (Chamberlain et al., 2016). Recent such efforts include addictive eating (AE), problematic pornography use (PPU), and problematic use of the internet (PUI) due to their associated psychological distress and poorer quality of life (Burmeister et al., 2013; Burrows et al., 2018; Camilleri et al., 2021; Fineberg et al., 2018; Floros & Ioannidis, 2021; Kuss et al., 2014; Raj et al., 2022). It is essential to acknowledge that none of these addictive behaviors have agreed-upon clinical criteria. Consequently, it is more appropriate to view them as problem behaviors positioned on a severity continuum. AE, PPU, and PUI may share some important features with substance addiction, including loss of control, craving, and emotional distress (Adams et al., 2017; Fineberg et al., 2018; Grubbs et al., 2015; Tiego et al., 2021). Addictive behaviors can be conceptualized using current neurocognitive 'dual-process' models of addiction, typified by excessive drive and reward-seeking coupled with impaired executive 'top-down' control (Volkow et al., 2019; Volkow & Morales, 2015). Dual process models have been further extended in non-substance addictive behaviors (Brand, 2022; Brand et al., 2019; Wei et al., 2017). However, addiction-specific neurocognitive functions have yet to be comprehensively evaluated in non-substance addictions. For example, it is unclear whether

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non-substance addictive behaviors share neurocognitive features. Substance use research has also shown inconsistent neurocognitive correlates (Ekhtiari et al., 2017; Lundqvist, 2005; Smith et al., 2014). Identifying the neurocognitive correlates of addictive behaviors is essential to progressing etiological understanding and facilitating the development of effective prevention and intervention strategies. This study investigates the *trans*-behavioral neurocognitive correlates of non-substance addictive behaviors; namely, AE, PPU, and PUI, in comparison to problematic alcohol use, to identify potential shared and distinct neurocognitive mechanisms.

Current consensus is that some neurocognitive deficits can serve as transdiagnostic markers of addiction, regardless of the specific type of behavior (Yücel et al., 2019). Self-regulation is often defined as being comprised of: *Inhibition*, the ability to stop or inhibit an undesirable automatic response (Chambers et al., 2009); *Shifting*, the ability to flexibly shift between tasks, mental sets, or demands (Kiesel et al., 2010); and *Performance monitoring*, the ability to monitor and evaluate action outcomes to adjust performance (Franken et al., 2018). Poorer executive functioning in individuals with addiction is marked by reduced inhibitory control, poorer performance monitoring, and inflexible task shifting (Franken et al., 2018; Odlaug et al., 2011; Rodrigue et al., 2018; Smith et al., 2014; Zhou et al., 2013). By contrast, the 'bottom-up' motivational processes associated with addiction are underpinned by heightened reward-seeking; chief among this is an increased preference for immediate over larger but delayed rewards or poor 'delay discounting' (Amlung et al., 2017), and heightened incentive attribution towards addiction-related cues (Berridge & Robinson, 2016). Unfortunately, most studies to date have focused on individual neurocognitive factors in isolation. Therefore, there is a lack of empirical evidence regarding how each domain is independently associated with addictive behaviors. This is a critical area of further investigation since neurocognitive functions associated with executive control and heightened reward-seeking significantly overlap with each other (Criaud & Boulinguez, 2013; Ridderinkhof et al., 2004).

Few studies have examined neurocognitive functioning associated with AE, PPU, and PUI. Existing studies have generally identified neurocognitive markers implicated in problematic alcohol use, including heightened attentional bias toward reward cues (Adams et al., 2019; Jeromin et al., 2016; Mechelmans et al., 2014; Nikolaidou et al., 2019) and a preference for immediate gratification over larger, later rewards (Cheng et al., 2021; Kowalewska et al., 2017; VanderBroek-Stice et al., 2017). Individuals with AE, PPU, and PUI also present with executive dysfunction, but in differing domains. PUI but neither AE or PPU has been shown to be associated with impaired response inhibition (Antons & Brand, 2018; Antons & Matthias, 2020; Hardee et al., 2020; Ioannidis et al., 2022; Meule et al., 2012; VanderBroek-Stice et al., 2017), and both AE and PUI have been shown to be associated with impaired performance monitoring (Franken et al., 2018; Rodrigue et al., 2018; Zhou et al., 2013). It is unclear whether these differences arise from methodological differences, for example selection of neurocognitive measures, sample characteristics, and inclusion (or lack there-of) of covariates. Because many studies only look at a single neurocognitive measure, it is entirely plausible that differing executive control profiles among AE, PPU, and PUI may be due to common neurocognitive function(s) that drive performance across measures. Further, sample characteristics often vary, including differing illness severities, and demographic features (e.g. sex, age). These studies also do not address comorbidities of other addictive behaviors. Assessing the relationship between neurocognition and multiple addictive behaviors in the same sample would account for these disparities, and help us evaluate whether AE, PPU, and PUI share common underlying neurocognitive processes.

Examining addictive behaviors in general community samples using a dimensional approach can lead to a more nuanced understanding of the neurocognitive functions underlying addictive behaviors. Clinical presentations of addiction represent only the tip of the iceberg, as the majority of addiction problems do not meet strict diagnostic thresholds (Grant et al., 2015; Hasin et al., 2013). Further, despite not meeting diagnostic thresholds, these addictive behaviors still contribute to burden of disease and are important to detect early. By adopting a dimensional approach and examining addictive behaviors across the full spectrum of severities, we can detect often more subtle effects, with direct implications for the development of early intervention strategies.

In addition to neurocognition, addictive behaviors are associated with trait impulsivity and compulsivity (Forsén Mantilla et al., 2022; Kuss et al., 2014; Murphy et al., 2014). Impulsivity can be defined as the tendency to rapidly react to a situation in a reward-driven manner, without forethought or consideration of the consequences (Moeller et al., 2001). Impulsivity is a multifaceted construct, commonly conceptualized and assessed in addiction research as being made up of four key facets: lack of planning, lack of perseverance, sensation seeking and emotion-driven rash action (urgency; Cyders et al., 2014). Compulsivity can be defined as repeated actions that are inappropriate to a given situation and lacks a clear connection to an overarching goal, often resulting in negative consequences (Dalley et al., 2011). Although previous research has found neurocognitive functions correspond with trait impulsivity (Christiansen et al., 2012) and compulsivity (Albertella et al., 2020), when assessed concurrently it is clear that they are not measuring the same underlying construct (Eisenberg et al., 2019). For example, convergent validity among task-related executive function and self-report questionnaires was only moderate in a large *meta*-analysis on self-regulation ability (Duckworth & Kern, 2011). Therefore, both trait-based and neurocognitive-based measures of impulsivity and compulsivity appear to contribute to addiction vulnerability in different ways.

This study sought to investigate the neurocognitive correlates of addictive behaviors. Using a tailored assessment battery that measures a comprehensive range of addiction-specific neurocognitive functions, the present study aims to evaluate the shared and distinct neurocognitive correlates of problematic alcohol use, AE, PPU, and PUI, adjusting for key covariates. A demographically targeted, general community sample was recruited to capture a broad spectrum of behavioral severity.

2. Methods

2.1. Participants and procedure

This study was embedded in a larger normative study for the BrainPark Assessment of Cognition (BrainPAC) neurocognitive battery (see supplementary material). Australian residents were recruited via Prolific, social media advertisements, and local community newsletters. Inclusion criteria were: 18 to 65 years old, not color blind, self-reported absence of a neurological disorder (i.e. stroke, brain injury, and dementia) or history of a psychotic disorder. Participants completed all measures online via the Qualtrics survey platform (https://www.qualtrics.com). The neurocognitive tasks were separated by self-report surveys (trait and behavior scales) and the order of task presentation was counterbalanced. The study was approved by the Monash University Human Research Ethics Committee [26088].

2.2. Neurocognitive measures

The neurocognitive battery (Table 1) was selected to measure expert-endorsed neurocognitive domains as associated with addiction and addiction-related outcomes (Yücel et al., 2019).

2.3. Self-report scales

Trait Compulsivity – The Cambridge-Chicago Compulsivity Trait Scale (CHI-T; Chamberlain & Grant, 2018; Tiego et al., 2023) is a 15-item scale. Items are summed into an overall score. Higher scores indicate higher compulsivity.

Trait Impulsivity – The Short UPPS Impulsive Behavior Scale (SUPPS-

Table 1
Neurocognitive assessment battery.

Function	Task	Brief description	Trials (practice)	Primary metric
Response inhibition	The BrainPAC Stop Signal Taks (SST) (Lee et al., 2023)	A gamified visual cue stop signal paradigm (Verbruggen et al., 2019) in a medieval war game format, with the goal of defeating a dragon. Players pass arrows to two archers (left/ right) as fast as they can (go signal) whilst avoiding the dragon's fire (stop signal) so they can shoot the arrows and defend their village.	150 (10)	Stop signal reaction time (SSRT). Higher RT indicates poorer response inhibition.
Reward learning (reward-related attentional bias)	The BrainPAC Value Modulated Attentional Capture (VMAC) Task (Lee et al., 2023)	A gamified version of the original VMAC task (Albertella et al., 2019; Le Pelley et al., 2015) following a soccer format. Players must kick the ball (left/right), with speed and accuracy to earn points. Some trials have players with different hair colors acting as distractors and indicating the potential reward value of that trial.	5x24 (6)	VMAC score averaged across the last two blocks of the task. Higher values reflect more reward-related attentional capture.
Reward learning (goal-directed vs habitual)	The BrainPAC Sequential Decision-Making Task (SDT) (Lee et al., 2023)	A gamified two-step choice task (Kool et al., 2016, 2017), presented in the form of an animal rescue game. Participants select a ranger to search two environments (the forest or the farmland) for lost animals. Model-based decision-makers learn which rangers are most effective at finding the maximum number of animals.	125 (25)	Mixing weight (*w*). Higher scores indicate more goal-directed (model-based) decision-making.
Reward valuation (risky decision-making under uncertainty)	The BrainPAC Balloon Analogue Risk Task (BART) (Lee et al., 2023)	A gamified version of the BART stretch variant (Lejuez et al., 2002) paradigm in which players inflate a series of balloons to earn hypothetical money (maximum earning of $128 AUD p/ balloon). Each balloon has a pseudorandomized burst threshold (mean burst point at $64 AUD), resulting in any potential earnings being lost.	30 (10)	Mean pre-committed pumps across all balloons. Higher values indicate riskier choice in the face of uncertainty.
Flexible updating	N-back Task (Ragland et al., 2002; Inquisit 5, 2018)	A letter sequencing go/no-go task. Participants respond to "M" in 0-back trials, to the previous letter in 1-back trials, and to the letter two trials back in 2-back trials, and so on.	3x60 (9)	3-back d' (parametric measure of sensitivity). Higher d' values indicate more flexible updating/ better working memory performance.
Goal selection; updating, representation and maintenance	Category Switch Task (CST) (Friedman et al., 2008; Inquisit 5, 2018)	Participants are presented with a word they must categorize in terms of A) 'living', or B) 'size'. Each trial is accompanied by a cue that indicates to the participant whether they are required to categorize the object according to conditions A or B.	65 (80)	Latency switch cost. Higher values indicate poorer task switching.
Performance monitoring	Error Awareness Task (EAT) (Hester et al., 2007; Inquisit 5, 2018)	A visual go/no-go paradigm in which participants indicate their error awareness following any commission error.	2x150 (70)	Percentage error awareness (commission errors). Higher values indicate better error awareness.
Temporal discounting	Monetary Choice Questionnaire (MCQ) (Kirby et al., 1999)	A 27-item questionnaire asks the participant to choose between two hypothetical reward options, a smaller reward now, or a larger reward at some point in the future e.g. "Would you prefer $15 today or $35 in 13 days".	27 (NA)	Log *k* Higher values indicate a preference for sooner but smaller rewards.

P; Cyders et al., 2014) is a 20-item scale. Three scores were calculated: urgency (combining negative and positive urgency subscales), lack of perseverance and premeditation (combining lack of perseverance and premeditation subscales), and sensation seeking (SS: sensation seeking subscale). Higher values indicate greater impulsivity.

Psychological Distress – The Depression Anxiety Stress Scale (DASS-21; Szabó, 2010) is a 21-item scale used to assess current psychological distress. Items were summed into form a total score. Higher scores indicate greater distress.

2.4. Dependent variables

Participants were asked to respond reflecting on the past three months.

Problematic Alcohol Use – The Alcohol Use Disorder Identification Test (AUDIT; Saunders et al., 1993) is a 10-item scale. A total score is summed, ranging from 0 to 40.

Addictive Eating – The modified Yale Food Addiction Scale version 2 (mYFAS 2.0; Schulte & Gearhardt, 2017) is a 13-item scale. A symptom count is computed, ranging from 0 to 11.

Problematic Pornography Use (PPU) - The Problematic Pornography Consumption Scale (PPCS-6: Bőthe et al., 2021) is a 6-item scale. A total score is calculated, ranging from 6 to 42.

Problematic Use of the Internet – The abbreviated Young's Internet Addiction Test (IAT-10; Tiego et al., 2021) is a 10-item scale. A total score ranging from 10 to 50 is computed.

2.5. Data cleaning

To ensure data quality, online neurocognitive assessment requires comprehensive screening protocols and post-hoc data cleaning. Bots and fraudulent responses were identified and excluded using features embedded in the Qualtrics survey platform. Implausible responses and poor performance presumedly due to lack of effort were identified and removed via a) attention check questions (e.g. "Please select the option *Piano Keys*"); b) neurocognitive task performance at less than chance levels (as per Lee et al., 2023; Albertella, Watson, et al., 2019); c) task-specific cleaning procedures (e.g. SST go trial accuracy, stop trial accuracy, [Verbruggen et al., 2019] and Independent Race Model check [Band et al., 2003]). Mann Whitney U and t-tests were used to investigate differences between individuals whose data was filtered out compared with included individuals on all variables (Table A1).

2.6. Data analysis

Individuals who reported not engaging in an addictive behavior in the past 3 months were assigned a zero for the corresponding problem behavior scale. Statistical outliers on neurocognitive measures ≥ 3 standard deviations from the mean were removed (Field et al., 2012). All analyses were conducted on complete data sets (i.e. participants who provided data for all variables of interest). Bivariate Spearman correlations, adjusting for multiple comparisons (Holm method: Holm, 1979), investigated relationships among all variables (Table 3). The distributions of all four addictive behavior scales were positively skewed, constituting the choice of linear regression models with bootstrapping (5,000 samples) (Neal & Simons, 2007). Multicollinearity was assessed for each model independently, with VIF values less than 2.5 indicating no issue of multicollinearity (Johnston et al., 2018). Age, sex, psychological distress, trait impulsivity, and compulsivity were included as covariates in each regression model (Eisenberg et al., 2019; Sjoberg & Cole, 2018; Starcke et al., 2016). G-Power 3.1 (Faul et al., 2007) was used to calculate the minimum sample size required for multiple regression analyses with 15 predictors and an alpha error probability set to 0.05. A sample of N = 139 was deemed sufficient to find a medium effect ($f^2 = 0.15$, Power = 0.80).

3. Results

3.1. Participants

Nine-hundred-and-forty-four participants were enrolled. Sixty-three withdrew during the assessment sessions, and 78 were identified as fraudulent responses (i.e. spam bots/not genuine responses). Eight-hundred-and-three participants completed the assessment, with 311 removed due to missing data on one or more variables of interest (i.e. those included in the regression models), failed attention checks, or poor neurocognitive task performance. After removing outliers based on neurocognitive task performance, a final sample of 475 individuals had complete datasets (see Fig. 1). Participant demographics are displayed in Table 2.

3.2. Multiple regression models

Correlation analysis findings are presented in Table 3. The multivariate models (Tables 4-7) showed the neurocognitive variables were not significantly associated with problematic alcohol use or AE. Poorer error awareness was significantly associated with greater PPU ($\beta = -0.10$, $p = .049$) and PUI ($\beta = -0.09$, $p = .028$), and less steep delay discounting was significantly associated with higher PUI ($\beta = -0.10$, $p = .025$). Higher levels of psychological distress were significantly associated with more problematic alcohol use ($\beta = 0.22$, $p = .003$), AE ($\beta = 0.26$, $p < .001$), PPU ($\beta = 0.20$, $p < .001$), and PUI ($\beta = 0.37$, $p < .001$). Higher levels of urgency were significantly associated with more PPU ($\beta = 0.14$, $p = .013$) and PUI ($\beta = 0.15$, $p = .003$). Sensation seeking was positively associated with problematic alcohol use ($\beta = 0.17$, $p = .003$) and negatively associated with AE ($\beta = -0.12$, $p = .004$) and PUI ($\beta = -0.09$, $p = .014$). Higher levels of trait compulsivity were significantly associated with more AE ($\beta = 0.18$, $p = .002$) and PUI ($\beta = 0.12$, $p = .010$). Age was positively associated with problematic alcohol use ($\beta = 0.16$, $p = .002$), and negatively associated with PUI ($\beta = -0.17$, $p < .001$). Being male was significantly associated with more PPU ($\beta = -0.46$, $p < .001$), and PUI ($\beta = -0.15$, $p < .001$) whilst being female was significantly associated with greater AE ($\beta = 0.19$, $p < .001$). None of the multivariate models showed problems with multicollinearity.

4. Discussion

This is the first study to comprehensively investigate and control for the neurocognitive correlates of non-substance addictive behaviors across AE, PPU, PUI, and problem alcohol use. We took a dimensional approach to identify correlates associated with these addictive behaviors at varying degrees of severity in the general community. Our findings indicate, in this sample, addictive behaviors are associated with a unique profile of neurocognitive functioning. Our multivariate models showed none of the neurocognitive domains were associated with AE or problematic alcohol use. Poorer performance monitoring was independently associated with more PPU and PUI, and a higher preference for delayed gratification was also independently associated with higher PUI. Importantly, these findings are identified whilst adjusting for known confounds (i.e. age, sex, psychological distress), as identified as a key methodological shortcoming of prior research (Christensen et al., 2023). Our findings suggest the need for a more nuanced approach to studying addictive behaviors that take into account the underlying neurocognitive mechanisms associated with each type of addiction.

Our performance monitoring findings are consistent with prior research (Zhou et al., 2013). However, this is the first study to show a link between poorer performance monitoring and PPU. Very little work has been done evaluating the potential neurocognitive mechanisms associated with PPU. Of the extant work, findings are mixed. For example, PPU has been associated with both improved and poorer inhibitory control (Antons & Brand, 2018; Antons & Matthias, 2020). Considerable research has investigated PUI, with studies showing PUI is associated with poorer working memory, response inhibition, and risk-

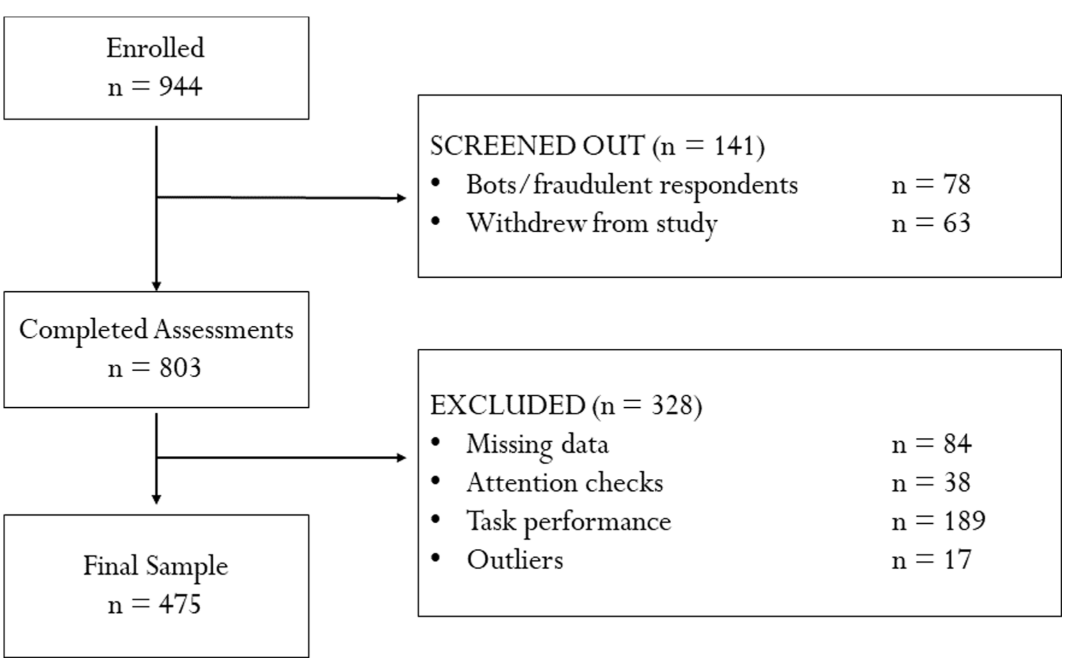

Fig. 1. Flow diagram mapping data collection, cleaning, and reasons for exclusion.

Table 2
Description of demographic characteristics of the sample.

Variables	N	
Sample	475	
Mean age (SD)	32.3 (11.8)	
Sex, N (%)		
Male	217 (45.7)	
Female	258 (54.3)	
Gender, N (%)Man	216 (45.5)	
Woman	254 (53.5)	
Non-binary	4 (0.8)	
Not listed/ Prefer not to say	1 (0.2)	
Race/Ethnicity, N		
Aboriginal or Torres Strait Islander	2	
African	2	
Asian	101	
Black or African American	2	
Hispanic or Latino	4	
Middle Eastern	4	
South Asian	30	
White or Caucasian	317	
Other	13	
Household income in AUD, N		
< $10,000	15	
$10,000 – $20,000	17	
$20,000 – $40,000	48	
$40,000 – $60,000	74	
$60,000 – $80,000	58	
$80,000 – $100,000	66	
> $100,000	197	
Addictive behaviors	**M (SD), range**	**Classified as problematic: N (%)**
AUDIT	5.09 (4.82), 0–30	Harmful/hazardous: 47 (10) Suspected dependence: 15 (3)
mYFAS	0.71 (1.78), 0–10	Mild: 28 (6) Moderate: 15 (3) Severe: 22 (5)
PPCS	9.61 (5.89), 6–42	31 (7)
IAT	16.31 (6.67), 10–48	163 (34)

Note: Sex was defined as biological sex. AUDIT: Alcohol Use Identification Test, no/low problem use (0–7), harmful/ hazardous use (8–14), likely alcohol dependence (≥15); mYFAS: modified Yale Food Addiction Scale 2.0, mild (2–3), moderate (4–5) severe (≥6) symptoms. PPCS: Problematic Pornography Consumption Scale, problematic use (≥20). IAT: an abbreviated version of Young's Internet Addiction Test, problematic use (≥17).

taking behaviors, as measured by the BART (for a *meta*-analysis: Ioannidis et al., 2019). Our study did not find these associations, potentially because the previous studies compared individuals with a PUI "diagnosis" to controls, while our sample included individuals with varying PUI severity. Further, if such deficits are related to vulnerability, they may be more strongly associated with presence vs absence of a disorder rather than its severity. Relatedly, it may be that deficits in these domains are evident in those with high levels of PUI, whereas the current study was conducted in a relatively normative sample. Performance monitoring is necessary to support higher-order functions such as cognitive control (Ferdinand & Czernochowski, 2018), and so reduced performance monitoring may be detectible before other cognitive functions, acting as an early *trans*-behavioral risk indicator for PPU and PUI. However, it is important to note the concurrence of PUI and PPU in our sample (Table 3). Given pornography is predominantly accessed via the internet, our PPU findings may instead be driven by problematic internet use to watch pornography, rather than specifically pornography-related functions.

Some of our findings diverge from that of previous work. For instance, the finding that more severe PUI was associated with less steep delay discounting, or a preference for later larger rewards, is contrary to substantial literature showing individuals with internet addiction are significantly steeper discounters compared to controls (for *meta*-analysis: Cheng et al., 2021). A potential interpretation relates to the fact that we are looking at PUI dimensionally, thus including individuals at both low and high levels of problem severity. Tiego et al. (2021) have argued that PUI as measured by the IAT has a unipolar distribution in which meaningful variance is found at the higher end of the severity spectrum. Given this, including individuals at lower PUI severity may have disrupted the expected effect. Further, the finding that the severity of AE symptoms was not associated with any neurocognitive variables contrasts with previous studies (Franken et al., 2018; Rodrigue et al., 2018; VanderBroek-Stice et al., 2017). One explanation for this may be that neurocognitive functions are more likely to be implicated in more severe AE. The aforementioned studies included samples with 35–100 % of participants endorsing mild-severe food addiction, compared to 18 % currently. Similarly, contrary to expectations, the present study did not find any of the neurocognitive variables were significantly associated with problematic alcohol use. The majority of our sample had no/low alcohol use problems, making it difficult to compare with previous work which has mostly been conducted in hazardous-severe alcohol use cohorts (Stavro et al., 2013). It is possible that neurocognitive risk or sequelae may not be detectable at mild levels of severity. However, our findings may be attributed to the study sample, with PUI being the most prevalent addictive behavior endorsed. This sample may differ significantly from traditional alcohol-focused research cohorts, suggesting a unique group of individuals in this study.

Psychological distress was a *trans*-behavioral correlate across all four addictive behaviors. This is consistent with previous research showing increased psychological distress is associated with multiple addictive and compulsive behaviors (Albertella et al., 2021; Albertella, Pelley, et al., 2019; Sepas et al., 2021). This finding is likely to present a bidirectional relationship between psychological distress and addictive behaviors, a) that addictive behaviors are motivated by way of coping with psychological distress (Burnatowska et al., 2022; Rodriguez et al., 2020), and b) addictive behaviors may themselves enhance distress (Yang et al., 2022).

The present study suggests that different problematic behaviors may be associated with differing trait impulsivity and compulsivity thresholds. Higher SS was significantly associated with more problematic alcohol use, and less AE and PUI. Our alcohol findings are in keeping with the literature in that SS is consistently associated with higher levels of alcohol use, albeit with a small effect (Hittner & Swickert, 2006). Further, our AE findings replicate that of Burrows et al. (2017) who showed a negative relationship between SS and food addiction. Less SS has also been linked with more time spent online (Müller et al., 2016). We also found AE and PUI were significantly positively associated with trait compulsivity, which is in line with previous findings (Albertella et al., 2021). Taken together we see a pattern emerge according to behavior type: after controlling for key covariates, substance-related addictive behaviors (i.e. alcohol use) may be more driven by the desire for sensation, presumably the reinforcing effects of the substance; whilst non-substance addictive behaviors may be more compulsively driven. It is important to note that this does not refute the role of impulsivity in non-substance-related addictive behaviors, nor compulsivity in substance addiction both of which have been well evidenced elsewhere (Everitt & Robbins, 2016; Lee et al., 2019). Rather, the present findings may speak to the relative contributions of these constructs per addictive behavior type (Tiego et al., 2019), particularly in less severe, non-clinical general population cohorts.

4.1. Limitations and future directions

Despite the strengths of our study, namely, a large sample size, the assessment of multiple addictive behaviors, and a comprehensive evaluation of addiction-specific neurocognitive correlates for each behavior, our findings should be considered in light of several limitations. The most notable limitation is the relatively low levels of severity (see appendix Fig. A1) in the study sample preventing the generalizability of

Table 3
Spearman correlations corrected for multiple comparisons.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1.mYFAS	5.09	4.82	–																		
2.PPCS	9.61	5.89	0.00	–																	
3.IAT	16.31	6.67	**0.29*****	**0.37*****	–																
4.AUDIT	0.71	1.78	0.07	0.10	−0.02	–															
5. SST: SSRT	0.36	0.09	0.02	**−0.17***	**−0.17***	−0.04	–														
6. VMAC: VMAC score	0.01	0.05	−0.02	0.04	−0.01	−0.03	−0.06	–													
7. BART: *M* pre-committed pumps	57.29	16.51	−0.08	0.11	0.01	0.06	−0.12	0.05	–												
8. CST: Switch cost latency	0.30	0.20	0.01	0.00	−0.03	−0.05	0.13	−0.03	−0.06	–											
9. DDT: Log *k*	−4.60	1.67	0.01	0.08	−0.06	0.03	−0.04	0.03	0.01	0.04	–										
10. EAT: Error awareness	67.00	34.88	−0.03	−0.04	−0.02	0.04	−0.14	−0.04	0.02	−0.09	−0.15	–									
11. SDT: *w*	0.51	0.36	−0.07	0.10	−0.01	−0.03	−0.11	0.05	0.00	−0.03	**−0.18***	0.15	–								
12. N-Back: 3-back d'	2.15	1.16	−0.07	0.02	−0.02	0.06	−0.04	0.03	0.02	0.05	−0.12	**0.19***	0.14	–							
13. SUPPS-P: Lack of perseverance and premeditation	7.50	1.76	0.02	0.04	0.13	0.12	−0.10	0.02	0.06	−0.12	013	−0.04	−0.14	−0.04	–						
14. SUPPS-P: Urgency	8.42	2.45	**0.20*****	**0.23*****	**0.34*****	0.08	−0.03	0.01	−0.04	0.01	0.12	−0.10	−0.07	−0.07	**0.32*****	–					
15. SUPPS-P: Sensation seeking	9.41	2.79	−0.13	0.14	−0.01	**0.25*****	0.01	−0.01	**0.17***	−0.04	0.13	−0.06	−0.05	0.04	0.11	**0.25*****	–				
16. CHI-T: Trait compulsivity score	27.23	6.19	**0.27*****	0.11	**0.33*****	−0.03	−0.05	0.03	−0.05	0.02	0.02	0.02	−0.03	−0.03	**−0.28*****	**0.34*****	−0.02	–			
17. DASS: Total score	12.39	11.36	**0.35*****	0.15	**0.53*****	0.15	−0.08	−0.07	−0.08	0.00	−0.03	0.03	−0.01	−0.04	0.01	**0.35*****	−0.02	**0.40*****	–		
18.Age	32.32	11.85	−0.06	**−0.21*****	**−0.39*****	0.00	**0.34*****	−0.01	0.03	**0.21*****	−0.06	−0.09	−0.04	−0.06	**−0.17***	**−0.25*****	−0.09	**−0.17***	**−0.27*****	–	
19. Sex (F)	–	–	**0.25*****	**−0.52*****	−0.08	0.00	0.09	−0.01	**−0.18***	−0.03	−0.11	0.02	−0.08	−0.11	0.03	−0.08	**−0.24*****	0.02	0.12	0.03	–

Note: *p* values were adjusted for multiple comparisons using Holm method; **p* <.05, ***p* <.01, ****p* <.001.

Table 4
Linear regression model with bootstrapping for problematic alcohol use.

	β	*SE*	95 % CI		*p*
			Lower	Upper	
Demographics					
Age	0.16	0.02	0.02	0.10	0.002**
Sex (F)	−0.01	0.51	−1.09	0.94	0.921
Neurocognition					
SST: SSRT	−0.06	2.87	−8.39	3.14	0.332
VMAC: VMAC score	0.01	4.10	−7.55	9.05	0.912
BART: *M* pre-committed pumps	0.04	0.02	−0.02	0.04	0.458
CST: Switch cost latency	−0.02	0.00	−0.00	0.00	0.666
EAT: Error awareness	0.03	0.01	−0.01	0.02	0.606
SDT: *w*	−0.07	0.56	−2.05	0.15	0.088
N-Back: 3-back d'	0.04	0.15	−0.15	0.45	0.291
DDT: Log *k*	−0.00	0.12	−0.24	0.21	0.948
Covariates					
DASS: Total score	0.22	0.03	0.03	0.15	0.003**
SUPPS-P: Lack of perseverance and premeditation	0.04	0.16	−0.20	0.40	0.475
SUPPS-P: Urgency	0.05	0.11	−0.14	0.31	0.440
SUPPS-P: Sensation seeking	0.17	0.09	0.11	0.44	0.003**
CHI-T: Trait compulsivity score	−0.05	0.05	−0.13	0.06	0.503

Note. β: Unstandardized coefficient; SE: Standard error; **p* <.05, ***p* <.01, ****p* <.001.

Table 5
Linear regression model with bootstrapping for addictive eating.

	β	*SE*	95 % CI		*p*
			Lower	Upper	
Demographics					
Age	0.05	0.01	−0.01	0.02	0.310
Sex (F)	0.19	0.14	0.41	0.96	<0.001***
Neurocognition					
SST: SSRT	0.06	0.93	−0.79	2.94	0.257
VMAC: VMAC score	0.02	1.54	−2.40	3.77	0.698
BART: *M* pre-committed pumps	0.04	0.00	−0.00	0.01	0.350
CST: Switch cost latency	0.02	0.00	−0.00	0.00	0.714
EAT: Error awareness	0.01	0.00	−0.00	0.00	0.918
SDT: *w*	−0.03	0.23	−0.58	0.32	0.579
N-Back: 3-back d'	0.03	0.06	−0.06	0.16	0.391
DDT: Log *k*	0.07	0.05	−0.01	0.17	0.109
Covariates					
DASS: Total score	0.26	0.01	0.02	0.06	<0.001***
SUPPS-P: Lack of perseverance and premeditation	0.03	0.06	−0.08	0.14	0.621
SUPPS-P: Urgency	0.08	005	−0.03	0.14	0.195
SUPPS-P: Sensation seeking	−0.12	0.03	−0.14	−0.02	0.004**
CHI-T: Trait compulsivity score	0.18	0.02	0.02	0.09	0.002**

Note. β: Unstandardized coefficient; SE: Standard error; **p* <.05, ***p* <.01, ****p* <.001.

our findings to populations with more severe addictive behaviors. Although rates of AE and PPU corresponded with what has previously been estimated in general population samples (4–15 % for AE and 7 % for PPU; Mennig et al., 2020; Meule & Gearhardt, 2019), rate of hazardous alcohol use was well below Australian population estimates (22 %; O'Brien et al., 2020). We recommend that future research in community samples focus recruitment efforts to target individuals at more severe levels of addictive behavior. Contrary to this, the rate of PUI in the study sample was much higher than global estimates (6 %; Cheng & Li, 2014), suggesting our sample experienced more PUI than what would typically be observed in the general population. An additional limitation was the unsupervised nature of data collection. While online remote-access data collection is beneficial when wanting to target demographically diverse samples at scale, it also requires a rigorous data cleaning protocol which necessitated the removal of just under 40 % of the

Table 6
Linear regression model with bootstrapping for problematic pornography use.

	β	*SE*	95 % CI		*p*
			Lower	Upper	
Demographics					
Age	−0.04	0.02	−0.06	0.03	0.450
Sex (F)	−0.46	0.53	−6.47	−4.40	<0.001***
Neurocognition					
SST: SSRT	−0.04	2.26	−6.71	0.97	0.287
VMAC: VMAC score	0.03	4.09	−3.54	12.20	0.291
BART: *M* pre-committed pumps	0.01	0.01	−0.03	0.03	0.883
CST: Switch cost latency	0.00	0.00	−0.00	0.00	0.924
EAT: Error awareness	−0.10	0.01	−0.03	−0.00	0.049*
SDT: *w*	0.03	0.67	−0.75	1.88	0.400
N-Back: 3-back d'	−0.05	0.24	−0.70	0.21	0.298
DDT: Log *k*	−0.05	0.16	−0.49	0.15	0.327
Covariates					
DASS: Total score	0.20	0.03	0.04	0.16	<0.001***
SUPPS-P: Lack of perseverance and premeditation	0.04	0.20	−0.26	0.53	0.581
SUPPS-P: Urgency	0.14	0.13	0.06	0.59	0.013*
SUPPS-P: Sensation seeking	−0.03	0.09	−0.24	0.13	0.542
CHI-T: Trait compulsivity score	0.05	0.06	0.06	0.16	0.414

Note. β: Unstandardized coefficient; SE: Standard error; *p <.05, **p <.01, ***p <.001.

Table 7
Linear regression model with bootstrapping for problematic use of the internet.

	β	*SE*	95 % CI		*p*
			Lower	Upper	
Demographics					
Age	−0.17	0.02	−0.14	−0.05	<0.001***
Sex (F)	−0.15	0.54	−3.07	−0.98	<0.001***
Neurocognition					
SST: SSRT	0.01	2.90	−4.81	6.37	0.801
VMAC: VMAC score	−0.00	5.13	−10.66	9.10	0.886
BART: *M* pre-committed pumps	0.03	0.02	−0.02	0.04	0.444
CST: Switch cost latency	0.02	0.00	−0.00	0.00	0.597
EAT: Error awareness	−0.09	0.01	−0.03	−0.00	0.028*
SDT: *w*	−0.07	0.76	−2.81	0.22	0.093
N-Back: 3-back d'	−0.02	0.22	−0.55	0.31	0.555
DDT: Log *k*	−0.10	0.18	−0.75	−0.04	0.025*
Covariates					
DASS: Total score	0.37	0.03	0.15	0.29	<0.001***
SUPPS-P: Lack of perseverance and premeditation	0.08	0.19	−0.06	0.71	0.102
SUPPS-P: Urgency	0.15	0.14	0.13	0.67	0.003**
SUPPS-P: Sensation seeking	−0.09	0.09	−0.40	−0.04	0.014*
CHI-T: Trait compulsivity score	0.12	0.05	0.03	0.24	0.010*

Note. β: Standardized coefficient; SE: Standard error; *p <.05, **p <.01, ***p <.001.

dataset. Post-hoc comparisons of our sample for those whose data was screened out found that the individuals who were removed from the analysis had significantly higher AE, PUI, and lack of perseverance/premeditation than included participants (see appendix). As such, our sample may be biased towards less impulsive individuals which may not be representative of the wider community. Future research should consider the trade-off associated with unsupervised data collection.

The use of gamified neurocognitive tasks to assess aspects of neurocognitive function may also have impacted our findings. Whilst gamification can enhance engagement and motivation (Lumsden et al., 2016), the addition of game-like elements did cause some of the tasks to deviate from their traditional counterparts. For instance, enhanced complexity of the visual display which may affect the salience of visual cues, potentially impacting paradigms that rely on distractor cues such as the VMAC task. Further, the BrainPAC SST utilized a points element in which faster responses earned more points, potentially encouraging faster but less accurate responding and thus impacting SSRT calculations.

Finally, the cross-sectional nature of the present study limits our ability to determine causal relationships between the variables of interest. The next natural step would be to conduct a longitudinal evaluation of the same predictors to determine the key mechanisms that predict the development of AE, PPU, and PUI over time. This would better inform intervention and prevention targets for non-substance addictive behaviors and could shed light on the relative contribution of impulsivity and compulsivity (in terms of cognition or traits) at different stages of addiction (e.g. as relates to duration of addictive symptoms).

In conclusion, the present study revealed that different addictive behaviors may have unique neurocognitive mechanisms. There are likely partly distinct mechanisms or pathways to addiction depending on the addictive behavior in question. This has key implications for early intervention, in particular, our study supports the need for tailored treatments that focus on the specific behavior-related neurocognitive functions rather than assuming cognitive dysfunction is necessarily the same across addictions.

CRediT authorship contribution statement

Erynn Christensen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Lucy Albertella:** Conceptualization, Supervision, Writing – review & editing. **Samuel R. Chamberlain:** Writing – review & editing. **Maja Brydevall:** Software, Writing – review & editing. **Chao Suo:** Software. **Jon E. Grant:** Writing – review & editing. **Murat Yücel:** Funding acquisition, Supervision, Writing – review & editing. **Rico Sze Chun Lee:** Funding acquisition, Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Table A1
Variables that significantly differed between the sample retained in the study and the sample removed during data cleaning.

Variable	Mean(SD) Sample retained	Sample removed	Test statistic
mYFAS symptom count	0.72 (1.79)	2.39 (2.95)	47366***
IAT score	16.3 (6.68)	22.46 (8.86)	45768***
Lack of perseverance and premeditation	7.52 (1.77)	8.84 (2.19)	6.02***

Note: ***$p < .001$; Mann-Whitney U test was used for non-parametric comparisons (mYFAS and IAT); t-test was used for parametric comparison (lack of perseverance and premeditation).

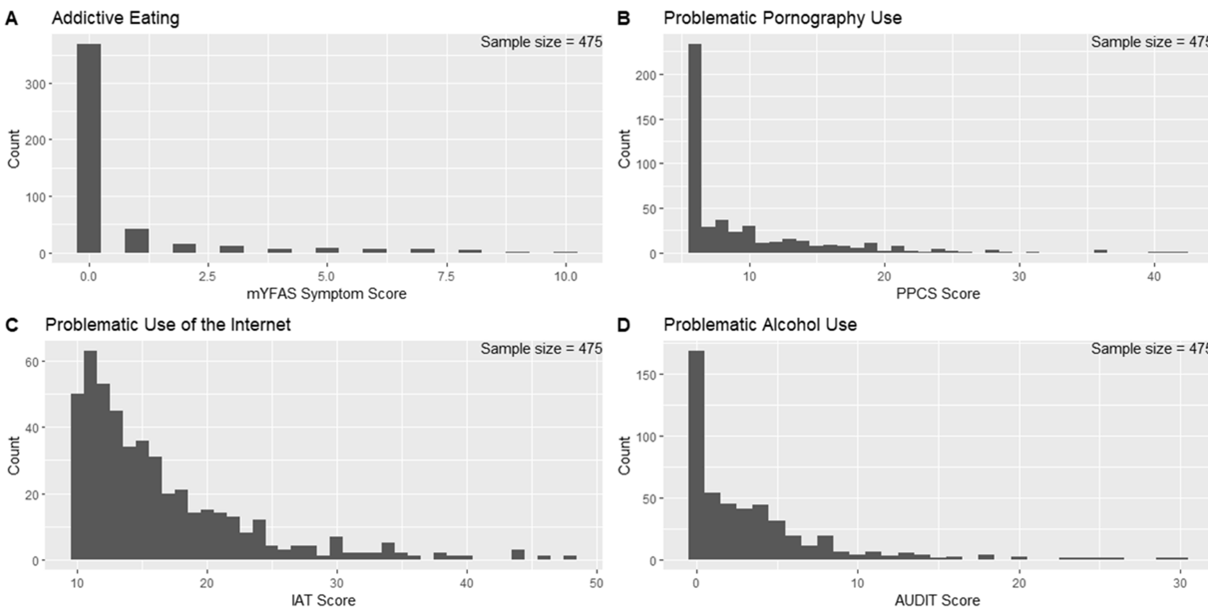

Fig. A1. Histograms of addictive behaviors in the sample.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2023.107904.

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