MONASH University

COMPONENTS OF COGNITIVE IMPULSIVITY AND THE ASSOCIATION BETWEEN IMPULSIVITY AND SOCIAL NETWORKING SITE USE

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Abstract

Impulsivity is the predisposition to act on immediate urges. At low levels impulsivity is considered normal, whereas, high levels are associated with negative outcomes in both healthy and clinical populations. We can improve our understanding of the aetiology of impulse-based behavioural problems through the identification of cognitive processes that underpin impulsive behaviour. The challenge is in isolating these mental processes, as the debate on how impulsivity should be defined, its main components and the most appropriate assessment tools is ongoing.

The aims of this thesis were twofold: to assess a tripartite structure of impulsivity, including attention interference, information sampling and response interference; and to examine whether individuals with a higher propensity towards impulsive behaviour exhibit problematic social networking site (SNS) use. Studies 1 and 2 (see Chapters 3 and 4) addressed the first aim, and Study 3 (see Chapter 6) addressed the second.

Study 1 examined 40 adults (age, M = 25, SD = 5.21, 26 female) who completed three sets of measures. These included, two novel cognitive measures of attention interference and information sampling, three standard cognitive impulsivity tasks and one multidimensional trait measure. Correlational analysis was used to assess convergent validity between the standard and novel tasks, repeated measures ANOVA to examine task specific construct validity, and independent t-tests to determine whether task performance distinguished between high and low levels of trait impulsivity. Study 2 examined 128 adults (age, M = 32.24, SD = 6.38, 66 male) recruited via Amazon Turk Prime. Participants completed six behavioural tasks: the Stop Signal, Go/No-Go, Visual Search, Sustained Attention to Response, AX-Continuous Performance and Jumping to Conclusions Beads Task. Principal components analysis was used

to examine the interrelatedness of behavioural indices purported to assess components of cognitive impulsivity. Study 3 included 159 participants (age, *M* = 28.22, *SD* = 7.92, 112 female) recruited from Facebook (*n* = 92) and an Amazon Turk Prime Panel (*n* = 67). Participants completed questionnaires on SNS use, negative mood and trait impulsivity. Regression analysis was used to determine the contribution of these variables to SNS use. Study 3 also collected data on cognitive impulsivity measures. As missing data precluded an adequately powered analysis, the findings are reported in Appendix A.

Findings from Study 1 indicated that the novel tasks did not offer a significant improvement over existing tasks in assessing impulsive cognitive processes. Neither did the cognitive components differentiate between high and low trait impulsivity. In Study 2, a four-factor model of impulsivity was extracted: one factor represented response interference, two reflected a single behavioural task and one reflected response time. Collectively, these findings signify that current theory built from indices of behavioural performance fall short of capturing impulsivity's heterogeneous nature. Finally, Study 3 demonstrated that negative mood and negative urgency are positively associated with problematic SNS use. Additionally, general SNS use was positively associated with negative mood, sensation seeking and positive urgency. Importantly, these findings show that impulsivity is associated with general, not just problematic SNS use.

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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List of Abbreviations

AI	Attention Interference
AIT	Attention Interference Task
AX-CPT	AX-Continuous Performance Task
DASS21	Depression Anxiety Stress Scale
DDT	Delay Discounting Task
DMT	Delayed Memory Task
FSMUS	Frequency of Social Media Use Scale
GAT	Gathering Task
GNG	Go/No-Go Task
IMT	Immediate Memory Task
IS	Information Sampling
JTC	Jumping to Conclusions Beads Task
PCA	Principal Components Analysis
QoL	Quality of Life
RLT	Reversal Learning Task
SART	Sustained Attention to Response Task
SEM	Structural Equation Modelling
SNS	Social Networking Site
SMDS	Social Media Disorder Scale
SONTUS	Social Networking Time Use Scale
SST	Stop Signal Task
ssrt	stop signal reaction time
RI	Response Interference
VST	Visual Search Task

Preface

This thesis reports the findings from three empirical studies. Two of these studies examined the underlying structure of cognitive impulsivity, namely attention interference, information sampling, and response interference; and one study investigated the relationship between impulsivity, negative mood and social networking site use (SNS). These studies used behavioural indices of cognition and self-report measures. Findings indicate that the behavioural indices used in the assessment of these components do not converge to a factor structure as they theoretically should. Further work is required to develop valid measures which reliably capture each component of cognitive impulsivity, particularly attention interference and information sampling. Furthermore, our findings showed that trait impulsivity is associated with SNS use, which varied depending on the type of use, either general or problematic. A theoretical implication of these findings is that task based models of impulsivity are tied to behavioural indices rather than the cognitions purported to underlie them. Practical applications for these findings include an avenue for the early detection and possible intervention of problematic SNS use, as findings suggest specific aspects of impulsivity are risk factors for problematic SNS engagement.

This thesis comprises seven chapters and an appendix. Chapter 1 includes a general introduction and narrative literature review of multidimensional studies that assess cognitive impulsivity. This review also outlines evidence on four of the most commonly examined cognitive components of impulsivity and states the overall aims and hypothesis of this thesis. Chapter 2 is an expanded methodology, which elaborates on the specific methods employed across the three studies described in Chapters 3, 4 and 6, including a more detailed description of the measures and procedures than is possible in the manuscripts.

Chapter 3 presents Study 1, entitled 'Cognitive impulsivity does not differ in those with high or low levels of trait impulsivity; and the development of two novel behavioural tasks to improve validity in the assessment of attention interference and information sampling'. This study set out to provide an initial examination of the validity of two novel behavioural tasks designed to assess the attention interference and information sampling components of cognitive impulsivity. This study also sought to determine if performance across any of the three components differed in individuals scoring high or low in trait impulsivity.

Chapter 4 details Study 2: 'Substantiating a structural model of behavioural impulsivity: Evidence for response interference'. This study examined the factorial interrelatedness of several cognitive tasks purported to underlie the mental processes related to impulsive behaviour with the aim of substantiating a tripartite model of impulsivity. Chapter 5 provides a preface to Study 3 by outlining the thesis's transition from an internally facing analysis of impulsivity to an external examination of impulsivity within an impulsive population; that is, problematic SNS users.

The third and final study investigated the contribution of different facets of impulsivity, both trait and cognitive, as well as compulsivity (a conceptually related construct) and negative mood on SNS use. The study is set out in Chapter 6, 'Trait impulsivity and negative mood states are associated with both general and problematic social networking site use', and Appendix A, 'Cognitive impulsivity and negative mood states are associated with both general and problematic social networking site use'. Chapter 7 consists of a general discussion and conclusion. It summarises the key findings from the three empirical studies reported in this thesis, explores the theoretical and practical implications, and identifies the limitations and overall strengths of this research.

Chapter 1: Introduction

1.1 Cognitive impulsivity

An impulsive response is one that is stimulus driven, enacted prior to adequate information sampling and irrelevant to the current task goal (Nigg, 2016). Cognitive impulsivity refers to the mental processes underlying this type of response. These mental processes are thought to manifest as behavioural responses. As behaviour is overt and measurable, it has dominated research on impulsivity. In contrast, little attention has been given to what produces an impulsive response, namely cognitive impulsivity. Researchers often use behaviour to estimate cognition. Such estimation is fruitful when the evidence linking behaviour and cognition is replicated over time. However, replication requires consistency in definition and assessment, both of which are lacking within impulsivity research (DeYoung, 2010; Sharma, Markon, & Clark, 2013).

The need for a commonly accepted definition and standardised assessment has led to growing concern that empirical progress in cognitive impulsivity is stagnating (Cyders, 2015; Cyders & Coskunpinar, 2011; Hamilton et al., 2015). This concern has prompted researchers to revisit the fundamental questions of what components of cognitive impulsivity should be measured and how best to measure them (Coffey, 2015). Both these questions are hotly debated (Chamberlain & Fineberg, 2015; Coffey, 2015; Cyders, 2015; Hamilton et al., 2015) and form the focus of this review. Our first aim is to identify the components of cognitive impulsivity that ought to be assessed, examining each in turn and discussing existing research linking each component with impulsive responding. The second aim, in response to question two, is to provide an overview of the current challenges in assessment methodology. Following this, a summary of impulsivity's ongoing significance from a clinical and general population perspective will be provided, with emphasis given to problematic social network site (SNS) use as an emerging research area. We will then identify potential ways forward and present the overall thesis aims and hypotheses.

1.2 Delimiting the components of cognitive impulsivity

To delimit potential components of cognitive impulsivity we first conducted a review of the literature, focusing on studies which examined the underlying structure of impulsivity. Searches were limited to articles available in the English language. Articles were included if they had been published in peer-reviewed journals and were either a meta-analysis or an original empirical study. Studies also needed to meet the following eligibility criteria. First, the study had to include a sample of human adult participants (i.e., 18 years or older), from either a clinical or general population. Second, the study had to be multidimensional, including four or more measures of impulsivity, two of which had to be laboratory measures (as behaviour is considered the overt manifestation of cognitive impulsivity). We restricted our search to four or more measures based on recommendations from Smith, Fischer, and Fister (2003), that a construct be evaluated using more than one assessment tool. Assuming there are at least two forms of impulsivity, trait and cognitive, then it follows that structural studies should use four or more measures of impulsivity. Third, the study had to include an analysis of the interrelatedness of performance indices with the aim of delimiting impulsivity's structure. Detailed information was extracted from the 12 articles that met the inclusion criteria for review. These articles were appraised based on the following characteristics: the type and number of measures used, sample size and type, the analysis used, and the number of components extracted (see Table 1 for a detailed description).

Table 1: Summary of multidimensional studies assessing the latent structure of impulsivity that included behavioural assessment

Study	Measures	Sample	Analysis	*N* Components
Reynolds, Ortengren, Richards and de Wit (2006)	Balloon Analogue Risk Task Delay Discounting Task Go/No-Go Task Stop Signal Task	99 university students Age *M* = 22.92 Male = 50%	PCA	2
Meda et al. (2009)	Balloon Analogue Risk Task BIS/BAS BIS-11 Experiential Discounting Task ImpSS Scale Padua Inventory SPSRQ	176 adults 89 controls 36 family history of alcoholism 20 former and 31 current cocaine users Age *M* = 31.84 Male = 44.3%	PCA	5
Cyders and Coskunpinar (2012)	Brown Peterson Task Delayed Memory Task GoStop Task Immediate Memory Task Single Key Impulsivity Paradigm Two Choice Impulsivity Task TIME Paradigm UPPS-P	77 university students Age *M* = 21.10 Female = 70%	PCA	7
Sharma et al. (2013)	Balloon Analogue Risk Task Delay Discounting Task Delayed Memory Task Go/No-Go Task Immediate Memory Task Iowa Gambling Task Matching Familiar Figures Task Porteus Maze Task Stop Signal Task Stroop Word Colour Task Wisconsin Card Sorting Task WCST	98 studies 46 clinical samples 46 university or community adult samples 5 adolescent samples	Meta-analytic PCA	4

Study	Measures	Sample	Analysis	*N* Components
Stahl et al. (2014)	Animal Matching Task Brightness Discrimination Shape Matching Task Stroop Matching Task Recent Probes Directed Forgetting 1 Directed Forgetting 2 Response Priming Number-letter Task Switching Colour-shape Task Switching Lexical Decision Delay Discounting 1 Delay Discounting 2	198 predominantly university students Age *M* = 25.46 Female = 66%	SEM	5
Kräplin et al. (2014)	BIS-11 Card Playing Task Iowa Gambling Task Stop Signal Task Stroop Word Colour Task Tower of London Task	198 adults 53 healthy controls 51 pathological gambling 45 alcohol dependant, 49 Gilles de la Tourette syndrome Age *M* = 39.83 Male = 72%	PCA	4
Nombela, Rittman, Robbins, and Rowe (2014)	BIS BIS/BAS Cambridge Gambling Task Frontal Assessment Battery (items 4 -5) Go/No-Go Task Hayling Sentence Completion Test Saccade No/Go Stop Signal Task Stroop Test Temporal Discounting Task Temporal Interval Estimation Task	60 adults 30 Parkinson patients 30 healthy control Age *M* = 64.40 Male = 46%	PCA	4

Study	Measures	Sample	Analysis	*N* Components
Caswell, Bond, Duka, and Morgan (2015)	BIS-11 Delay Discounting Task Immediate Memory Task Information Sampling Task Go/No-Go Task Matching Familiar Figures Task Monetary Choice Questionnaire Single Key Impulsivity Paradigm Stop Signal Task Two Choice Impulsivity Paradigm	160 university students Age *M* = 20.85 Male = 50%	EFA	4
MacKillop et al. (2016)	BIS-11 Connor's Continuous Performance Task Delay Discounting Task Go/No-Go Task Monetary Choice Questionnaire Stop Signal Task UPPS-P	1252 university students Age *M* = 21.5 Female = 62%	CFA	3
Barnhart and Buelow (2017)	Balloon Analogue Risk Task BIS-11 BIS/BAS CAARS Delay Discounting Task Frontal Systems Behaviour Scale FrSBe ImpSS Scale Stroop Word Colour Task	175 university students 28 ADHD Female = 43% Age *M* = 19.06 Female = 65%	PCA	3
Khadka et al. (2017)	Balloon Analogue Risk Task BIS/BAS BIS-11 Experiential Discounting Task ImpSS Scale Padua Inventory SPSRQ	440 university students Age *M* = 18.4 Female = 40%	Longitudinal (2 years) EFA & CFA	4

Study	Measures	Sample	Analysis	*N* Components
Kras et al. (2018)	BIS-11 Cambridge Gambling Task Go/No-Go Task Information Sampling Task Iowa Gambling Task Monetary Choice Questionnaire	72 Opioid dependant heroin users Age *M* = 35.64 Male = 72%	PCA	5

Note: BIS-11, Barratt Impulsiveness Scale; BIS/BAS, Behavioural Inhibition System and Behavioural Activation System Scales; CAARS, Connors Adult ADHD Rating Scale; SPSRQ, Sensitivity to Punishment and Reward Questionnaire; ImpSS Scale, Impulsive Sensation Seeking Scale of the Zuckerman-Kuhlman Personality Questionnaire III

There is a clear disparity between studies regarding how many components are extracted, and the measures used, which mirrors concerns that impulsivity suffers from a lack of unanimity. Studies have extracted anywhere from two (Reynolds et al., 2006) to seven (Cyders & Coskunpinar, 2012) impulsivity components, although the majority of studies endorse four (Caswell et al., 2015; Khadka et al., 2017; Kräplin et al., 2014; Nombela et al., 2014; Sharma et al., 2013). A possible cause of this disparity is the tendency to equate assessment measures with cognitive processes; that is, the assumption is made that a task accurately reflects a particular theory regarding what drives task performance (Poldrack et al., 2011). This can be problematic, as a single task can be associated with multiple cognitions and differing theories explaining task performance (e.g., Stroop word colour task)—a problem that is evident in multidimensional studies of impulsivity.

A consistent pattern across the studies reviewed is for impulsivity components to reflect the specific assortment of behavioural tasks chosen. For example, Cyders and Coskunpinar (2012) use six behavioural tasks and find six behavioural impulsivity components. Similarly, Kras et al. (2018) employed six measures to extract five components, and Reynolds et al. (2006) extracted two behavioural components from four behavioural tasks, using only a single outcome measure per task; a limitation noted by the authors themselves. Furthermore, MacKillop et al. (2016) extracted the same two cognitive components as Reynolds et al. (2006), with the addition of a third factor reflecting trait impulsivity. The additional third component is possibly due to MacKillop et al. (2016) incorporating self-report measures, where Reynolds et al. (2006) did not. This trend is also replicated at the meta-analytic level, albeit to a lesser degree, with one of the four impulsivity components extracted by Sharma et al. (2013) reflecting a single task. These examples illustrate the propensity for the type and mix of tasks to heavily predetermine the factor structure (Block, Goldberg, & Saucier, 1995).

The type and mix of tasks used to assess impulsivity also results in inconsistencies at the task level. For instance, most studies listed with three or more components include at least one measure of trait impulsivity, which typically loads onto a distinct trait component (e.g., Cyders & Coskunipar, 2012; MacKillop et al., 2016). There is also the study by Barnhart and Buelow (2017), which mostly used self-report measures and included only two behavioural tasks, finding that neither behavioural task loaded onto any of their three components. The same task level inconsistencies are seen in behavioural tasks. For example, Caswell et al. (2015) used ten tasks in their analysis but only six loaded onto any of the four components. Collectively, these studies illustrate how existing task based models fall short of capturing the broad nature of impulsivity. To overcome the heterogeneity in the number and type of impulsivity components which have been extracted across studies, a more stringent examination must be considered.

1.3 Components of cognitive impulsivity

We sought to use the 12 studies selected for review to identify which components are most robustly associated with cognitive impulsivity. To ensure a sufficient number of behavioural indices of impulsivity and rule out the potential confounding effects of disorder-related cognitive deficits which could obscure impulsivity's underlying structure we chose to further focus to studies using multiple cognitive tasks among healthy participants. Of the original 12 articles included for review, we focused on six, grouping the components extracted in each study by cognitive process (detailed in Table 2). Any components within these studies which were based solely on self-report measures were excluded. This review was restricted to cognitive rather than trait components of impulsivity, for which there is already a broadly accepted theoretical structure (see Cyders & Smith, 2007; Cyders et al., 2007; Whiteside & Lynam, 2001).

Across the six studies, the number of components extracted ranged from two (Reynolds et al., 2006) to seven (Cyders & Coskunpinar, 2012), and the behavioural tasks included numbered between four (MacKillop et al., 2016; Reynolds et al., 2006) and thirteen (Stahl et al., 2014). Appearing in all six studies, delay discounting and response interference, emerged as discrete components of cognitive impulsivity. Four studies endorsed attention interference as a component of impulsivity and three found evidence of information sampling. Based on this, we propose that cognitive impulsivity is converging on four distinct components. These components include: (1) attention interference, when a target task is interrupted by a competing stimulus; (2) information sampling, which is the failure to accumulate adequate information prior to responding; (3) response interference, when a target task is interrupted by a competing response; and (4) delay discounting, which is the preference for smaller, immediate rewards over larger, delayed rewards. Each of these four processes will be examined in turn to determine the extent to which they directly relate to the construct of impulsivity.

Table 2: Summary of cognitive impulsivity components across multidimensional studies that used three or more behavioural tasks

Description	Terminology	Process	Studies
The preference for smaller, immediate rewards over larger, delayed rewards. Involves the subjective assessment of value and reward.	Motivational impulsivity Impulsive choice Impulsive decision-making Temporal-impulsivity Deferment of reward Delay response Delay discounting	Delay Discounting	Reynolds et al. (2006) Cyders and Coskunpinar (2012) Sharma et al. (2013) Stahl et al. (2014) Caswell et al. (2015) MacKillop et al. (2016)
Inadequate acquisition of information prior to making a decision, including difficulty weighing options and taking appropriate risks.	Reflection impulsivity Disadvantageous decision-making Decisional impulsivity Impulsive decision-making	Information Sampling	Stahl et al. (2014) Caswell et al. (2015) MacKillop et al. (2016)
Inability to withhold a response or supress a response that has been initiated.	Impulsive disinhibition Behavioural disinhibition Inhibition Motor impulsivity Impulsive action Prepotent response inhibition Response inhibition Response interference Rash response impulsivity	Response Interference	Reynolds et al. (2006) Cyders and Coskunpinar (2012) Sharma et al. (2013) Stahl et al. (2014)* Caswell et al. (2015) MacKillop et al. (2016)
Inability to avoid interference from distracting task irrelevant stimuli.	Attention-deficit impulsivity Attention impulsivity Inattention Distractor interference Stimulus interference	Attention Interference	Cyders and Coskunpinar (2012) Sharma et al. (2013) Stahl et al. (2014) Barnhart and Buelow (2017)
Inability to supress goal-irrelevant cognitions or mental representations.	Proactive interference	Proactive Interference	Cyders and Coskunpinar (2012) Stahl et al. (2014)
Ability to respond quickly or shift mental sets when task demands change.	Shifting	Shifting	Sharma et al. (2013)
Distortions in judging elapsed time.	Distortions in elapsed time	Time Distortion	Cyders and Coskunpinar (2012)

Note: *This study further split response interference into two related but separate components.

1.3.1 Attention interference

Emerging evidence suggests attention interference mediates the relationship between task directed behaviour and impulsive responding (Hanif et al., 2012). Task directed behaviour can be interrupted when a task irrelevant stimulus becomes the focus of attention, acquiring disproportionate attentional resources. Evidence supporting this theory comes from studies on stimulus salience, the quality by which a stimulus stands out relative to others. Evidence indicates that salience is a strong predictor of a stimuli's ability to capture attention, regardless of its task relevance (Kerzel & Schönhammer, 2013; Theeuwes, 2010), unless actively supressed (Gaspelin & Luck, 2018). The stronger the stimulus salience, the greater its capacity to capture and hold attention and, to some extent, direct it (Hester & Luijten, 2014). A stimulus may standout naturally, such as a red balloon; however, it can also acquire salience through learnt associations.

Humans learn to associate specific stimuli with a specific outcome, especially if that outcome is rewarding. This learnt association can produce an attentional bias, which is the automatic direction of attention towards emotionally valued stimuli (Kerzel & Schönhammer, 2013). For instance, someone who finds Cadbury chocolate delicious may see the Cadbury purple and associate it with the rewarding experience of eating chocolate. This association or stimulus pairing is activated automatically and is a well-established phenomenon within addiction research. For example, the presence of a drug or alcohol related stimuli has been found to differentially capture attention and disrupt inhibitory control (Dias et al., 2015; Field & Cox, 2008; Field & Eastwood, 2005; Hester, Dixon, & Garavan, 2006). A finding which has been replicated in overweight individuals with food cues (Bazzaz, Fadardi, & Parkinson, 2017; Meule, de Zwaan, & Müller, 2017; Meule & Platte, 2016; Yokum, Ng, & Stice, 2011). In this way, the presence of a salient cue, learnt or otherwise, can push someone to act in a way that is unaligned with their current goal(s).

In addition to natural or learnt stimulus salience, attentional processing can be influenced by internal states, such as motivation and emotion. This occurs because stimuli can have an emotional valence, that is, it can arouse positive or negative feelings (Gable & Harmon-Jones, 2010). Additionally, stimuli can have an approach motivational intensity and direction, whereby the intensity of the urge to approach or avoid the stimulus reflects the strength of that motivation (Gable & Harmon-Jones, 2010). Together, emotional valence and motivational intensity and direction differentially influence what we pay attention to. For example, studies show that positive affect low in approach motivational intensity (strength of the drive to approach or avoid an object) widens our attentional focus, while positive affect high in approach motivational intensity narrows it (Domachowska et al., 2016; Gable & Harmon-Jones, 2010, 2011). Returning to the chocolate example, if chocolate has a positive emotional valence, because we have learnt it tastes delicious and experience a high approach motivation towards it (e.g., desire), then our attentional focus will narrow onto the chocolate, which may interrupt our initial task of making coffee. What we may find ourselves doing is making an impulsive food choice.

1.3.2 Information sampling

Inadequate information sampling within the context of impulsivity is the predisposition to make fast decisions without adequately sampling from the available information (Kagan, 1966). When we respond to a green pedestrian signal by crossing the road we are acting on information acquired from both our external and internal environment. This process of information acquisition is known as information sampling namely, a process through which we acquire a portion of the infinite amount of information available to us (Chamberlain & Sahakian, 2007). Our limited capacity to sample information means we must balance the accuracy of a decision with the speed of that decision, known as the speed–accuracy tradeoff (Forstmann et al., 2008). The speed–accuracy tradeoff determines how much and for how long information is sampled before the decision threshold is reached—the point at which a choice is made regarding how to respond (Doneva & De Fockert, 2014). If the information sampling process is terminated too early the response may be inappropriate for the current environmental demands and therefore impulsive (Banca et al., 2016; Caswell et al., 2015; Huddy et al., 2013). Research has identified several factors that impact how information is acquired.

Humans use a cost benefit analysis to determine whether more information should be sampled. This analysis includes a comparison of the value of obtaining additional information against the cost of accessing that information, where cost is measured in time (Meier & Blair, 2013). Due to this time cost, choosing the correct sampling strategy is critical for maintaining task driven behaviour (Fu & Gray, 2006). Therefore, the sampling strategy chosen directly reflects whether an individual places emphasises on response speed or accuracy. Additionally, the choice to emphasise speed or accuracy is balanced against environmental demands. For example, if someone was running late for work they might impulsively grab their partner's lunch container from the fridge because they did not take the time to identify the correct one. These constraints, such as a lack of time, force us to weigh the cost of seeking new information against the utility of that information (Fu & Gray, 2006).

Emerging evidence suggests the decision threshold—the point at which information sampling ceases—is influenced by specific factors. For example, individuals vary in their tendency to set either a conservative, slower response with a longer sampling period, or a liberal, faster response with a shorter sampling period (Doneva & De Fockert, 2014; Helton, Head, & Russell, 2011). The tendency to favour a liberal response criterion, where the emphasis is on response speed, has been associated with impulsivity (Stahl et al., 2014). Moreover, individuals update their decision criteria in response to alterations in perceptual load, where a lighter load results in a more liberal criterion (Doneva & De Fockert, 2014; Helton et al., 2011). This research suggests that high access costs, in the form of time or complexity, combined with the tendency to emphasise speed over response accuracy increase the likelihood of acting on impulse.

1.3.3 Response interference

When you get into someone else's car and realise the indicator is on the left, but instead reach towards the right, you are experiencing response interference. In this context, the task directed behaviour of using the indicator on the left is interrupted by a competing but irrelevant response, reaching to the right. This interference of a target task by a competing response is referred to as response interference and it represents a propensity to act immediately, in a manner out of context with current environmental demands (Hamilton et al., 2015). Moreover, response interference is one of the most consistently studied aspects of impulsivity (see Bari, Kellermann, & Studer, 2016; Bari & Robbins, 2013). Response interference can be identified by the failure to withhold or cancel a motor response that is contrary (failure to resolve interference), and it can occur at different stages of the action selection and execution process.

Research has identified two different forms of response interference (Hamilton et al., 2015). The first form of response interference occurs early, during the selection of a response, the second form occurs late, when a response is about to be executed (Stahl et al., 2014). Evidence suggests these two forms of response interference are driven by discrete processes

(Stahl et al., 2014) that are neurobiologically distinct (Hamilton et al., 2015). The difference between these forms of response interference is partially explained by the way the brain attempts to resolve competition.

The competition between relevant and irrelevant responses, produced in response interference, causes conflict, which activates control processes (Nigg, 2016). These control processes resolve conflict through inhibitory mechanisms (Cooper & Shallice, 2000), encapsulated broadly as the ability to supress dominant automatic responses (Bechara, 2005). Additionally, consistent with evidence differentiating early from late response interference, inhibitory mechanisms operate via two distinct modes: proactive and reactive (Aron, 2011; Braver, 2012; Burgess & Braver, 2010). When conflict is expected, regulatory processes can function proactively, activating control at the point of conflict (Braver, 2012; Chevalier, Martis, Curran, & Munakata, 2015). Conversely, reactive control resolves interference after its commencement (Braver, 2012), making it more resource efficient but less effective in supressing interference. Using the car indicator example, if our expectation is that the indicator in this car is different from our own, then proactive control would have us withhold the contrary response; however, if reactive control is engaged, we may reach halfway towards the incorrect side before stopping our response.

1.3.4 Delay discounting

A frequently examined expression of impulsivity is the preference for smaller, immediate rewards over larger, delayed rewards, known as delay discounting. Delay discounting has consistently been used to explain impulsive choice in both humans (Albein-Urios, Martinez-González, Lozano, & Verdejo-Garcia, 2014; Brevers et al., 2012; Broos et al., 2012; Kirby, 2009) and animals (Broos et al., 2012; Galtress & Kirkpatrick, 2010; Renda, Stein, & Madden, 2014; Tedford, Persons, & Napier, 2015). In its simplest form, delay discounting proposes that the subjective value of a reward decreases as a function of the delay until the reward is received (Smith, Marshall, & Kirkpatrick, 2015). This can be described by a hyperbolic discounting function, where shorter delays result in a steeper discounting of the reward value, while longer delays have a more gradual discounting function (Odum, 2011a). Although methods to quantify delay discounting are well-established, its underlying mechanisms remain elusive.

It is theorised that the discounting of expected rewards is due to a combination of three mechanisms (Kurth-Nelson, Bickel and Redish, 2012). First, future outcomes are evaluated through a search which occurs via the forward projection of an episodic self-representation (Kurth-Nelson et al., 2012); that is, we imagine ourselves projected into a future where we have the reward we are evaluating. Second, that rewards are evaluated proportionately to how easy they are to locate within this search process. Third, the temporal distance to the reward influences this search process, where the closer in time the reward is to us, the easier it is for us to imagine ourselves with it (Kurth-Nelson et al., 2012).

Consistent with these three mechanisms, research has shown the episodic memory system contributes to consciously pre-experiencing possible future events (Addis, Wong, & Schacter, 2007). The ability to consciously pre-experience future events is associated with a reduction in delay discounting (Peters & Büchel, 2010). Additionally, engaging the episodic system has been associated with increased cognitive flexibility (Roberts et al., 2017), which simulates the reconstruction of past events into novel future simulations (Addis & Schacter, 2008). Evidence of a future orientated mental search also comes from Addis and Schacter (2008), who found greater levels of neural activation when individuals imagined future events compared to past events. This suggests that as the temporal distance of the future event increases, so does the intensity of relational processing required to construct a coherent episodic representation. Thus, the further into the future the reward is, the harder it is for us to imagine ourselves achieving it. Delay discounting is frequently examined as a form of impulsivity; however, whether it is best conceptualised as a state or trait measure remains debated (Odum, 2011b).

1.3.5 Delay discounting: State or trait variable?

Delay discounting is a well replicated phenomenon, yet little research has been conducted to formally determine whether it is a trait or state variable. To be deemed a trait, delay discounting must be an enduring characteristic that is relatively consistent across situations (Allport, 1931), whereas state variables refer to a momentary reaction to an internal or external trigger. Research indicates that delay discounting is relatively enduring across one year in adults (Kirby, 2009) and between one (Martínez-Loredo, Fernández-Hermida, Carballo, & Fernández-Artamendi, 2017) and two years (Anokhin, Golosheykin, & Mulligan, 2015) in adolescents. Further, the reliability of delay discounting has been replicated across different task versions (Duckworth & Kern, 2011; Matusiewicz, Carter, Landes, & Yi, 2013). Taken together, this research indicates delay discounting is temporally enduring, but to be considered a trait it must also be consistent across situations.

Evidence in favour of delay discounting as a trait also comes from studies using varying reward commodities (e.g., money versus food). For instance, Weatherly, Derenne and Terrell (2011) found that discounting rates were relatively consistent across 10 different commodities. Although individuals tended to discount economic rewards (e.g., money, cigarettes) more steeply than intangible rewards (e.g., ideal body image or legislation)

(Weatherly et al., 2011; Weatherly, Terrell, & Derenne, 2010). A finding which is contrary to that of Estle, Green, Myerson and Holt (2007), who found probabilistic rewards of money and consumables were discounted consistently. Furthermore, smokers discount several types of outcomes more steeply than non-smokers (Friedel, DeHart, Madden, & Odum, 2014). Overall, evidence indicates that individuals tend to discount different outcomes relatively consistently (Odum, 2011b). This consistency, in conjunction with its enduring nature, suggests delay discounting may be a trait rather than a state variable.

In sum, the current classification of delay discounting is ambiguous and requires further research. Adding to this ambiguity, research indicates that although delay discounting is not purely a state variable, it also does not conceptually overlap with trait impulsivity (Smith & Hantula, 2008). As such, we cannot consider delay discounting a purely cognitive component of impulsivity and, after consideration of the evidence, are more inclined to consider it a trait variable. In line with this, any future referral to cognitive impulsivity within this thesis will not include delay discounting.

1.4 Current challenges in cognitive impulsivity assessment

The second aim of this thesis is to identify appropriate assessment measures of attention interference, information sampling and response interference. Assessment methodology is currently under debate, with researchers unclear on how to best measure cognitive impulsivity. Valid and reliable measurement is critical if we are to accurately determine the unique contribution of each component to mental disorders and deleterious health behaviours. This is critically important when we consider that findings subsequently inform clinical interventions, practice and future research. Advancing impulsivity assessment also depends on standardisation; however, some components of impulsivity have received more attention than others.

1.4.1 Attention interference assessment

There is no behavioural task consistently applied to assess attention interference. However, the Brown Peterson, Porteus Maze, Immediate and Delayed Memory, Stroop and modified Matching tasks have been used across various studies (Cyders & Coskunpinar, 2012; Sharma et al., 2013; Stahl et al., 2014). In addition, the Sustained Attention to Response Task (SART) may reflect attention interference. Although, it is unclear which component of impulsivity the SART is capturing—attention interference, response interference or, perhaps, both (Seli, 2016). As a group, these tasks share little in common, other than their being used as a measure of attention interference, differing in stimuli, response type, presentation format and performance indices.

The Brown Peterson task assesses working memory (Peterson & Peterson, 1959). In this task participants are presented with a sequence of three-letter constructs called trigrams and are asked to perform simple algebraic computations between each trigram, where the aim is to remember the letters on the trigram. There is no evidence outside Cyders and Coskunpinar (2012) validating the Brown Peterson task as a measure of attention interference. In contrast, the Porteus Maze task, a nonverbal test of executive function which requires participants to solve increasingly complex mazes (Porteus, 1950), has been used to assess impulsivity in a limited capacity (Glicksohn, Hadad, & Ben-Yaacov, 2016; Lee & Pau, 2002). Despite this, evidence suggests performance on the Porteus Maze task does not reflect impulsivity (O'Keefe, 1975).

Another task which has been used to capture attention interference is the Immediate and Delayed Memory task (IMT/DMT). In the IMT/DMT, participants are sequentially presented with a series of numbers and must indicate when the number presented matches the one which immediately preceded it (IMT) or when it matches the number presented prior to a filler sequence (DMT) (Dougherty, Marsh, & Mathias, 2002). Aside from Sharma et al. (2013), there have been two multidimensional studies which used the IMT/DMT. The first found that both tasks loaded onto a factor they labelled proactive interference (Cyders & Coskunpinar, 2012), while the second, which used only the IMT, found the task loaded onto a factor unto itself (Caswell et al., 2015). Adding to the evidence against the IMT/DMT as a measure of attention interference, both tasks have been used to assess response inhibition in clinical populations, such as multiple sclerosis (Toro et al., 2018), and antisocial and bipolar personality disorder (Swann, Lijffijt, Lane, Steinberg, & Moeller, 2011). In sum, findings suggest the construct validity of the IMT/DMT is relatively weak.

Another task used to assess attention interference in conjunction with response interference is the Stroop Task. In the Stroop task, stimuli are typically words representing a colour printed in an incongruent colour (e.g., the word blue is printed in green font). Participants are required to respond to the meaning of the word while ignoring the colour of the print. Both attention and response interference are implicated in the interference effect in the Stroop task (Chen, Bailey, Tiernan, & West, 2011; Chen, Tang, & Chen, 2013). As such, the Stroop task is often employed as a measure of response interference (Kräplin et al., 2014; Nombela et al., 2014); however studies which have used both the Stroop and Stop Signal Tasks (a typical response interference task) indicate that Stroop performance does not correlate with the Stop Signal Task; evidence that these two tasks are tapping different components (Kräplin et al., 2014; Nombela et al., 2014). Furthermore, despite evidence that both attention and response interference are influencing performance on the Stroop task, these two forms of interference are not separated in the literature, with studies using generalised terms such as impulsivity (Yamamuro et al., 2017) or inhibitory control (Strasser et al., 2016) to describe Stroop Task performance. The inconsistent use of the Stroop task, in conjunction with the lack of psychometric evidence, limits its validity as a measure of attention interference.

The modified Matching tasks used by Stahl et al. (2014) to assess attention interference are based on the Shape Matching task (Friedman & Miyake, 2004). In the Shape Matching Task, a participant compares a target stimulus to a reference stimulus and must indicate if the result is a match (Friedman & Miyake, 2004). No validity data is available for either the modified or original Shape Matching tasks, nor have they been used as a measure of impulsivity beyond the study by Stahl et al. (2014). Thus, there is minimal evidence of the Matching tasks suitability to asses attention interference. Finally, studies have demonstrated that the SART (Robertson, Manly, Andrade, Baddeley, & Yiend, 1997), designed to assess sustained attention, is sensitive to impulsivity (Head & Helton, 2013; Helton, 2009). In this task participants must respond to each number presented in a sequential series but withhold a response when the number is a three. It has been suggested that the SART reflects response interference (Head & Helton, 2013; Helton, 2009), or even information sampling (Helton et al., 2011; Wilson et al., 2018); however, the error score (sum of commission and omission errors) may reflect interference in attention. Errors on the SART are produced when either the stimulus itself enters working memory producing response competition (Seli, 2016), or the stimulus fails to enter working memory due to a lapse in attention, that is, distraction (Robertson et al., 1997). Further examination of the SART as measure of attention interference is required.

In sum, there are no tasks with strong evidence of validity or reliability in the measurement of attention interference. Moreover, some tasks have been used flexibly to asses both attention and response interference. This cross contamination between attention interference and response interference measures could be due to a lack of specificity in the literature between interference types. Attention, along with response and proactive, are forms of interference, all of which have been linked to impulsivity (Stahl et al., 2014) and, like action restraint and cancellation (Bari & Robbins, 2013), are often studied as a single construct in the literature (e.g., Yamamuro et al., 2017). Adding to this complexity, response and attention interference are moderately correlated (Friedman & Miyake, 2004) and often both present within a single task, such as the Stroop task. (Chen et al., 2013).

1.4.2 Information sampling assessment

There are three laboratory tasks used to assess information sampling within the context of impulsive responding: the Information Sampling Task (IST), the Jumping to Conclusions Beads Task (JTC) and the Matching Familiar Figures test. The IST and the JTC share the same underlying framework, they both require participants to sample from a set of available but unknown information before making a probabilistic decision. Contrastingly, in the Matching Familiar Figures test all the information required to make the decision is immediately available. Both the IST and Matching Familiar Figures test were specifically designed to assess information sampling, however there has been minimal examination of the psychometric properties of these tasks.

The IST instructs participants to open boxes from a 5 x 5 tiled square, one at a time. When the box is opened it is revealed to be one of two colours. The participant is able to sample as many boxes from the larger tile as they prefer before deciding which of the two colours is the majority (Clark, Robbins, Ersche, & Sahakian, 2006). The IST was used by both Caswell et al. (2015) and Kras et al. (2018) in their examinations of impulsivity's structure and has been used to assess information sampling in substance abusers (Clark et al., 2006), young adult binge drinkers (Townshend, Kambouropoulos, Griffin, Hunt, & Milani, 2014) and cannabis users (Solowij et al., 2012). The IST has recently come under criticism for over-estimating information sampling (Bennett et al., 2017), however evidence indicates it is both valid and internally consistent (Clark et al., 2006).

In the JTC (Garety, Hemsley, & Wessely, 1991) participants are presented with two jars filled with red and blue beads of known probabilities (e.g., 60:40). The participant must decide which jar the computer is sampling the beads from and, in doing so, can ask the computer to sample as many beads as they prefer until a decision is made. The JTC was originally designed to assess decision making based on limited information in individuals with delusions (Garety et al., 1991), but has been used successfully to assess information sampling in impulsive individuals. For example, the JTC has been used to identify Parkinson's patients with impulsive, compulsive behaviours (Djamshidian et al., 2012) and, in a study using both the IST and JTC, the JTC was able to differentiate binge drinkers from controls, where the IST did not (Banca et al., 2016). Aside from studies using the JTC in impulsive populations, there has been no formal assessment of its validity as a measure of impulsive information sampling.

The Matching Familiar Figures test requires participants to repeatedly select, from several alternative figures, the one that matches a standard (Kagan, 1966). Both the reliability and internal consistency of the Matching Familiar Figures test is acceptable (Glow, Lange, Glow, & Barnett, 1981) and a recent examination of its psychometric validity in detoxified alcoholics suggests the test does tap impulsivity (Weijers, Wiesbeck, & Böning, 2001). However, use of the Matching Familiar Figures test in multidimensional studies has produced inconsistent results. For instance, Sharma et al. (2013) report the Matching Familiar Figures test reflects response inhibition, whereas Caswell et al. (2015) found it not only represented information sampling but also correlated with the IST, providing evidence of convergent validity. Overall, evidence indicates the Matching Familiar Figures test demonstrates adequate psychometric properties but its use in studies of impulsivity has thus far been limited and produced inconsistent results.

1.4.3 Response interference assessment

Response interference has received considerable attention, making it one of the most commonly assessed cognitive components of impulsivity (Bari et al., 2016). Predominant laboratory tasks used to assess response interference include, the Go/No-Go (GNG), Continuous Performance and Stop Signal (SST) tasks. These tasks all share the requirement of inhibiting a prepotent response to an infrequently presented stimuli.

The GNG task requires participants to respond to a 'Go' stimulus while withholding a response to an infrequently presented 'No-go' stimulus. The GNG task has been adapted by many researchers and exists in numerous forms (e.g., Langenecker, Zubieta, Young, Akil, & Nielson, 2007; Nosek & Banaji, 2001; Tottenham, Hare, & Casey, 2011). Due to task variations, it is difficult to compare GNG results across studies. However, two studies on the psychometric properties of the GNG task were able to demonstrate moderate to high levels of reliability (Weafer, Baggott, & de Wit, 2013; Wöstmann et al., 2013). The GNG task also demonstrates adequate concurrent validity, correlating with the SST in some (Reynolds et al., 2006; Sharma et al., 2013) but not all (Caswell et al., 2015) factor analytic studies. Despite limited formal assessment, Hamilton et al. (2015) concludes that the GNG task is a robust measure of response interference, although they also caution that the multiple task variations limit the tasks internal validity.

The Continuous Performance Task was designed to assess selective and sustained attention (Conners, 2004). Within this task participants must press the spacebar in response to sequentially presented letters of the alphabet but withhold a response to the letter 'X'. The Continuous Performance Task correlates with the GNG and SST (MacKillop et al., 2016), evidence of convergent validity, and demonstrates high test-retest reliability (Weafer et al., 2013). This task is frequently employed in clinical samples (Wright, Lipszyc, Dupuis, Thayapararajah, & Schachar, 2014), but often as a measure of sustained attention (Harmell et al., 2014) and vigilance (Huang-Pollock, Karalunas, Tam, & Moore, 2012) rather than response interference. In comparison to the GNG and SST, the Continuous Performance Task is the weaker alternative.

The SST requires participants to execute an action in response to a 'Go' stimulus and withhold a response to an infrequent and unpredictable stop signal, which occurs just prior to the presentation of the 'Go' stimuli (Verbruggen, Logan, & Stevens, 2008). The SST is frequently employed as a measure of response interference (Caswell et al., 2015; MacKillop et al., 2016; Reynolds et al., 2006; Sharma et al., 2013). In addition, the SST demonstrates convergent validity, correlating with the GNG task (Reynolds et al., 2006; Sharma et al., 2013), and moderate test-retest reliability (Weafer et al., 2013; Wöstmann et al., 2013). The SST has also been used extensively as a measure of response interference in clinical populations, such as substance addiction (Smith, Mattick, Jamadar, & Iredale, 2014), obsessive-compulsive disorder (OCD) (Sung Yun, Jee In, Namkoong, & Kim, 2014) and problem gambling (Brevers et al., 2012). Furthermore, evidence suggests that the primary performance index of the SST, the stop signal reaction time (ssrt)—the time it takes a respondent to respond to the stop signal—is a valid and reliable index of response interference (Congdon et al., 2012). Of the three tasks discussed, the SST is the most robust and broadly used assessment tool.

1.5 Improving construct validity in cognitive impulsivity assessment

In the previous section we presented evidence which illustrates that tasks purported to assess aspects of cognitive impulsivity lack psychometric validation. To overcome challenges in assessment research could seek to improve construct validity. Construct validity is the process of evaluating the extent to which a measure assesses the construct it is deemed to measure (Strauss & Smith, 2009), and it encompasses all forms of validity evidence (content, predictive, concurrent etc.) (Loevinger, 1957). Hence, any evaluation of construct validity is simultaneously a test of the validity of the underlying theory (Loevinger, 1957; Strauss & Smith, 2009). To improve construct validity it is recommended that five principles be adhered to; (1) the careful articulation of each individual component, (2) reliable assessment of each component using multiple measures, (3) investigation of incremental validity at the component level (e.g., attention interference), (4) use of measures which represent a single component (not a combination), and (5) the critical assessment of whether or not the components all reflect a single broad construct (Smith et al., 2003). The application of these principles to cognitive impulsivity assessment methodology will allow us to identify avenues to strengthen construct validity.

The first principle, the meticulous articulation of components (Smith et al., 2003), requires that each component be sufficiently elaborated so that its meaning can attain consensus amongst researchers (Block et al., 1995). Put simply, the component must first be defined or explicated (Kane, 2001). However, cognitive impulsivity components are often defined differently across studies. Without a common definition there is no consistent conceptual basis from which tests of each component can be evaluated. The second principle, reliable assessment using multiple measures (Smith et al., 2003) is critical to incremental improvements in construct validity due to the method variance inherent in all psychological measures (Strauss & Smith, 2009). Moreover, as tests of relations between measures reflects the validity of both the measure and the theory driving the measure (Strauss & Smith, 2009), research should endeavour to use multiple tools when assessing each individual component. Validation research with numerous measures per component (e.g., Stahl et al., 2014) will contribute to achieving a stable model of cognitive impulsivity.

The third principle from Smith et al. (2003), includes the assessment of validity at the component level (e.g., attention interference), rather than construct level (e.g., cognitive impulsivity). Improving component level validity allows for the accurate and reliable assessment of how individual components relate to each other and also whether they are differentially associated with outcomes of interest (Smith et al., 2003). There have been previous efforts to validate individual cognitive impulsivity components (Hamilton, Littlefield, et al., 2015; Hamilton, Mitchell, et al., 2015), however a key point is that many of the studies investigating the relationship between cognitive impulsivity and other constructs of interest (e.g., alcohol use) do not include a measure of each component (e.g., Verdejo-Garcia et al., 2010; Yamamuro et al., 2017; Zhou, Zhou, & Zhu, 2016). Further multidimensional studies, such as those conducted by Kras et al. (2018) or (Kräplin et al., 2014) are needed to advance component and therefore construct validity.

The fourth principle stresses the importance of using measures which represent a single component, also known as the purity problem (Smith et al., 2003). Ideally, behavioural tasks are carefully designed to capture a specific process while controlling for extraneous variables (Cyders & Coskunpinar, 2011). Behavioural tasks intending to measure components of impulsivity suffer from this purity problem, that is, they capture various concurrent processes, such as memory and attention (Dougherty et al., 2002). Task impurity can lead to ambiguous conclusions regarding predictive value (i.e., which element of the composite is actually explaining the outcome) and obscure existing relationships with outcomes of interest (Cyders, 2015).

The fifth and final principle involves the critical assessment of whether or not each component taps a broad construct (Smith et al., 2003). To improve construct validity researchers must clearly delineate the structure of cognitive impulsivity. When the structure of a construct is not clearly identified validation research may appear ad hoc, opportunistic and uninformative (Kane, 2001). Moreover, components should be sufficient in number so that the breadth of the behaviour is represented and discriminating hypothesis can be generated (Block et al., 1995). Whether the various components of cognitive impulsivity can be combined into a broader impulsivity construct remains unknown (Kras et al., 2018).

To advance theory we must first identify an assessment approach which adds to the validity of theory and measurement (Strauss & Smith, 2009). Moving forward research on impulsivity should aim to carefully and accurately define each component (principle 1), diligently measure each component via multiple tools of adequate purity (principles 2 & 4) and examine validity at both the component and construct level (principle 3 & 5). Adherence to these five principles will serve to advance the construct validity of cognitive impulsivity.

1.6 Negative outcomes associated with impulsivity

Despite challenges in both conceptualising and assessing impulsivity, it remains a topic of considerable importance given it is consistently linked with negative health outcomes across both clinical and healthy populations. This includes behavioural disorders, substance use disorders and personality disorders, as well as deleterious health behaviours, all of which negatively impact quality of life (QoL).

1.6.1 Impulsivity in clinical populations

High levels of impulsivity are linked to several disorders with significant public health implications. For instance, impulsivity is a core symptom of attention-deficit hyperactivity disorder (ADHD) (American Psychiatric Association, 2013), for which the hyperactivity-impulsivity component is heritable (Greven, Rijsdijk, & Plomin, 2011). Impulsivity is also a central feature of OCD (Sung Yun et al., 2014; Yamamuro et al., 2017), for which impulsivity is an enduring symptom, persisting across time and treatment (Yamamuro et al., 2017). Both ADHD (Klassen, 2005; Velo, Kereszteny, Szentivanyi, & Balazs, 2013) and OCD (Asnaani et al., 2017; Ruscio, Stein, Chiu, & Kessler, 2010) are associated with poorer QoL.

Elevated impulsivity is a vulnerability marker for substance use disorders (Verdejo-Garcia, Lawrence, & Clark, 2008). Impulsivity is implicated in the inability to attain and maintain abstinence (Stevens et al., 2015; Stevens et al., 2014), and dampens treatment based improvements in social and psychological QoL (Rubenis, Fitzpatrick, Lubman, & Verdejo-Garcia, 2017). Further, impulsivity is associated with behavioural addictions, such as gambling disorder (Brevers et al., 2012; Lorains, 2014; Wiehler & Peters, 2015), with evidence indicating that impulsive behaviour during childhood is a significant risk factor for adult gambling (Shenassa, Paradis, Dolan, Wilhelm, & Buka, 2012).

Impulsivity is also implicated in personality and mood disorders. For instance, impulsivity is a diagnostic feature of borderline personality disorder (McHugh & Balaratnasingam, 2018). Research on borderline personality disorder indicates that delay discounting persists from adolescence into adulthood relative to healthy controls (Urošević, Youngstrom, Collins, Jensen, & Luciana, 2016). Cognitive (Feliu-Soler et al., 2013) and trait impulsivity (Bøen et al., 2015) is also elevated in individuals with borderline personality and bipolar disorder. Furthermore, impulsivity is differentially associated with mania and depression in individuals with bipolar disorder (Swann, Steinberg, Lijffijt, & Moeller, 2008). Another disorder characterised by poor impulse control is antisocial personality disorder (Swann, 2011). This relationship deepens in severity with a co-morbid presentation of antisocial and bipolar personality disorders (Swann et al., 2011). Although impulsivity is discretely associated with poorer QoL in individuals with antisocial personality disorder (Chamberlain, Stochl, Redden, & Grant, 2017), these disorders are all significant predictors of QoL above and beyond socio-economic and somatic health variables (Cramer, Torgersen, & Kringlen, 2006).

Obesity also has strong ties to Impulsivity (Delgado-Rico, Río-Valle, González-Jiménez, Campoy, & Verdejo-García, 2012; Leitch, Morgan, & Yeomans, 2013). Obesity is a major health concern, as individuals who are overweight or obese are at an increased risk of developing numerous chronic diseases, such as cardiovascular disease and diabetes (Kopelman, 2007). Uncontrolled eating has been associated with a lack of information sampling (Leitch et al., 2013), while negative and positive urgency (facets of trait impulsivity) significantly predict BMI in adolescents (Delgado-Rico et al., 2012). Furthermore, a recent meta-analysis demonstrated that multiple components of impulsivity are positively linked with BMI, including response interference, attention interference and delay discounting (Emery & Levine, 2017).

1.6.2 Impulsivity in the general population

Moving beyond clinical populations, impulsivity is implicated across a range of behaviours which have a negative impact on health within the general population. This includes, cigarette smoking (Friedel et al., 2014), overspending (Dittmar & Bond, 2010), antisocial behaviour (Lynam & Miller, 2004), risky sexual activity (Jardin, Sharp, Garey, & Zvolensky, 2016) and problematic SNS use (Lee et al., 2012). All of these behaviours can be harmful to both the individual themselves and society more broadly.

Different forms of Impulsivity have been linked to cigarette smoking, a key determinant of cardiovascular disease deaths in Australia (Dhaliwal, & Welborn, 2009). For example, cigarette smokers discount delayed outcomes more steeply (Friedel et al., 2014), and non-planning impulsivity predicts relapse in treatment seeking smokers (López-Torrecillas, Perales, Nieto-Ruiz, & Verdejo-García, 2014). Age of smoking onset also impacts response interference, with early onset smokers exhibiting greater response interference compared to late onset smokers (Mashhoon, Farmer, Betts, & Lukas, 2015). Poor impulse control is also associated with overspending (Dittmar & Bond, 2010), and compulsive buying (Williams, & Grisham, 2012). Buyers tend to cluster into two types, (1) compulsive-impulsive buyers, characterised by high levels of impulsivity and compulsivity, and (2) impulsive excessive buyers, characterised by high impulsivity and low compulsivity (Yi, 2013). In addition, negative urgency, a facet of trait impulsivity, is implicated in compulsive buying (Alemis & Yap, 2013; Billieux, Rochat, Rebetez, & Van der Linden, 2008).

Antisocial, delinquent and risky sexual behaviour are discreetly associated with different forms of impulsivity. To illustrate, trait impulsivity is positively associated with adolescent delinquency (Chen, & Jacobson, 2013), while facets of traits of impulsivity, including a lack of premeditation and elevated sensation seeking, are linked with deviant and antisocial behaviour (Lynam & Miller, 2004). Correspondingly, research on male youth found a higher peak in the age-arrest curve for those with elevated cognitive impulsivity and a low IQ (Loeber et al., 2012). Another potentially damaging health behaviour linked to elevated impulsivity is risky sexual activity (Dir, Coskunpinar, & Cyders, 2014). In their meta-analysis, Dir, Coskunipar and Cyders (2014) demonstrated that all facets of the UPPS-P, except for positive urgency are associated with risky sexual behaviour in adolescents. Similarly, recent findings suggest that individuals who experience negative affect linked to impulsive behaviour, are more inclined to engage in risky sexual behaviour (Jardin, Sharp, Garey, & Zvolensky, 2016).

A new and emerging area of research is the link between impulsivity and problematic engagement with technology. Technology use is deemed problematic when it is uncontrolled, involves a growing motivation and tension to use (Andreassen, 2015), and results in impairments in psychological health and wellbeing (Shensa et al., 2017). Research has implicated impulsivity in problematic internet use (Chen, Lo, & Lin, 2017; Lee et al., 2012; Zhou, Zhou, & Zhu, 2016), mobile use (Hayashi, Miller, Foreman, & Wirth, 2016; Wilmer & Chein, 2016), video game use (Billieux et al., 2011; Buono et al., 2017) and the use of SNS (Chen et al., 2017; Wilmer & Chein, 2016).

Specifically, research demonstrates that different forms of impulsivity are consistently associated with dysfunctional technology use, including response interference (Chen et al., 2017; Zhou et al., 2016), the cognitive, motor and non-planning dimensions of the Barratt Impulsiveness scale, a measure of trait impulsivity (Lee et al., 2012), and delay discounting (Hayashi et al., 2016; Wilmer & Chein, 2016). This is particularly concerning, given the strong evidence linking problematic SNS use with negative mood states such as stress, depression and anxiety in young adults (Banyai et al., 2017; Shensa et al., 2017). Not only do young adults more readily engage with SNS's (Kemp, 2018), they are also more vulnerable to depression (Mojtabai, Olfson, & Han, 2016), and going through a period of development demarcated by heightened impulsivity (Harden & Tucker-Drob, 2011). This has resulted in a growing concern for what has been dubbed 'Facebook addiction' (Andreassen, Torsheim, Brunborg, & Pallesen, 2012).

1.7 Conclusion and ways forward

Although impulsivity has been investigated from various perspectives, debate is ongoing as to how it should be defined, its main components and which tools are most appropriate for assessment. This review identified four potential components of cognitive impulsivity—attention interference, lack of sufficient information sampling, response interference and delay discounting—examining each component's unique contribution to impulsive behaviour. We settled on a tripartite model of cognitive impulsivity, which includes all components except delay discounting due, to the possible consideration of delay discounting as a state variable. To further the study of impulsivity, the grouping of these three dissociable cognitive components must be validated; however, in accordance with Mischel (2009) and as stated by Duckworth and Kern (2011, p. 12), success of such validation relies ‘not only upon field-unifying theories and well-designed studies, but also upon valid, consensually understood measures’.

Impulsivity research suffers from a rather extraordinary variation and duplicity of assessment measures. This multiplicity of tools has led to confusion, as the same construct can be assessed with different measures or even as a different construct using measures with an analogous label. Researcher confusion has prompted debate as to whether these measures are tapping into the same underling construct. As Cyders (2015) notes, standardised measures of impulsivity need to be both validated and agreed upon. There are numerous behavioural tasks which have been used to assess components of impulsivity, however how these tasks relate to each other and what cognitive processes they assess remains unclear. Given that measures of impulsivity have been linked to clinical treatment outcomes (Rubenis et al., 2017; Stevens et al., 2015; Stevens et al., 2014), improvements in the precision and standardisation of impulsivity assessment could be applied to understanding the aetiology of negative behavioural problems for which impulsivity is a core feature.

Prior to applying standardised assessment tools in a clinical population, Hamilton et al. (2015) suggest we must first deconstruct impulsivity assessment and focus on selecting and validating measures in the general population. This means extending research beyond the realms of college or university samples, as is the norm for multidimensional studies of impulsivity (Caswell et al., 2015; Cyders & Coskunpinar, 2012; MacKillop et al., 2016; Stahl et al., 2014). Particularly given student samples are likely to be of higher than average intelligence and from a middle class socio-economic background (Harvey, 2016; James et al., 2008), labelled colloquially as Western, educated, industrialised, rich and democratic, or 'WEIRD' (Henrich, Heine, & Norenzayan, 2010). After the fundamentals of impulsivity are revisited in a healthy population using standardised measures, the assessment of populations linked with elevated impulsivity can be revisited.

Although there is little conceptual overlap (Cyders & Coskunpinar, 2011) or empirical evidence of concordance between state and trait measures of impulsivity (Broos et al., 2012; Caswell, Bond, Duka & Morgan, 2015; Stahl, et al., 2014), there is a strong argument to include both methods when assessing a heterogenous construct such as impulsivity (Sharma et al., 2013). Without a multidimensional approach, a comprehensive understanding of how each component of impulsivity influences negative behaviours will not be achievable. As such, future research would benefit of the inclusion of measures which capture both forms of impulsivity.

In summary, it is not the construct of impulsivity itself hindering empirical advancement, but its indiscriminate use and broad application. Moving forward, what is most critical to ascertain is not when or where impulsivity occurs but the mechanisms and processes underlying it (Higgins & Eitam, 2014). The identification of the mechanisms underlying impulsive behaviour is critical given that cognitive impulsivity remains an important research construct in clinical and healthy populations. Therefore, this thesis will examine the validity of attention interference, information sampling and response interference as components of cognitive impulsivity; then investigate their predictive value in an impulsive population.

1.8 Aims and hypotheses

This section summarises the aims and hypotheses developed after the review of the literature presented in the preceding sections. This thesis has two aims, which are addressed with three studies.

Aim 1: *To assess a tripartite structure of impulsivity, including attention interference, information sampling and response interference in healthy adults.*

To achieve this aim, we conducted two studies. The first was an exploratory study in which we designed two novel behavioural tasks—one each to assess attention interference and information sampling—to improve construct validity in the assessment of cognitive impulsivity. The second study was informed by and extended the first, with the aim of substantiating a tripartite structure of impulsivity, including attention interference, information sampling and response interference.

<u>Study 1</u>:

Hypothesis 1: Performance on the novel attention interference and information sampling tasks will be positively associated with existing measures of these constructs.

Hypothesis 2: Performance on the novel attention interference and information sampling tasks will decrease as task difficulty increases.

Hypothesis 3: Performance on the attention interference, information sampling and response interference tasks will be associated with elevated, as compared to low, levels of trait impulsivity.

Study 2:

Hypothesis: The behavioural indices of six laboratory measures of impulsivity will cluster into three discrete factors reflecting interference from a competing response, interference from a competing stimulus, or inadequate information sampling.

Aim 2: *To examine whether a higher propensity towards impulsive behaviour and elevated symptoms of negative mood are associated with general and/or problematic SNS use.*

To address aim two, we conducted one multidimensional study incorporating both self-report and behavioural tasks. The behavioural data is reported in Appendix A, as is the specific hypothesis pertaining to cognitive impulsivity and SNS use.

Study 3:

Hypothesis: Trait impulsivity, specifically negative urgency, positive urgency, sensation seeking, premeditation and perseverance, as well as negative mood will be positively associated with problematic but not general SNS use.

Chapter 2: Expanded Methodology

2.1 Introduction

This chapter provides an overview of the methodology used across the three studies which comprise this thesis, containing a more comprehensive description of the methodology than is possible in each individual manuscript. In this chapter, emphasis is given to the development of each of the three novel assessment tasks used in this research, as well as the procedures used for online participant recruitment and data collection. Existing tasks for which descriptions are available in the broader impulsivity literature, such as the SST, are briefly detailed in each empirical chapter. As such, the contents of this chapter include the software used in task coding and administration, the rationale, structure and administration of each of the novel behavioural tasks, and details regarding the online recruitment platforms, recruitment procedure and data collection, including quality assurance procedures.

Table 1 outlines the study design, assessment measures, participants and the statistical analysis implemented within each study. All the procedures used across the three studies were approved by the Monash University Human Research Ethics Committee. Project approval numbers are: Study 1, CF16/261–2016000121; Study 2, MUHREC, 1364; and Study 3, MUHREC, 9061.

Table 1: Summary of each study's design, participants, assessment measures, and statistical technique

Study	Design	Participants	Assessment Measures	Statistical Analysis
1	Exploratory behavioural study	40 healthy adults female, 65%; age, $M = 25$	*Attention Interference Task (AIT) Sustained Attention to Response Task (SART) Jumping to Conclusions Beads Task (JTC) *Gathering Task (GAT) Stop Signal Task (SST) UPPS-P Impulsive Behaviour Scale	Correlational analysis was used to compare outcome measures on the novel with standard tasks. Repeated measures ANOVA were applied to assess the internal validity of each novel task. Finally, independent samples *t*-tests were used to determine if performance across behavioural tasks differed in those with elevated versus low levels of impulsivity, determined by a median split half.
2	Factor analytic study	128 healthy adults female, 48% age, $M = 32.24$	Sustained Attention to Response Task (SART) Visual Search Task (VST) Jumping to Conclusions Beads Task (JTC) AX-Continuous Performance Task (AX-CPT) Stop Signal Task (SST) Cued Go/No-Go Task (GNG)	Principal components analysis was employed to examine how the selected performance measures aligned with attention interference, information sampling and response interference.
3	Self-report study	159 healthy adults female, 70% age, $M = 28.22$	Frequency of Social Media Use Scale (FSMU) Modified Social Networking Time Use Scale (SONTUS) The Social Media Disorder Scale (SMDS) UPPS-P Impulsive Behaviour Scale The Depression Anxiety and Stress Scale 21 (DASS21)	Two multiple regression analyses were used to examine the association between trait impulsivity, negative mood states (depression, anxiety and stress), age, education and SNS use. One model was for general SNS use and the other for problematic use.

*Indicates a novel task, created specifically to address the research aims of the thesis. Note: Study 3 also included behavioural measures of impulsivity reflecting information sampling and response interference, as well as a measure of delay discounting and compulsivity. Missing data precluded an adequately powered analysis of the data, so we chose to include it in Appendix A. This subgroup included 71 healthy adults (Age $M = 30.93$, female 63%). Participants completed the Jumping to Conclusions Beads Task, Probabilistic Reversal Learning Task, Delay Discounting Task and Social Media Go/No-Go Task. Two multiple regression analyses were used to examine the association between behavioural impulsivity, negative mood states, compulsivity, age, education and SNS use. One model was for general SNS use and the other for problematic use

2.2 Study 1—Cognitive impulsivity does not differ in those with high or low levels of trait impulsivity; and the development of two novel behavioural tasks to improve validity in the assessment of attention interference and information sampling

Study 1 examined two novel assessment measures (designed specifically to address Study 1, Hypotheses 1 and 2). One novel task was developed to assess attention interference and one task to assess information sampling. In this study we also examined if performance on behavioural measures representing the three components identified in our review, AI, IS and RI, differed between high and low levels of trait impulsivity. To achieve this, we took a multidimensional approach, using three sets of measures: (1) the two novel measures, (2) three existing measures, one each per behavioural component of impulsivity, and (3) the UPPS-P, a well-validated, multidimensional measure of trait impulsivity, summarised in Table 2. The protocol was administered face-to-face in a testing lab at Monash University, Clayton.

Table 2: Summary of assessment measures used in Study 1

Impulsivity Component	Experimental Task
Attention Interference	*Attention Interference Task (AIT) Sustained Attention to Response Task (SART)
Information Sampling	Jumping to Conclusions Beads Task (JTC) *Gathering Task (GAT)
Response Interference	Stop Signal Task (SST)
Trait Impulsivity	UPPS-P Impulsive Behaviour Scale (UPPS-P)

*Indicates novel task

2.2.1 Software used for novel task development

The novel computerised behavioural tasks were developed through the cross platform experiment generation software Open Sesame (Version 2.9.6) (Mathôt, Schreij, & Theeuwes, 2012), using a PsychoPy back-end (Peirce, 2007). Open Sesame is a front-end interface developed specifically for psychology and neuroscience experiments which runs off an independent back-end (the software layer that deals with input [e.g., keyboard] and output [e.g., display and sound]). For our experiment, we used a PsychoPy back-end, as it is recommended for use with complex stimuli or where precise timing is important. PsychoPy has been employed in psychophysics and cognitive neuroscience (Peirce, 2007). Prior to coding each task, research was conducted to determine the most appropriate parameters for the cognition under examination. A rationale for building each task, as well as the design elements, are detailed below.

2.2.2 Rationale for the Attention Interference Task

Within the Attention Interference Task (AIT), participants are presented with a stimulus array and must respond to a randomly generated 'Go' cue, while ignoring any distracters. In developing the AIT, we aimed to create a relatively pure and valid measure of task interruption from distracting stimuli. We sought to minimise fatigue, practice effects, suboptimal performance (e.g., motivation) and any other factors not explicitly manipulated as much as practical. To achieve this, we limited non-essential motor movement, minimised perceptual discrimination demands, provided a wide visual field, randomised timings, used a stepwise difficulty progression, included an acquisition phase and provided performance feedback. Each of these elements was built on to an underlying framework based on the SART (Robertson et al., 1997).

The original SART (SART random) (Robertson et al., 1997) uses a go/no-go paradigm and random stimulus presentation (digits between one and nine are individually and randomly presented, where 'three' is the No-go stimulus). However, the random stimulus generation used in the SART random has unintentionally resulted in the task capturing response interference, rather than attention slips, as it was designed to do (O'Connell et al., 2009). To overcome this the SART was modified and the fixed presentation version developed (SART fixed) (Manly et al., 2003). In the SART fixed stimuli are presented in a predictable fixed sequence (digits individually and sequentially presented from one to nine, where 'three' is the No-go stimulus). The SART fixed is sensitive to sustained attention (O'Connell et al., 2009); thus, we based the AIT on the underlying response format of the SART fixed.

Although closely related, sustained attention differs from attention interference. Attention interference refers to the point at which task directed focus is interrupted; whereas, sustained attention is self-sustaining, task directed focus, in a context with minimal exogenous stimulation (Robertson & Garavan, 2004); it by definition excludes distraction from external stimuli. As such, the requirements of the AIT differ from the SART, in that the AIT must include a mechanism that captures attention interruption rather than sustained focus.

2.2.3 Attention Interference Task structure and administration

Each trial begins with a visual array of 12 stars (4 x 3, yellow outline) on a white background (to heighten contrast). The choice to use a visual array consisting of identical stimulus rather than a single, centralised, sequentially presented string of changing stimuli, served the dual purpose of reducing perceptual discrimination processing and widening the visual area, thereby increasing the size of attentional field. Further, the simple shape of a star was chosen as it has no associative value, such as a food cue might. We also limited non-essential motor movement by using a single key response requiring a fixed hand position.

Participants are instructed to respond by pressing the space bar to a 'Go' cue as quickly and accurately as possible. Using a single key-press from the resting 'home' position of the space bar avoids differential response times produced by the movement preparation required when using different response keys.

To limit a participant's ability to predict target onset, and therefore prepare a motor response, in each trial the stimulus array is presented for a varying stimulus-onset asynchrony (SOA) randomly generated from a pool of 10 timings (90, 100, 150, 200. 450, 500, 750, 900, 1200 and 1500 ms). The stimulus array is immediately followed by either the presentation of the Go stimulus (90 ms, star lights up), or a distractor (90 ms, star partially lights up), which is also randomly generated. Both the Go cue and distractors appear for 90 ms to encourage vigilance and increase task difficulty (Greenberg, 2007), critical for maintaining task sensitivity in a healthy population. In trials which include a distractor the duration of the SOA (the time between distractor offset and Go cue onset) is also randomly generated from the same pool of ten timings. Following the presentation of the Go cue, a fixation array is presented for 500 ms, independent of response time, indicating the beginning of a new trial. Responses are terminated after 500 ms (i.e., the maximal response time) if no key is pressed. A visual depiction of a single AIT trial is presented in Figure 1.

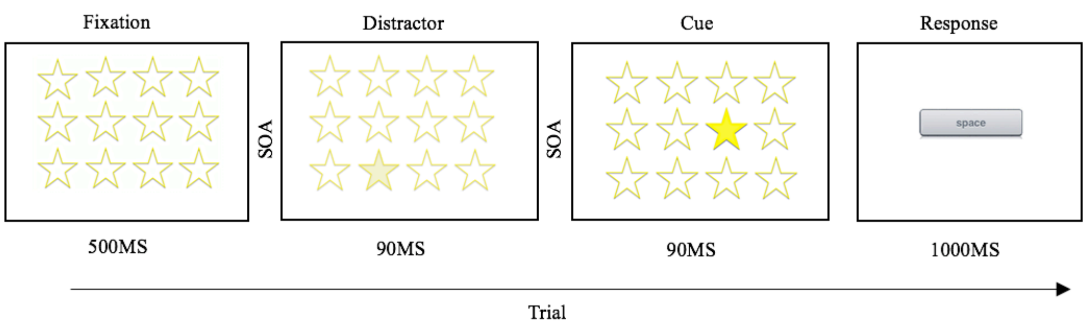


Figure 1: Visual depiction of a single AIT trial with distractor

The AIT begins with a brief practice round (five trials), to train participants in the experimental condition. Once this practice phase is over, participants complete three test blocks (40 trials each, 120 trials total). Blocks two and three include a stepwise difficulty progression to improve the construct validity of the task by ensuring a broader range of task performance is assessed (Smith, Fischer, & Fister, 2003). The stepwise progression is as follows. In the first test block there are no distractors (an acquisition block), promoting attentional focus, similar to the SART fixed (Manly et al., 2003). In block two, one distractor is introduced, occurring randomly on 60% of the trials, disrupting the previously learnt fixed pattern. Finally, in block three, a second distractor is randomly presented on 40% of the distractor trials.

At the end of each block, feedback is presented to facilitate continual task engagement and motivation. Feedback includes the average response time (ms) and accuracy (% correct) over the preceding block. The primary outcome measure for the AIT is an overall error score, including commission and omission errors, as both indicate that the target behaviour has been interrupted. Commission errors occur when the space bar is pressed when a key-press should have been withheld, while omission errors occur when the space bar is not pressed when a key-press was required.

2.2.4 Rationale for the Gathering Task

The Gathering Task (GAT) instructs participants to discretely sample from a dataset of unknown information and then make a probabilistic decision based on the evidence sampled. In developing the GAT, the primary objective was to produce a relatively pure and valid measure of information sampling, which, in the context of impulsivity, is the tendency to enact responses prior to sufficiently considering all the available evidence (Stahl et al., 2014).

To achieve this, we chose not to emphasise response speed or accuracy, minimised perceptual demands, used a simple two choice response format, did not reward or punish responses, used a large pool of information and employed a stepwise difficulty progression. We also sought to minimise fatigue, practice effects and suboptimal performance (e.g., motivation), as much as is practicable. The underlying framework of the GAT is based on the IST (Clark et al., 2006), which was developed to assess information sampling within the context of impulsivity.

There are three primary weaknesses in using the IST as a measure of impulsive information sampling: validity of the primary performance index, task impurity and low ecological validity. First, the IST quantifies an individual's tolerance for uncertainty by P(correct) (Clark et al., 2006). P(correct) is the probability of the participant being correct at the point of decision. The validity of P(correct) has recently come under scrutiny as inaccurate and likely representing several cognitive functions (Axelsen, Jepsen, & Bak, 2018; Bennett et al., 2017; Bennett, Yücel, & Murawski, 2018), such as flexibility and learning. Most studies published using the IST use P(correct); however, Clark and Robbins (2017) suggest the average number of boxes opened should be used as a coarse, yet unequivocal, measure of information sampling.

Second, the IST reward contingencies may impact task purity. According to Schiebener and Brand (2017), in tasks that use conditions of uncertainty or ambiguity, no explicit information should be provided about the rules of the task governing positive and negative consequences. If such rules are provided, then the task becomes one of risk rather than uncertainty (Schiebener & Brand 2017). Even though the available information in the IST is uncertain, the consequences are explicit, meaning it is not purely a task of uncertainty but also of risk (a task that has explicit rules governing gains and losses) (Brand, Labudda, &

Markowitsch, 2006). This is particularly relevant in the decreasing win condition of the IST, where losses accumulate as more information is sampled. Furthermore, under conditions of risk the use of executive functions is elevated, whereas in conditions of uncertainty the importance of higher order functions is minimal (Brand et al., 2006; Brand, Recknor, Grabenhorst, & Bechara, 2007). As such, the IST may be less pure than intended, as decisions involving risk engage executive functions, such as cognitive flexibility, set shifting and monitoring (Brand et al., 2006; Schiebener & Brand, 2017).

The third and final weakness pertains to both ecological validity and the primary performance index. Decisions within the IST are probability based and the probability is variable—both the predominant colour (blue or yellow) and the colour ratio shift between trials. Consequently, the participant is always in a state of uncertainty. This is a weakness in two ways: first, in ecological or natural decision-making environments, we generally know with some degree of certainty the likelihood of a particular outcome and, second, according to Clark et al. (2006) (the designers of the IST), the foremost aim of an impulsive information sampling task is to slow decision-making so accuracy becomes a function of the extent to which information is sampled. As the IST has a randomly variable ratio, even if the same quantity of information is sampled across every trial, the accuracy based off this sample will vary (also a criticism of P(correct)), meaning a naturally occurring information strategy would be difficult for a participant to employ. This is because the IST produces uncertainty on two levels: the decision itself is uncertain, as is the utility of collecting an additional sample (opening another box).

2.2.5 Gathering Task structure and administration

Participants are first presented with the task instructions, which inform them that they will be presented with a blank tile and they must determine the predominant colour of the tile by revealing one coloured row at a time until they come to a decision. The instructions do not emphasise either the speed or accuracy of response so as not to influence the participants' information sampling strategy. The tile consists of 10 x 10 individual squares, each of which is coloured in one of two colours (which vary by block). Each colour is chosen to contrast with its pair; for example, purple was paired with white, to reduce any perceptual ambiguity that might arise when attempting to distinguish between like colours.

Each trial begins with a blank tile (black outline and white square 10 x 10 matrix). The participant is required to reveal one row at a time using the space bar, until they come to a decision regarding which of the two colours is the predominant colour (e.g., purple or white). Participants indicate the predominant colour using either the 'Z' or 'M' key, with the colour of each key assigned in the instructions at the beginning of each block. There were no time restrictions placed on a participant's response and no points system included. We chose not to reward or punish participants because research indicates that natural sampling tendencies are influenced in the direction of the reward when a points system is included (Forstmann et al., 2008; Rae, Heathcote, Donkin, Averell, & Brown, 2014). The beginning of a new trial is triggered by the participant's response, refreshing the tile to its original blank state.

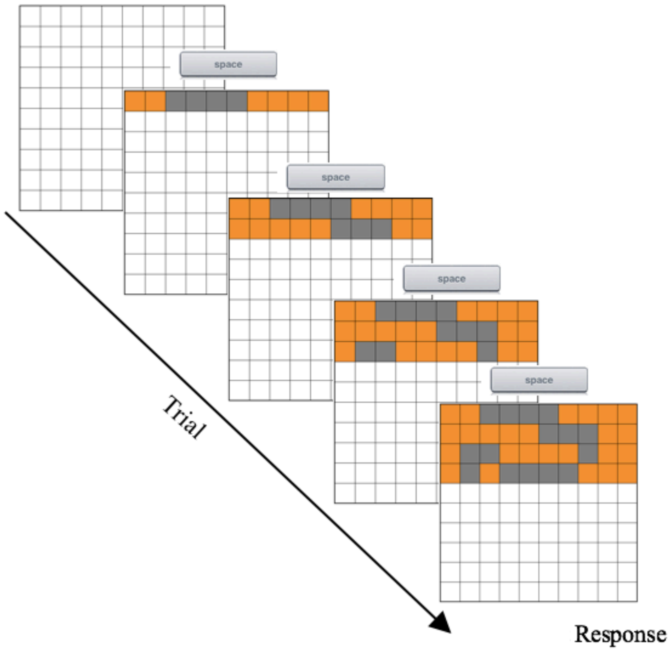


Figure 2: Visual depiction of a single GAT trial in the 8:2 block

The GAT consists of a single practice trial followed by three test blocks of 10 trials (31 trials in total). The blocks become successively more difficult via alterations in the colour ratio, from 8:2 in block one, to 7:3 in block two and 6:4 in block three. The colour pairs consisted of purple and white (practice trial), orange and grey, yellow and green, and red and blue, across the three blocks respectively. Primary outcome indices include the average number of rows revealed per block and overall. A lower average number of rows revealed was considered indicative of a liberal response criterion, reflecting impulsive responding (Stahl et al., 2014).

2.3 Study 2—Substantiating a structural model of behavioural impulsivity: Evidence for response interference

To substantiate a tripartite model of impulsivity, including, attention interference, information sampling and response interference Study 2, used principal component analysis. Two suitable measures were chosen to assess each individual component. Each measure is identified below in Table 3.

Table 3: Summary of experimental tasks per impulsivity component

Process	Experimental Task
Attention Interference	Visual Search Task (VST) Sustained Attention to Response Task (SART)
Information Sampling	Jumping to Conclusions Beads Task (JTC) AX-Continuous Performance Task (AX-CPT)
Response Interference	Stop Signal Task (SST) Go/No-Go Task (GNG)

A fully online, mixed questionnaire and behavioural design was employed. This included online participant recruitment via database and secure online data collection via the experimentation software Millisecond Inquisit Web. Although these techniques are not new, the use of online data collection is a novel experimentation method, particularly for behavioural tasks, which are traditionally conducted in controlled laboratory conditions. These methods afford certain strengths but are not without their limitations. The strengths and limitations and procedures used to ensure data quality are outlined below.

2.3.1 Online recruitment and data collection

Many studies on impulsivity's structure are conducted using college or university samples, characterised as western, educated, industrialised, rich and democratic, or 'WEIRD' (Henrich et al., 2010). However, samples from the general population are required if research on impulsivity is to empirically advance (Hamilton et al., 2015). To obtain a dataset from the general population we utilised Amazon Turk Prime, a popular online participant database for academic research (Chandler & Shapiro, 2016). Turk Prime samples are demographically diverse (Buhrmester, Talaifar, & Gosling, 2018; Sheehan, 2018), offer a valid alternative to face-to-face testing with behavioural tasks (Crump, McDonnell, & Gureckis, 2013), and provide better quality data than comparative means of convenience sampling (Shao et al., 2015). Due to this, hundreds of papers have been published in top ranked social science journals using data collected from Amazon (Chandler & Shapiro, 2016).

Participants (known as workers) volunteer for studies via Human Intelligence Tasks (HITs), posted by the researcher (known as a requester) and are reimbursed for their time in United States (US) dollars. In deciding on a HIT, workers are presented with a brief explanation of the work, the estimated completion time (mins) and the monetary amount they will be reimbursed. Although Turk Prime provides some basic quality assurance procedures, such as a unique identifier which tracks worker performance so participants cannot complete the same HIT twice, inbuilt quality mechanisms are limited (Chandler & Shapiro, 2016). The lack of inbuilt quality mechanisms and the experimental setting has raised concerns regarding the quality of data.

Of principal concern to researchers is the uncontrolled environment in which participants complete the study. Yet, research on the validity of data collected from Turk Prime suggests there is little evidence to sustain concerns that the lack of environmental control produces meaningful differences in data. For instance, Crump et al. (2013) tested several behavioural tasks, including those that rely on precise response latencies and brief stimulus presentation, such as the Stroop Task or Attentional Blink, finding that even for extended experiments the data is in line with laboratory results. A large-scale replication study on the comparability of crowdsourced data corroborated the finding that there is no significant difference in quality between online or laboratory methods (Klein et al., 2014). Additionally, research on the quality of questionnaire data using Turk Prime found high concurrent and convergent validity (see Chandler & Shapiro, 2016). Overall, research suggests data collected on Turk Prime is just as valid as data collected using traditional methods; nevertheless, as researchers cannot directly verify that participants thoroughly and attentively complete the experiment, it is imperative that specific practices for data collection are followed.

Prior to posting a live HIT it is crucial that the functionality and completion times are tested (Sheehan, 2018). Pretesting not only confirms that all parts of the experiment are working correctly but provides information that can be used to determine whether workers are completing the study too quickly or slowly. We conducted three fully functioning pre-tests prior to posting the live link; that is, any test with resulted in a functionality problem resulted in another three tests. Following this, the experiment was pilot tested with a handful of volunteers and feedback collected regarding user experience and any technical difficulties encountered. The testing data was used to set a priori minimum and maximum completion time (mins) for use in data cleaning. The data was then collected in phases.

Discrete phases were used to download and screen responses so that workers who failed to fully complete the experiment, completed too quickly or slowly, or displayed inappropriate responding could be rejected for payment (the rejected workers are replaced until the predetermined sample threshold is reached). The rejection rate for this study was approximately 20%, with the most common reason for worker rejection being incomplete responses, followed by speed of completion.

As recommended by Buhrmester et al. (2018) we set a priori data exclusion criteria, based on previous research for each task. Previous studies on the SST have used both lenient exclusion criteria, failing to demonstrate above-chance accuracy (≥ 66%) on 'Go' trials (Lee, 2014) or conservative criteria, failing to demonstrate ≥75% accuracy on 'Go' trials (Congdon et al., 2012). Based on this, we removed cases with omission errors ≥30% in either the SART or SST; as evidence of task disengagement. In addition, findings indicate that the average number of commission errors on the SART is approximately 24%, (Manly et al., 2000), leading to exclusion criteria of ≥75% (Congdon et al., 2012). Therefore, cases were removed for both the SART and SST where commission errors were ≥90%. Using the JTC to assess impulsivity, Banca (2016) found healthy participants sampled on average eight beads, whereas Djamshidian et al. (2012) found on average one bead was drawn in the 80:20 condition and three in a 60:40 condition. Therefore, we excluded participants for whom the average number of beads drawn across the task was ≤ 2. With regards to the GNG task, we excluded cases with an error rate of either 0% or 100% for 'Go' trials, as prior research reported that omission errors accounted for between 1% and 1.5% of 'Go' trials (Fillmore, 2006; Hong, Wang, Sun, Li, & Tong, 2017). Finally, we omitted cases for which the Visual Search Task (VST) average response time was ≤ 200 ms (based on Manly et al., 2000, who found the average 'Go' cue response time was 375 ms) or the proportion correct was ≤30%, similar to the criteria imposed on the SART and SST.

We imposed the above exclusion criteria on the data to ensure the sample was comparable to one obtained in a more controlled setting, however this meant a significant amount of the data had to be removed. This is a known weakness of online sampling, with attrition expected to be approximately 30% (Zhou & Fishbach, 2016). Due to data loss, the pre-screened sample must be significantly larger than a priori power calculations recommend. Although pre-screening participants can reduce attrition stemming from ineligibility (e.g., over 45 years of age), it is recommended that all participants be allowed to complete the study and screening be conducted post data collection to dissuade workers from being dishonest on demographic questions, including screening questions.

2.4 Study 3—Trait impulsivity and negative mood states are associated with both general and problematic social networking site use

Emerging evidence indicates that SNS use influences both cognition and affect (Barr, Pennycook, Stolz, & Fugelsang, 2015). Study 3 sought to examine how individual differences in cognition and affect contribute to both general and problematic SNS use. Use is considered problematic when it is uncontrolled and impairs health and wellbeing (Shensa et al., 2017; Turel & Bechara, 2017). Specifically, we wanted to examine how behavioural and trait impulsivity, compulsivity and negative mood states contribute to SNS use. This study employed a fully online mixed methods design, including one novel task designed to assess response interference within a SNS context. A summary of the experimental tasks is given in Table 4. For participant recruitment in Study 3 we used a mixture of an Amazon Prime Panel and Facebook advertisements. For data collection we utilised Qualtrics and Millisecond Inquisit Web.

Table 4: Summary of experimental tasks

Variable	Experimental Task
Problematic SNS use	Social Media Disorder Scale (SMDS)
SNS diversity	Frequency of Social Media Use Scale (FSMU)
General SNS use	Social Networking Time Use Scale (SONTUS)
Trait impulsivity	UPPS-P
Negative mood states	DASS21
Compulsivity	Probabilistic Reversal Learning Task
Behavioural impulsivity	Jumping to Conclusions Beads Task
	Social Media Go/No-Go Task
Impulsivity	Delay Discounting task

2.4.1 Online recruitment and data collection

Amazon Turk Prime Panels is an iteration on Amazon Turk Prime that affords the researcher more control over the sample characteristics. Using Prime Panels, requesters can selectively recruit participants based on a diverse set of criteria, such as age, gender, race, income and education, employ quota sampling or match the sample to the US census characteristics, if desired. Further, Prime Panel workers are more naïve than those from Mechanical Turk, according to Amazon, and samples are not limited to the US, Canada or India.

As the focus of study three was SNS use we also chose to use Facebook advertising as a means of recruitment. Using SNS for recruitment in research is growing in popularity because it allows researchers to obtain broader or difficult to reach populations (Gelinas et al., 2018). Although, there is little empirical research on the effectiveness of SNS recruitment, evidence suggests that both paid and unpaid Facebook posts, are efficient, and that paid advertisements are significantly more cost effective on Facebook when compared to Twitter or Google (Musiat et al., 2016). Furthermore, Facebook may be better than Amazon Turk at obtaining a geographically diverse sample (Winnie et al., 2015).

The biggest challenge to online recruitment in studies 2 and 3 was attrition. In study 3, attrition from the Amazon Turk Prime Panel can mostly be attributed to inappropriate responding, whereas for Facebook it was incomplete responses; although, this is partially due to participants being placed into a prize draw rather than receiving individual reimbursement. To combat selective attrition within the Facebook sample we switched the experimental order of the self report and behavioural tasks mid-way through recruitment (at n = 71). Beginning the experiment with the self-report measures first, then switching so that participants started on the behavioural tasks. When we began the experiment, incomplete responses were particularly frequent towards the end of the experimental session (behavioural tasks) but after we switched the task presentation there was an increase in participants completing the behavioural tasks, although dropout became more prevalent for the self report measures.

2.4.2 Social media Go/No-Go task

To examine whether response interference differed within the context of SNS stimuli, we developed the Social media Go/No-Go task (Social GNG). This task uses the structure of the cued GNG by Fillmore (Fillmore, Rush, & Hays, 2006) but is based on a study by Turel, He, Xue, Xiao, and Bechara (2014), who developed a Facebook-specific GNG task to assess response interference in Facebook users. The Social GNG task includes two conditions: a social media condition and a control condition. In the social media condition we used icons from 12 of the most popular SNS in Australia (Kemp, 2018) and the US (Pew Research Center, 2018). These icons represented Facebook, Messenger, Instagram, Snapchat, YouTube, LinkedIn, Twitter, Skype, WhatsApp, Pinterest, Google+ and Gmail. Conversely, the stimulus in the control condition consisted of street signs, similar to the Facebook GNG task developed by Turel et al. (2014).

Participants are instructed to press the space bar as quickly as possible when presented with a picture from one category (e.g., social media icons) and to withhold a response when presented with the other category (e.g., street signs). At the beginning of each block participants are told which is the Go category, indicating that they should press the space bar when a picture from that category appears. Each trial begins with a fixation cross in the centre of the screen, which is displayed for an interval randomly generated from a pool (1500, 2000, 2500, 3000, 3500 ms). Following this, the stimuli, either Go or No-go, is presented for 500 ms, followed by a fixation cross that is presented until either a response is made or 2000 ms elapses.

The Social GNG consists of three blocks, including one practice block of 22 trials, 11 per condition (social media and traffic signs), followed by two test blocks, one per condition. Each test block consists of 48 trials (75% Go trials and 25% No-go trials). Behavioural performance indices include the false alarm rate (frequency of responding to No-go trials); accuracy on Go trials (hit rate); the sensitivity index (d'), which quantifies how readily an individual is able to distinguish between target (Go) and non-target (No-go) stimuli; and decision bias (*C*), the extent to which one response is more likely than the other, for both task conditions. The sensitivity index and decision bias were calculated based on signal detection theory, as follows.

Sensitivity index:

$$d' = Z_{hit\ rate} - Z_{false\ alarm\ rate}$$

Decision bias:

$$C = -.5 \times \left(Z_{hit\ rate} + Z_{false\ alarm\ rate}\right)$$

Chapter 3: Cognitive Impulsivity Does Not Differ in Those with High or Low Levels of Trait Impulsivity; and the Development of Two Novel Behavioural Tasks to Improve Validity in the Assessment of Attention Interference and Information Sampling

Abstract

Evidence indicates that impulsivity, the tendency to react to stimuli, without adequate thought, when a more appropriate response is available, is subsumed by three components: attention interference (AI), information sampling (IS) and response interference (RI). This study attempted to improve the assessment validity of AI and IS by designing two novel computerised behavioural tasks. Our principal aim was to assess the validity of each novel task, although we also examined whether AI, IS and RI were able to distinguish between high and low levels of trait impulsivity. We administered three sets of measures, including the two novel cognitive measures of attention interference and information sampling, three standard cognitive impulsivity tasks (to assess the convergent validity of the novel measures) and one multidimensional trait measure (to assess the relationship between novel measures and personality pathways to impulsive behaviour), in 40 participants recruited and tested at Monash University. Bivariate correlations revealed convergent validity between the IS but not the AI tasks, while repeated measures-ANOVA indicated a lack of construct validity at the component level. Furthermore, AI, IS and RI were not able to differentiate between high and low levels of trait impulsivity.

1. Introduction

Impulsivity is the tendency to react to stimuli, without adequate thought, when a more appropriate response is available (Nigg, 2016; Potenza & Taylor, 2009); for example, when a driver accelerates through an amber traffic light when the appropriate response is to slow down. This definition straddles both the behavioural and cognitive levels of analysis because researchers use measurable behavioural outcomes to examine the cognitive processes they hypothesise underlie impulsivity. The measurement of behaviour as a proxy for cognition has resulted in impulsivity assessment that centres on broad behavioural domains (e.g., preferring smaller immediate over larger delayed rewards). As a result, it is not always clear which cognitions are producing the behaviour. This problem has become the focus of a recent discussion on impulsivity assessment, which gives particular emphasis to the construct validity of impulsivity measurement (Coffey, 2015).

According to Smith, Fischer and Fister (2003), there are five principles required to achieve improvement in construct validity: (1) the clear articulation of each impulsivity component, such as AI; (2) the reliable assessment of each component via multiple measures; (3) investigation of incremental validity at the component level (not construct level; i.e., impulsivity); (4) the use of measures that represent a single component; and (5) critical assessment of whether the components reflect the broader construct of impulsivity. In agreement with these principles, Cyders (2015) argues that current impulsivity assessment methods lead to ambiguous conclusions regarding predictive utility (i.e., which component is actually explaining the behavioural outcome) and produce inconsistencies across studies resulting in the stagnation of scientific advancement. Therefore, to improve validity in the assessment of impulsivity, measurement should be approached through these five principles.

Examining the first of Smith et al. (2003) principles, the articulation of individual components, we find that the structure of impulsivity varies. That is, while several studies have sought to identify the components of cognitive impulsivity, each has produced differing conclusions (Caswell, Bond, Duka, & Morgan, 2015; Cyders & Coskunpinar, 2012; Fineberg et al., 2014; MacKillop et al., 2016; Stahl et al., 2014). Models include anywhere between three (MacKillop et al., 2016) and five (Stahl et al., 2014) components, which often fail to overlap, and in the rare cases they do, the terminology and assessment measures do not. To define each of our impulsivity components we extracted the most consistently cited cognitive processes from existing models. This resulted in the identification of three cognitive processes: (1) attention interference (AI), the interruption of task directed behaviour by a competing stimulus (Bickel, Jarmolowicz, Mueller, Gatchalian, & McClure, 2012; Cyders & Coskunpinar, 2012; Sharma, Markon, & Clark, 2013; Stahl et al., 2014); (2) response interference (RI), which occurs when a competing response interrupts task directed behaviour (Caswell et al., 2015; Fineberg et al., 2014; MacKillop et al., 2016); and (3) information sampling (IS), inadequate collection of information prior to responding (Caswell et al., 2015; MacKillop et al., 2016; Stahl et al., 2014).

The second principle proposed by Smith et al. (2003) states that multiple reliable measures should be used to assess each component of impulsivity. The inclusion of multiple measures is thought to increase statistical confidence in the validity of assessment (Arce & Santisteban, 2006). Although it is also imperative that each measure represents a single component (principle 4) in all its breadth (principle 3). Principle three requires that any tests measure the full range of variations of performance within a task, known as incremental validity at the component level. This requires the task to capture the full range of inter-individual variability within a single component such as Response Interference. However, few studies have assessed individual variations in task performance for the purpose of delimiting performance boundaries on impulsivity tasks (see Hamilton et al., 2015).

With regards to principle four, the tasks also need to measure a single component. As impulsivity assessment has borrowed tasks from different traditions, such as attention research, behavioural tasks purporting to measure impulsivity, or some aspect of it, suffer from the purity problem; that is, they assess multiple concurrent processes, such as memory and attention (Dougherty, Marsh, & Mathias, 2002). As such, the assessment of impulsivity components via multiple tasks that are incrementally valid and pure presents a steep challenge. This is problematic when a single score reflects multiple components, because variation among individuals on that score will lack clarity of meaning (Strauss & Smith, 2009). Not adhering to these principles can contribute to inconsistent results, for instance, Caswell et al. (2015) implemented three distinct motor impulsivity tasks, finding that all three loaded onto different components. In sum, multiple tools should be chosen which reflect both the construct of interest, such as response interference, and the constructs variance, in this case inter-individual variability in the ability to withhold a response.

For example, RI, the inability to withhold and interfering motor response, is the most researched (Coffey, 2015). One of the most commonly used behavioural tasks to asses RI is the SST, which has considerable evidence of construct validity (for a review see Hamilton et al., 2015). The SST assesses an individual's ability to cancel an initiated response by asking respondents to stop a prepotent motor response when presented with a signal (e.g., a sound). Despite some debate regarding its predictive value (see Sharma et al., 2013), the Stop Signal Task (SST) has been widely deployed as a metric of RI (Verbruggen, & Logan, 2008). It has successfully been used to identify impulsivity in cocaine and methamphetamine users, heavy drinkers and those with internet and gambling addiction (Smith, Mattick, Jamadar, & Iredale, 2014). In addition, the SST displays component level incremental validity (Hamilton et al., 2015). This makes the SST a robust and valid measure of RI.

The fifth and final principle refers to the critical assessment of whether individual components reflect the broader construct, in this case cognitive impulsivity. This challenge has largely been overcome within trait impulsivity, a relatively stable characteristic in which an individual displays a predisposition towards rapid, unplanned reactions (DeYoung, 2010). Through their empirical work within trait impulsivity, Whiteside and Lynam (2001) developed a seminal model that organised what was then a growing diversity of dimensions and inventories. This model, now known as the UPPS-P model of trait impulsivity, includes five components: negative urgency, positive urgency, lack of perseverance, lack of premeditation and sensation seeking, and is broadly employed across impulsivity research (see Cyders et al., 2007). Current efforts to advance behavioural impulsivity aim to reach a point of standardisation similar to what trait impulsivity achieved after the development of the UPPS-P model.

To improve construct validity in the assessment of cognitive impulsivity we designed two novel computerised behavioural tasks, one each to assess AI and IS, using Smith et al.'s (2003) first, third and fourth principles of construct validity. We did not develop a novel task to assess RI, as the SST is a robust and well-validated measure of this component (Hamilton et al., 2015). As such, the aim of this study was twofold: to assess the preliminary validity of each novel behavioural task, and to assess whether tasks purporting to assess AI, IS and RI, distinguish between high and low levels of trait impulsivity. It is hypothesised that:

Hypothesis 1: Performance on the novel Attention interference (AI) task will be positively associated with the Sustained Attention to Response Task (SART), and performance on the novel Information Sampling (IS) task will be positively associated with the Jumping to Conclusions Beads Task (JTC).

Hypothesis 2: Performance on the novel AI and IS tasks will decrease as the difficulty level within each task increases.

Hypothesis 3: Poorer performance on AI, IS and RI tasks will be associated with high compared to low levels of impulsivity.

2. Method

2.1 Participants

The sample comprised 40 healthy adults, 26 female (65%) and 14 male, between 18 and 39 years of age (*M* = 25, *SD* = 5.21). Participants were recruited via poster advertisements placed on campus at Monash University, community noticeboards and social media. The eligibility criteria included: adults 18 to 45 years, who are not currently diagnosed with a mental illness or taking psychotropic medication, as indicated by self-report. The recruitment process for each stage of the study is depicted in Figure 1.

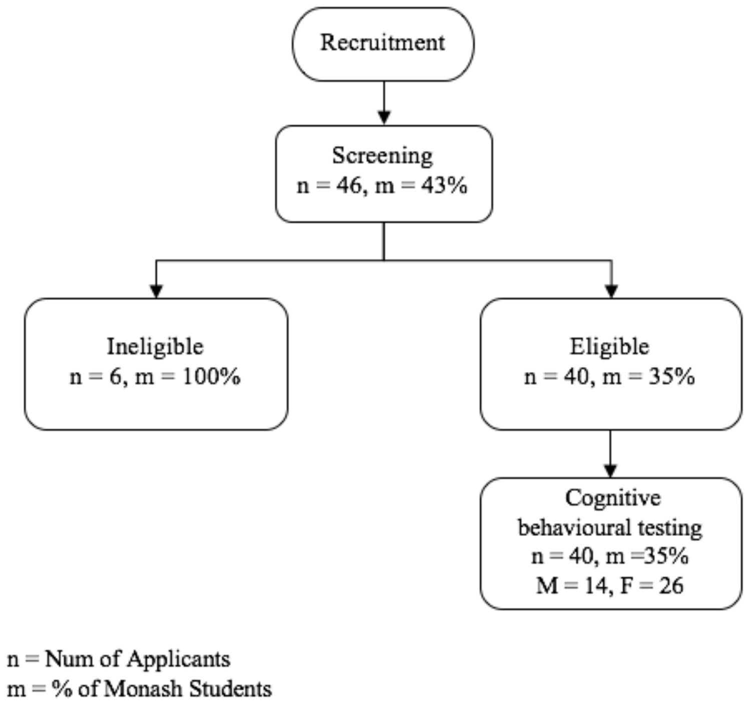


Figure 1: Flowchart of the recruitment process

2.2 Materials

2.2.1 Rationale for task selection

To assess impulsivity, we used three sets of measures including: (1) the newly developed novel measures; (2) existing measures of each behavioural component of impulsivity, to assess the convergent validity of the novel measures; and (3) a well-validated, multidimensional measure of trait impulsivity, to assess the relationship between the new measures and different pathways to impulsive behaviour. Because there is no composite behavioural index of cognitive impulsivity, a conceptually related comprehensive assessment measure of trait impulsivity was chosen to determine whether the three behavioural components are associated with the broader construct of impulsivity. The use of a measure that is external to the behavioural tasks themselves is important. As we cannot show that a predictor of impulsivity is valid unless we can demonstrate that the predictor relates to other indicators of impulsivity. Table 1 depicts the tasks used to assess each of the three cognitive processes examined. Details of each task and the trait measure of impulsivity are provided below.

Table 1: Summary of experimental tasks used to assess cognitive process

Process	**Experimental Task**
Attention Interference	*Attention Interference Task (AIT) Sustained Attention to Response Task (SART)
Information Sampling	Jumping to Conclusions Beads Task (JTC) *Gathering Task (GAT)
Response Interference	Stop Signal Task (SST)

*Indicates novel task

2.2.2 Attention interference

Sustained Attention to Response Task (SART: Robertson, Manly, Andrade, Baddeley, & Yiend, 1997)—A measure of sustained attention shown to be sensitive to impulsive responding (Helton, 2009). The SART assess AI by capturing the extent to which distracters activate task irrelevant responses. Participants are presented with a series of randomly generated single digits (1 through 9) and are instructed to respond by pressing the space bar to each digit as fast as possible unless presented with the number 3 (withhold response). The digits are randomly presented every 1.15 s, for 250 ms, followed by a 900 ms mask. Each presentation of a digit corresponds to a single trial (225 trials, 25 for each digit). The main outcome variable is the error score, consisting of key presses when no key should be pressed (i.e., after a '3', commission errors) and no press when a key should have been pressed (i.e., after anything but a '3', omission errors), indicating that task directed behaviour was disrupted by distracting stimulus.

Attention Interference Task (AIT: novel task)—A novel task developed to assess the ability to ignore distracting stimulus. The AIT is based on the SART (Robertson et al., 1997). Although, the SART is sensitive to impulsive responding (Helton, 2009) it is via a feed forward motor program which produces a prepotent response. Therefore, the SART reflects both RI and AI, making it difficult to fully identify the predictive value of each outcome index; that is, the extent to which each performance index reflects AI or RI. As such, key features were introduced in the AIT to improve its ability to identify interference in attention. New features include the presentation of stimulus in an array, rather than a single centralised stimulus. By presenting several stimuli the attentional field is widened and the available sources of interferences are increased. Further, we introduced not one, but multiple distractors, for which a response must be withheld. Finally, the distractors were integrated in a stepwise manner, to produce an incremental increase in task difficulty, which is intended to capture incremental validity at the component level.

Participants are presented with an array of 12 stars, (4 x 3, yellow outline) on a white background. Each trial begins with the array of stars displayed for a random stimulus-onset asynchrony (SOA), which is followed by the presentation of the Go stimulus (90 ms, star lights up). Following this, a fixation cross is presented for 500 ms. Respondents are instructed to press the space bar as fast as they can when presented with a Go stimulus and are given until the beginning of the next trial to respond. The SOA is randomly generated from a pool which varies between 90–1500 ms. The task consists of one practice round (five trials) and three test blocks (40 trials each), which increased in difficulty. Block 1 had no distractors, block 2 introduced one distractor (a star that became partially lit), which occurred randomly on 60% of trials. Block 3 included up to two distractors per trial, with a second distractor presented on 40% of distractor trials. At the end of each block feedback was provided and included the average response time (ms) and accuracy (% correct). The primary outcome variable is the error score, akin to the SART error score. It consisted of both commission and omission errors, indicating the interruption of task directed behaviour by a competing stimulus.

2.2.3 Information sampling

Jumping to Conclusions Beads Task (JTC: Garety, Hemsley, & Wessely, 1991)—A probabilistic reasoning task sensitive to dysregulation in IS (Banca et al., 2016; Djamshidian et al., 2012). Participants are presented with two jars (A and B), each with different ratios of red to blue beads (85:15 or 60:40). Participants are informed that '*the computer will draw one bead at a time and always return the bead to the jar before it draws the next bead'*. The participant's task is to decide which jar the computer is drawing the beads from. Participants can choose as many beads as they want before deciding on which jar the computer is drawing from. Participants are reminded which beads have been drawn by a sequence of small red and blue beads at the bottom of the screen. At the end of each trial, performance feedback is provided for that individual trial. The version used in this study included two blocks: one practice block with five trials in which the probability was 85:15, and one test block with 15 trials in which the probability was 60:40. The primary outcome measures were the average number of beads drawn, as drawing fewer beads has been linked to impulsivity (Banca et al., 2016; Djamshidian et al., 2012).

Gathering Task (GAT: Novel task)—A novel task designed to capture an individual's information sampling behaviour. The AIT is based on the Information Sampling Task (IST: Clark, Robbins, Ersche, & Sahakian, 2006). The IST was designed to assess impulsivity by quantifying an individual's tolerance for uncertainty, however it has inherent weaknesses which we attempted to overcome with the development of the GAT. Namely, validity of the primary performance index, task impurity and low ecological validity. For instance, the IST includes both a fixed win, in which the respondent wins points for answering correctly, and decreasing win condition, in which respondents start with points and lose them per piece of information sampled. However, utilising a points system can influence a respondents' natural sampling tendencies in the direction of the reward (Forstmann et al., 2008; Rae, Heathcote, Donkin, Averell, & Brown, 2014). To improve construct validity, we chose to provide minimal feedback with no reward or punishment, refrain from emphasising response speed or accuracy within the instructions, which influence the information sampling strategy used by the participant, used a larger pool of information than is employed within the IST, and implemented a stepwise difficulty progression to capture variance in inter-individual performance.

In the GAT participants are presented with a tile (10 x 10 squares) and are required to decide the predominant colour (from two colours which vary by block). The participant reveals one row at a time, using the space bar, until they come to a decision. The task consists of one practice trial plus three blocks of 10 trials each (31 trials in total). As the colours vary per block, participants are informed at the beginning of each block, which two colours are going to be used and which answer key (‘Z’ or ‘M’) corresponds to each colour. Each test block becomes successively more difficult via alterations in the colour ratio from, 8:2, in block 1, to 7:3 in block 2 and 6:4 in block 3. A correct response resets the tile indicating the trial has ended and the participant begins the process anew. Outcome measures include the average number of rows revealed, with less rows revealed corresponding to a liberal response criterion and indicative of impulsive responding (Stahl et al., 2014).

2.2.4 Response interference

Stop Signal Task (SST: Verbruggen, Logan, & Stevens, 2008)—is an index of inhibitory control processes (Verbruggen & Logan, 2008) found to be longer in impulsive individuals (Dalley, Everitt, & Robbins, 2011; Eagle et al., 2008). At the start of each trial participants are presented with a white fixation circle (250 ms) on a black screen. This circle is followed by a thick white left or right facing arrow. Participants are instructed to press ‘K’ on their keyboard for a right arrow, ‘D’ for a left arrow and to withhold a response when they hear an auditory signal, which occurs on a random subset of trials. To manipulate the probability of inhibition, the delay between the presentation of the Go stimulus and the stop signal is adjusted in steps of 50 ms (up and down) based on performance. Starting at 250 ms and moving up to 1150 ms. A correct response reduces the delay by 50 ms, while an incorrect response increases the delay by 50 ms. There is one test block of 32 trials, including eight signal trials and 24 no signal trials (3:1), and three test blocks of 64 trials, which include 16 signal and 48 no signal trials (3:1). The primary outcome variable for the SST is the stop signal reaction time (ssrt), calculated by subtracting the mean stop signal delay from the mean response time in Go trials, with a longer ssrt indicative of impulsive responding (Dalley, Everitt, & Robbins, 2011; Eagle et al., 2008)

2.2.5 Trait impulsivity

UPPS-P Impulsive Behaviour Scale (UPPS-P: Cyders et al., 2007; Whiteside & Lynam, 2001)—is a 59-item inventory designed to measure five distinct personality facets of impulsivity. All items are scored on a 4-point Likert scale from (1) *Agree Strongly* to (4) *Disagree Strongly.* The UPPS-P assesses (1) Negative Urgency, the tendency to act on cues when experiencing negative affect (12 items, α = 0.87, example: '*when I am upset I often act without thinking*'); (2) Perseverance (lack of), the inability to follow through on tasks (10 items, α = 0.85, example: '*I generally like to see things through to the end*'); (3) Premeditation (lack of), a proclivity to act without contemplating potential consequences (11 items, α = 0.85, example: '*I like to stop and think things over before I do them*'); (4) Sensation Seeking, a propensity to engage in high energy and thrill behaviours (12 items, α = 0.86, example: '*I generally seek new and exciting experiences and sensations*'); and (5) Positive Urgency, a tendency to act on cues when experiencing positive affect (14 items, α = 0.93, example: '*when I am really ecstatic, I tend to get out of control'*) (reliability coefficients from Whiteside & Lynam, 2001). The UPPS-P produces both an overall impulsivity score, as well as scores for each individual subscale. Due to having a small sample we chose to use the overall score; a psychometrically acceptable global index (Pompeia et al., 2018)

2.3 Procedure

This study included two phases, (1) eligibility screening and (2) computerised testing.

2.3.1 Eligibility phase

Participants who expressed interest in the study by way of email were sent a brief outline of the study and a link to the eligibility survey. Using the online survey platform Qualtrics, participants were briefed, consented and eligibility information obtained. Questions regarding psychopathology included: psychiatric diagnosis (if any), time since diagnosis (<12 months, 12–24 months and 2+ years) and current medications (if any). Each participant was assessed for eligibility by the PhD student and sent a notification of suitability to complete phase two.

2.3.2 Computerised testing

In the second phase of the study, eligible participants were invited to attend a 90-minute testing session at Monash University, Clayton, at a time of their convenience (9 am to 5 pm, Monday to Friday). Respondents were seated in front of a Macbook Air (13inch, resolution 1440 x 900), positioned on a table ~50cm in front of them in a quiet and well-lit testing room. Millisecond Inquisit Lab (version 5.0), OpenSesame (version 2.9.6) and Qualtrics web platform were used for stimulus presentation and response collection. The presentation of all tasks was randomised. After completing both phases of the study respondents were reimbursed for their time with a $30 Coles voucher. The Monash Human Research Ethics Committee approved this study.

2.4 Statistical analysis

Data analysis was conducted using the Statistical Package for Social Sciences (SPSS V23). First, we assessed the data for missing cases and outliers. We found missing data for five cases spread uniquely across behavioural tasks, which was treated with listwise deletion as less than 1% of the sample was missing (Tabachnick, 2013). Univariate outliers were identified as $Z < 3.29$ and treated with Winsorizing, assigning it a lesser weight (Field, 2013).

To address hypothesis one, we conducted bivariate correlations to determine whether the primary outcome measures of the novel tasks were positively associated with measures on the validated tasks. Following this, to address hypothesis two we used repeated measures analysis of variance (ANOVA) to compare individual performance across test blocks in each novel task, to evaluate component level validity. Sphericity was assessed using Mauchly's test and a Greenhouse-Geisser correction applied where appropriate (Field, 2013). We than ran post hoc pairwise comparisons using Bonferroni corrections. In addition, we also conducted bivariate correlations between the outcome variables of each novel task to examine the direction and strength of the association between variables (e.g., response time and errors). Finally, to assess hypothesis three we used the median UPPS-P overall score to split the sample into high and low impulsivity groups. Independent samples *t*-tests were then conducted for each outcome variable to determine if task performance differed between low and high levels of trait impulsivity. VanVoorhis and Morgan (2007) recommend a minimum cell size of 30 for both correlations and *t*-tests, based on a medium effect size.

3. Results

The descriptive statistics for the primary outcome variables of each task are shown in Table 2.

Table 2: Descriptive statistics for primary outcome variables

Measure	N	Min	Max	Mean	SD
UPPS-P total score	40	95.0	171.00	123.98	20.13
SART error score	39	7.0	64.0	24.69	11.91
JTC beads drawn	40	1.0	73.0	17.38	17.01
AIT errors	40	9.0	70.0	31.35	14.71
GAT rows revealed	39	2.0	10.0	5.64	2.10
SST ssrt	39	5.76	180.3	56.02	43.99

3.1 Comparison of novel and validated tasks

Bivariate correlations between the primary outcome measures of the novel and validated IS tasks revealed a moderate positive association between the number of beads drawn on the JTC and rows revealed on the GAT, $r = .47$, $p <.01$. No significant relationship was found between the AIT error score and the SART, although there was a moderate positive correlation between response times, $r = 0.39$, $p < .05$.

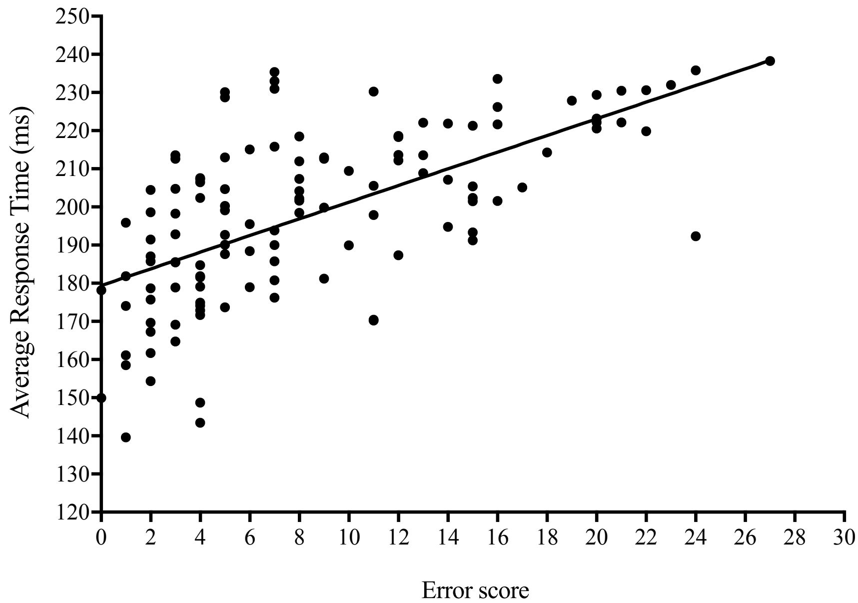
3.2 Internal validity of the novel behavioural tasks

Repeated measures-ANOVA on the AIT test blocks indicated that errors were significantly different across blocks, $F(2,78) = 86.01$, $p < .0001$, $\omega^2 = .40$. Post hoc tests using a Bonferroni correction revealed a statistically significant increase of 8.50 in the mean error score between block one and two ($p < .0001$), however this pattern was reversed between block two and three, with a mean reduction of 8.92 errors ($p < .0001$). Response time also differed across test blocks, $F(2,78) = 29.22$, $p < .0001$, $\omega^2 = .22$. Post hoc tests using a Bonferroni correction showed that there was an average decrease of 25.98ms between block one and two ($p < .0001$), and an average increase of 11.71ms between block two and three ($p < .01$). The descriptive statistics for each block are presented below in Table 3.

Table 3: AIT internal descriptive statistics

Measure	M	SD	SE
Error score			
Block 1	5.90	5.07	.80
Block 2	14.4	5.99	.95
Block 3	5.48	3.62	.57
Response time			
Block 1	184.76	20.19	3.19
Block 2	210.74	15.98	2.53
Block 3	199.03	22.52	3.56

Furthermore, the average response time across the sample was 199.84ms (SD = 14.39), which correlated positively with the error score, $r = .76$, $p < .001$, as per Figure 2 below.



Note: Practice trials were removed from the analysis.

Figure 2: Scatterplot of response time against error score in the AIT

Next, we examined the internal performance of the GAT. A repeated measures ANOVA with a Greenhouse-Geisser correction showed that performance significantly varied across the three difficulty conditions, $F(1.58,58.55) = 5.41$, $p < .01$, $\omega^2 = .08$. Post hoc tests using a Bonferroni correction indicated that a decrease of .57 rows sampled between block two (70:30) and three (60:40) ($p < .05$). The descriptive statistics for each condition are presented in Table 4.

Table 4: GAT internal descriptive statistics

Error score	**M**	**SD**	**SE**
Block 1 (80:20)	2.23	1.51	.24
Block 2 (70:30)	1.85	0.99	.16
Block 3 (60:40)	1.28	1.07	.17

The average response time across the sample was 198.21ms (SD = 22.31), which correlated negatively with the number of rows revealed, $r = -.59$, $p < .001$, see Figure 3 below.

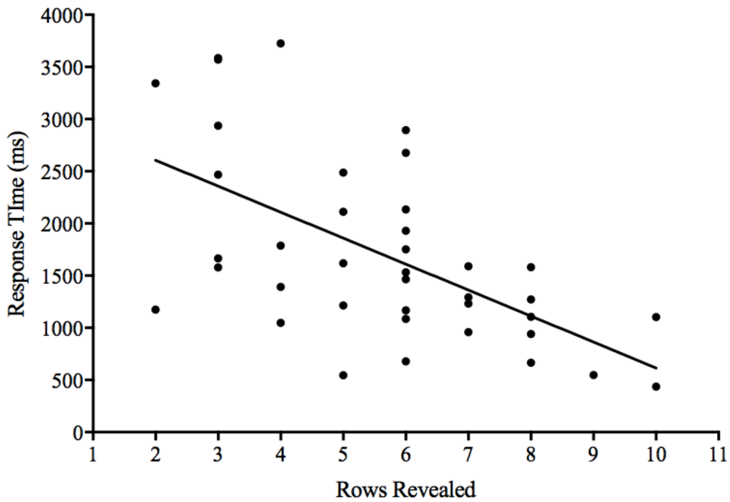


Figure 3: Scatterplot of response time against rows revealed in the GAT

3.3 Comparing task performance in high versus low impulsivity

Independent *t*-tests revealed no significant differences across behavioural tasks between those with high and low trait impulsivity, as per Table 5.

Table 5: Independent samples t-tests for behavioural tasks comparing high and low trait impulsivity

	High		**Low**		**95% CI Mean Difference**			
Task	**M**	**SD**	**M**	**SD**		***t***	**df**	**Sig**
SART error score	26.45	13.05	22.84	10.62	–11.35, 4.14	–0.94	37	.35
SST ssrt	55.58	45.52	56.48	43.57	–28.03, 29.85	0.06	37	.95
JTC beads drawn	19.80	18.55	14.95	15.39	–15.76, 6.06	–0.90	38	.37
AIT error score	28.25	12.85	34.45	16.10	–3.12, 15.52	1.35	38	.19
GAT rows revealed	5.84	1.95	5.45	2.26	–1.76, 0.98	–0.58	37	.57

4. Discussion

We found evidence to support one of our three hypotheses. In partial support of hypothesis one, concordance was found between the novel and validated IS tasks; however, this relationship was not replicated for AI. Hypothesis two was unsupported; despite some ability to differentiate inter-individual performance, the novel tasks were not able to discriminate appropriately at the component level. Similarly, there was no evidence in favour of hypothesis three, that decreased performance across the three components would be associated with elevated trait impulsivity.

More specifically, we found a significant association between the gathering (GAT) and jumping to conclusions (JTC) tasks, which is consistent with hypothesis one. Although, this provides preliminary evidence in favour of the GAT as an index of IS, some aspects of the task did not work as expected, leading us to reject hypothesis two; that the GAT would display validity at the component level. For instance, contrary to what we predicted, shorter response times were associated with a greater amount of IS. Typically, shorter response times are characterised by less sampling (Helton, Head, & Russell, 2011). We suggest that this response pattern arose from the task design itself. For example, the upper sampling limit within the GAT is 10 (100 tiles sampled by row), restricted the range, which may have masked true response variance. Furthermore, although performance differed across test blocks two and three, it was in the opposite direction to what would be expected if the task was capturing component level variance. Participants sampled less information as the conditions became more difficult. As such, further work is needed to satisfy Smith et al.'s (2003) third principle, component validity.

Examining hypothesis one, we did not find an association between the novel and validated attention interference task (AIT). Hypothesis two was also rejected for the AI task, due to the failure of the stepwise difficulty procedure, meaning the task was unable to discriminate at the component level. A closer inspection of AIT response patterns indicates that flaws in the task design are contributing to this result. For instance, both response times and error rates increased between blocks one and two; however contrary to expectations this pattern was reversed when the difficulty was increased between blocks two and three. Further, there was an unanticipated positive association between response time and errors within the AIT. This pattern is contrary to the theory that elevated errors in attentional tasks result from anticipating or incomplete processing of stimulus leading to a rapid and incorrect response (Dougherty et al., 2003). Similar to the GAT, further work is needed to refine the response format of the AIT to ensure its sensitivity at the component level.

Our final hypothesis regarding AI, IS, RI and elevated impulsivity was unsupported. This finding is consistent with previous research, which reports poor associations between trait and behavioural measures of impulsivity (Broos et al., 2012; Caswell, Bond, Duka &

Morgan, 2015; Cyders & Coskunpinar, 2011; Stahl, et al., 2014). However, Sharma et al. (2013) note that, like individual items on a survey, single behavioural tasks used in isolation are unable to aggregate true variance due to the task impurity problem (Miyake & Friedman, 2012). Essentially, each behavioural task, like a single survey item, measures only a portion of the broader construct. Thus, any sole task may not reflect what is captured by comprehensive self-report measures (Sharma et al., 2013). As such, the lack of association between trait and behavioural measures of impulsivity could be due to differences between assessment approaches. In light of this, aggregating across tasks to produce a composite behavioural index may overcome the methodological differences between laboratory and self-report measures and assist in the assessment of whether the components reflect the broader construct of impulsivity.

The nature of this study was preliminary and thus must be appraised within the context of several limitations. Firstly, this was a small-scale study conducted with a university sample. As such, we lack adequate power to generalise the results beyond our sample. Further, given that participants were predominantly university students, it is likely that they have higher than average levels of intelligence and are from a middle class socio-economic background (Harvey, 2016; James et al., 2008). Finally, our sample was gender imbalanced, being predominantly female. Given these limitations, replication with larger and more diverse sample in which variables such as education and socio-economic status are controlled for are warranted. Future assessment may also benefit from testing with a composite measure of behavioural impulsivity, as suggested by Sharma et al. (2013).

To improve validity in the assessment of AI and IS we developed two novel behavioural tasks. Although our efforts were unsuccessful, we gained invaluable knowledge on how our task parameters influenced performance in a healthy adult sample. Pending further adjustment and validation the GAT may offer a purposefully designed alternative to current measures which are often borrowed from adjacent traditions. Further, the evidence did not support a relationship between cognitive and trait impulsivity Future research is required to assess the individual components of AI, IS and RI and their relationship with the broader construct of cognitive impulsivity.

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Chapter 4: Substantiating a Structural Model of Behavioural Impulsivity: Evidence for Response Interference

Abstract

Debate is ongoing as to how impulsivity should be defined, its main components and appropriate assessment tools. This study attempted to substantiate a structural model of impulsivity using a factor analysis of theory-driven impulsivity indices. Evidence suggests that the interplay between three discrete cognitive processes produces impulsive behaviour: (1) response interference, (2) attention interference and (3) inadequate information sampling. We administered cognitive tasks sensitive to each of these components in 128 participants recruited and tested via Amazon Turk Prime. Participants, once screened, completed six randomly generated online behavioural tasks, namely the SART, SST, Go/No-Go, Visual Search, AX-CPT and JTC tasks. Two tasks were chosen to assess each of the three cognitive process proposed to underlie impulsivity. Principal component analysis yielded a four-factor solution, explaining 65% of the variance. The largest factor represented response interference, the interruption of a target task by a competing response. A second component reflected response time across tasks. The two other components reflected a single behavioural task each. While we were unable to identify a model of impulsivity aligned with our original assumptions, our findings support response interference as a core component of impulsivity.

1. Introduction

A driver hears their phone beep and reaches down to pick it up. In doing so, they fail to look back over their shoulder before changing lanes and hit the car in the lane beside them. In the context of task-directed behaviour, such as driving, impulsivity is a term given to the failure to suppress interfering responses, inhibit attention to irrelevant stimuli, or take in relevant information prior to responding (Stahl et al., 2014). This derailing of task directed behaviour is thought to be the manifestation of state related fluctuations in cognitive processing. These fluctuations in cognition are studied as potential dissociable neurocognitive subtypes of impulsivity (Chamberlain & Fineberg, 2015). However, both the nature of these underlying cognitions and how they can best be assessed, remains a topic of debate (Coffey, 2015). Two critical questions have emerged from recent literature: what aspects of impulsivity should be measured and how are they best measured?

Starting with question one, what aspects of impulsivity should be measured, several cognitive processes are linked with impulsive responding; however, three appear consistently: (1) response interference, the interruption of a target task (e.g., driving) by a competing response (e.g., reaching for a phone) (Caswell, Bond, Duka, & Morgan, 2015; Fineberg et al., 2014; MacKillop et al., 2016); (2) attention interference, when a target task is interrupted by a competing stimulus (e.g., a ringing phone) (Bickel, Jarmolowicz, Mueller, Gatchalian, & McClure, 2012; Cyders & Coskunpinar, 2012; Sharma, Markon, & Clark, 2013; Stahl et al., 2014); and, (3) information sampling, when a response is made prior to enough information being collected (e.g., a failure to shoulder check) (Caswell et al., 2015; MacKillop et al., 2016; Stahl et al., 2014). An implication of this research is that these three processes interact to produce impulsive behaviour. Our study examined all three of these processes in tandem to substantiate a structural model of impulsivity, which can serve as the basis for further research.

How to assess the structure of impulsivity is a topical subject. Previous studies have used theory-driven approaches, such as structural equation modelling, where the model is predefined, and the data is tested for fit (e.g., MacKillop et al., 2016; Stahl et al., 2014). While such methods are useful for testing well-established theories using clear-cut measures, the construct of impulsivity is still a moving target and measures of behavioural impulsivity are diverse and inconsistent among different studies (e.g., Caswell et al., 2015; MacKillop et al., 2016; Stahl et al., 2014). Therefore, the tendency towards prestructuring has resulted in research that identifies inconsistent subtypes of impulsivity (e.g., Fineberg et al., 2014; Reynolds, Ortengren, Richards, & de Wit, 2006; Stahl et al., 2014) and neglects the critical assessment of whether the factors reflect the same broad construct of impulsivity (Smith, Fischer, & Fister, 2003). To reduce inconsistencies across studies, a concerted effort must be made towards unanimity on which subtypes to assess (Coffey, 2015), along with standardised tools to assess them (Cyders, 2015).

The utility of any model of impulsivity sits within its heuristic value and ability to integrate evidence from different domains of analysis, such as the biological and cognitive domains (Gullo, Loxton, & Dawe, 2014). The utility of existing models is low, as no single model has been adopted and applied to a relevant impulsivity population (e.g., substance users), suggesting that a new approach to identifying the structure of impulsivity is needed. Thus far, studies have employed a theory-driven approach to test structural models of impulsivity. However, to our knowledge, no studies have examined whether a data-driven approach supports the tripartite structure of attention interference, information sampling and response interference that has been emerging from recent research. Consequently, this study aims to substantiate a structural model of impulsivity with three components using a principal component analysis of six behavioural indices (two suitable measures of each component). We hypothesised that the behavioural indices will cluster in three underlying factors reflecting interference from a competing response, interference from a competing stimulus, or inadequate information sampling.

2. Method

2.1 Participants

The sample included 128 participants (Age, $M = 32.24$, $SD = 6.38$, 66 Male) recruited from the United States (US) via Amazon Turk Prime, an online research participant database. Turk Prime samples are demographically diverse (Buhrmester, Talaifar, & Gosling, 2018) and offer a valid alternative to face-to-face testing with behavioural tasks (Crump, McDonnell, & Gureckis, 2013). To be eligible for the study, participants had to be between 18 and 45 years and not currently diagnosed with a mental illness or taking psychotropic medication, as indicated by self-report. The demographic characteristics of the sample and the scores on impulsivity measures are shown in Table 2.

2.2 Procedure

Using the online survey platform Qualtrics, participants were briefed and consented. We then collected demographic information on age, gender, current and past mental health, and disability. Questions regarding mental health included: diagnosis (if any), time since diagnosis (<12 months, 12 – 24 months and 2+ years), and current medications (if any). Questions regarding disability included: disability (if any) and the nature of the disability (if any). Participants were then provided with a link that automatically downloads the Millisecond Inquisit Web Player (version 5.0) and runs each of the six behavioural tasks in a randomly generated order. Participants were reimbursed for their time with US$6. The Monash Human Research Ethics Committee approved this study (MUHREC, 1364).

2.3 Measures

We chose two behavioural tasks to assess each of the hypothesised cognitive processes, which include attention interference, information sampling and response interference. The details for each task are outlined below.

2.3.1 *Attention interference*

Sustained Attention to Response Task (SART: Robertson, Manly, Andrade, Baddeley, & Yiend, 1997)—The SART is a measure of sustained attention, including specific indices of response (dis)inhibition, which is a form of impulsivity (Helton, 2009; Helton, Weil, Middlemiss, & Sawers, 2010). Participants are presented with a series of randomly generated single digits (1 through 9) and are instructed to respond by pressing the space bar to each digit as fast as possible, unless presented with the number ‘3’ (withhold response). Each presentation of a digit corresponds to a single trial (225 trials, 25 for each digit). Outcome indices include the reaction time coefficient of variability (*SD* RT/mean RT), a measure of attention instability that has been associated with ‘attentional slips’ (akin to impulsive responses) (Carriere, Cheyne, Solman, & Smilek, 2010), and commission errors, a measure of prepotent or impulsive responding.

Visual Search Task (VST: based on Becker, 2009)—The VST assesses the influence of competing stimuli on task-directed responding. Each trial begins with a black fixation cross (300 ms) followed by a randomly generated stimulus set. A stimulus set includes three, six or nine shapes (e.g., hexagon, square, triangle), which are arranged in a circle around the centre point of the screen. Participants are instructed to press the space bar if the target stimulus, a circle, is present within the stimulus set. Each set size, three, six or nine, is randomly presented 100 times with a 50:50 target present ratio. Indices include the proportion correct and the mean reaction time (the time it took the subject to detect the target among the distractors), which indicates a susceptibility to interference from competing stimuli, found to be elevated in impulsive individuals (Kóbor, Takács, Honbolygó, & Csépe, 2014).

2.3.2 *Information sampling*

Jumping to Conclusions Beads Task (JTC: Garety, Hemsley, & Wessely, 1991)—JTC is a probabilistic reasoning task sensitive to impulsive responding produced by a lack of information sampling (Banca et al., 2016; Djamshidian et al., 2012). In this task, participants are presented with two jars (A and B), each with a different ratio of red to blue beads (either 85:15 or 60:40). Participants are informed that '*the computer will draw one bead at a time and always return the bead to the jar before it draws the next bead'*. There is no limit to how many beads the participants can draw within each trial. As each bead is drawn, they appear at the bottom of the screen. Participants must decide which jar (A or B) the computer is drawing beads from, ending the trial. The JTC includes four randomly presented blocks: two blocks with probabilities 85:15 and two blocks with probabilities 60:40, each consisting of three trials. This task produces indices, including the median number of beads drawn (60:40 condition only). Drawing less beads has been linked to impulsivity (Banca et al., 2016; Djamshidian et al., 2012) and the proportion correct, which has been associated with a liberal response criterion that is reflective of an impulsive response style (Stahl et al., 2014).

AX-Continuous Performance Task (AX-CPT: Barch et al., 1997)—This task requires participants to use contextual information to predict the nature of ensuing stimuli (i.e., target or distractor). Within each trial participants are sequentially presented with four randomly generated single letters. The letters are presented centrally, on a black background (300 ms) in uppercase, 24-point Helvetica font. Participants are instructed to press the 'E' key in response to a target cue probe sequence (A = cue, X = probe) or the 'I' key to a non-target cue probe sequence (BX, BY or AY). In between the cue and probe are two distractors (target, **A**–F–H–**X** or non-target, **B**–J–W-**X**). All letters of the alphabet serve as distractors, except for K and Y, which are excluded due to their visual similarity to the letter X. Letters are presented in a pseudorandomised order, such that target (AX) trials occur with 70% frequency and non-target trials occur with 30% frequency. We calculated two variables: the difference in proportion correct between A and B cue trials and the difference in mean response time between A and B cue trials, both of which we used to assess the response criterion as a liberal criterion is associated with impulsive responding (Stahl et al., 2014).

2.3.3 Response interference

Stop Signal Task (SST: Verbruggen, Logan, & Stevens, 2008)—SST assesses an individual's ability to cancel an initiated response. This is associated with impulsive behaviour (Dalley, Everitt, & Robbins, 2011). Each trial begins with a white fixation circle (250 ms) on a black screen. The circle is followed by a thick white arrow, either right or left. Participants are instructed to press the 'D' key on their keyboard for a left arrow and the 'K' key for a right arrow and to withhold a response when they hear an auditory signal, which occurs on a random subset of trials. A stepwise procedure adjusts the duration (in ms) between the go (arrow) and stop (auditory signal) stimulus. The delay starts at 250 ms and is varied in steps of 50 ms based on performance. Correctly withholding a response increases the delay by 50 ms; however, failing to withhold a response reduces it by 50 ms. There are four blocks: one test block of 32 trials, with a 'no signal' to 'signal' ratio of 3:1; and three test blocks, each with 64 trials, also with a 3:1 ratio. Primary indices include the stop signal reaction time (ssrt), which is a critical index of inhibitory control processes (Verbruggen & Logan, 2008) and which is found to be longer in impulsive individuals (Eagle et al., 2008), as well as the probability of reacting to a stop signal.

Cued Go/No-Go Task (GNG: Fillmore, Rush, & Hays, 2006)—This task assesses an individual's ability to inhibit a response. Participants are presented with a cue, the black outline of a rectangle, that turns either green or blue after a specified stimulus-onset asynchronicity (SOA). Participants are instructed to press the space bar when the cue becomes green (the 'Go' signal), but to withhold a response when it becomes blue (the 'No-go' stimulus). The rectangular cue may appear in either a horizontal or vertical orientation. A vertically orientated rectangle has a high probability of being green (a 'Go' signal), while a horizontally orientated rectangle has a high probability of being blue (a 'No-go' signal). This task utilises a factorial design with five different SOAs (100, 200, 300, 400, 500 ms). There are 250 trials in total: 100 vertical green (Go) rectangles (20 per SOA); 25 horizontal green (Go) rectangles (five per SOA); 100 horizontal blue (No-go) rectangles (20 per SOA); and 25 vertical blue (No-go) rectangles (five per SOA). Primary indices of behavioural inhibition are commission errors—responding when a response should have been withheld (Wright, Lipszyc, Dupuis, Thayapararajah, & Schachar, 2014)—which are a reliable measure of impulsive motor responses (Weafer, Baggott, & de Wit, 2013), and the mean response time.

2.4 Statistical analysis

Data analysis was conducted using the Statistical Package for Social Sciences (SPSS V23). First, we identified missing cases, which were treated by listwise deletion. We then removed participants whose data exhibited a pattern of responses indicating that they either failed to understand the instructions or could not perform the task successfully. Criteria for removal were as follows: SST omissions ≧30%, SART omissions ≧30%, JTC average beads drawn < 2, a GNG error rate of zero, or an error rate of 100 for Go trials. For the VST, an average response time < 200 ms or a proportion correct of zero. Next, we used an iterative process to identify univariate outliers ($Z < 3.29$), which we treated by Winsorizing, assigning it a lesser weight (Field, 2013). Normality was assessed with Kolmogorov Smirnov tests and Box-Cox transformations were applied (Hubert, Rousseeuw, & Verdonck, 2009).

To examine the link between cognitive impulsivity and attention interference, information sampling and response interference, we chose a variance focused approach, testing our hypothesis using principal component analysis (PCA) to reduce the data into a smaller set of oblique components. We used Promax rotation, which is best suited for oblique (correlated) factors (Russell, 2002). The criteria used to determine the suitability of the model included a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of $\geqq 0.6$ (Hutcheson, 1999), an R matrix determinant above $|R| > 0.00001$ (Field, 2013) and a significant Bartlett's test of sphericity ($p < 0.05$). The suitability of each variable within the final model was assessed through communalities, which based on our sample size, must be a minimum of 0.5, ideally above 0.6. (Field, 2013; Russell, 2002). The final number of factors was chosen based on eigenvalues above Kaiser's criterion of 1.0 and the inflection point of the scree plot.

3. Results

A four-factor solution with Promax rotation provided the best defined factor structure, explaining 65% of the variance. We initially entered all 12 primary outcome variables into the PCA, which produced suitable model statistics with a Promax rotation; however, the variable Visual Search (VST) proportion incorrect displayed a communality of 0.27 so we removed it and re-ran the analysis. Removal of the VS variable produced suitable model statistics, KMO = 0.67, an acceptable $|R| = 0.07$ and a significant Bartlett's test of sphericity ($\chi 2\ (55) = 308.8$, $p < .001$). All commonalities were above 0.5, most above 0.6, confirming that each item shared some common variance with other items. Solutions for three and four factors were each examined; however, we retained a four-factor solution with Promax rotation, as a three-factor structure produced communalities below 0.5.

Table 1 shows the factor loadings after rotation. All loadings are above 0.5, which is considered significant with a sample above 100 (Stevens, 2009). Factor one reflects response interference, while factors two and four are task-specific, reflecting the AX-CPT and the JTC respectively. The third and final factor represents response time. Cronbach's alpha indicated very low reliability across all factors, one, $\alpha = .51$, two, $\alpha = -.009$, three, $\alpha = -.095$ and four $\alpha = .16$.

Table 1: Principal components analysis results *(N* = 124)

Variable	**Component**			
	1	**2**	**3**	**4**
SST Stop signal reaction time	.75			
SST Probability of stopping on a stop signal	.78			
SART Coefficient of variability	.75			
SART Total commission errors	.62		–.52	
GNG Error rate	.69			
AX Proportion correct A v. B		.87		
AX Difference in mean response time A v. B		–.87		
JTC Median beads drawn				.77
JTC Proportion correct				.82
VST Average response time			.80	
GNG Average response time			.70	
Eigenvalues	3.02	1.72	1.28	1.16
Percentage of total variance	27.44	15.59	11.67	10.51
Number of factors	5	2	3	2

Note. SST, Stop Signal Reaction Time Task; SART, Sustained Attention to Response Task; GNG, Go/No-Go Task; AX, AX-Continuous Performance Task; JTC, Jumping to Conclusions Beads Task; VST, Visual Search Task.

4. Discussion

We identified a clear-cut factor that groups different indices reflecting interruption of a target task by a competing response. Therefore, our findings support one of the three cognitive processes that we proposed to substantiate impulsivity—that of response interference. The other three factors were either task-specific or linked to superficial characteristics of the tasks, including the type of stimuli (e.g., visual) or type of outcome (e.g., reaction time). Our findings support response interference as a component of impulsivity and provide valuable insights into how assessment methodology might be improved for future studies.

Evidence for a response interference component is consistent with previous factor analytic studies (Caswell et al., 2015; MacKillop et al., 2016; Sharma et al., 2013; Stahl et al., 2014). Collectively, these findings indicate that the inability to withhold or cancel a response is a robust component of impulsivity. In addition, the grouping of both the GNG and SST on this component aligns with research, supporting the validity of these tasks in the assessment of response interference (Hamilton et al., 2015). Also grouped within this factor was the SART, which previous research indicates is sensitive to the inability to suppress a response; although, we initially classified it as a measure of attention interference (Head & Helton, 2013; Helton, 2009). This finding supports the 'motor decoupling' view of SART errors, which posits that errors in the task are driven by a feed forward motor program and not by lapses in perceptual vigilance as an attentional account would predict (Head & Helton, 2013, 2014). In this context, our results suggest that the SART can be reclassified as an index of response interference.

Components two and four reflect a single behavioural task each, the AX-CPT and JTC respectively. Both the AX-CPT and JTC were employed to assess information sampling and thus expected to load onto a single factor; however, differences in task requirements, including response time constraints, stimulus presentation (rapid versus static) and response format (key-press versus mouse-click) may be the cause of these tasks loading onto separate factors. For instance, the AX-CPT uses harsh temporal constraints, demanding swift action to obtain a correct response, whereas the JTC relaxes this parameter allowing participants to respond at their leisure. Instructions for both tasks emphasise accuracy and speed; however, tight time restrictions facilitate a response strategy favouring speed, while easing this constraint shifts the strategy to accuracy (Meier & Blair, 2013). In this way, it is possible that the AX-CPT and JTC are tapping into different information sampling strategies, speed over accuracy or vice versa due to disparate response formats. However, differing task demands is also a strong explanation for this finding.

The third and final component of our model reflects response time. Within component three, an increase in decision time is associated with a decrease in commission errors on the SART, as illustrated by the negative beta weight, but this does not extend to GNG errors. One explanation for this finding is that the ceiling effect in our sample for GNG commission errors resulted in significantly less variation when compared to SART commission errors. This negative association is consistent with evidence linking response speed with commission errors (Dutilh et al., 2012; Hendrick, Ide, Luo, & Li, 2010). This provides evidence in support of the link between impulsive responding and a liberal decision criterion; that is, making a faster, albeit less accurate, decision (Stahl et al., 2014). Thus, while commission errors indicate a lapse in cognitive control, the response time itself represents an adjustment in the decision threshold (i.e., more conservative).

Our findings must be considered with the following limitations in mind. First, according to Field (2013) we had a small, although acceptable sample, which decreases the stability of each component extracted, particularly when the correlations between variables are only moderate. Further, the individual components exhibited low reliability indicating poor internal stability, which signifies that some of the measures were either unrepresentative of the construct, or not representative enough to capture the construct's diversity. Additionally, despite using a data-driven approach to distinguish the underlying structure of impulsivity, our model cannot speak to other unmeasured related variables, such as proactive interference (Stahl et al., 2014). Notwithstanding these limitations, our findings have important implications for the behavioural assessment of impulsivity.

To overcome weaknesses in assessment methodology, our study took a data-driven approach to substantiating a structural model of impulsivity. Although we were unable to identify a model of impulsivity aligned with our original assumptions, our study adds to mounting evidence in support of response interference as an important component of impulsivity (Caswell et al., 2015; Fineberg et al., 2014; MacKillop et al., 2016). Further, previous work mirrors our own findings that variables, such as response time, group with other variables based on similarity and the overall assortment of tasks chosen, rather than distinct underlying cognitions (Block, Goldberg, & Saucier, 1995). Overall, these findings support response interference as a key component of impulsivity and highlight the need for further theoretical and measurement research to define other potential components.

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Table 2:Demographic statistics for the sample (*N* = 128*)*

	Mean/N(%)	**SD**
Age	32.2	6.39
Sex (M/F)	66 (51.6%)	
SST Stop signal reaction time	260.22	71.64
SST Probability of stopping on a stop signal	53.46	17.84
SART Coefficient of variability	.24	.09
SART Total commission errors	9.69	5.51
GNG Error rate	.02	.02
GNG Average response time	357.63	45.81
AX Proportion correct A vs B	.16	.27
AX Difference in mean response time A vs B	33.17	68.60
JTC Median beads drawn	8.74	7.75
JTC Proportion correct	.72	.18
VST Average response time	634.10	143.11
VST Proportion incorrect	.09	.12

Note. SD, Standard Deviation; SST, Stop Signal Reaction Time Task; SART, Sustained Attention to Response Task; GNG, Go/No-Go Task; AX, AX-Continuous Performance Task; JTC, Jumping to Conclusions Beads Task; VST, Visual Search Task.

Chapter 5: Thesis Aim Two: Impulsivity and Social Networking Site Use

5.1 Introduction

Within the previous two empirical chapters (Chapter Three and Four) we assessed a tripartite structure of impulsivity including, attention interference, information sampling and response interference, to address thesis aim one. We will now move towards the application of cognitive impulsivity into a population arguably characterised by heightened impulsivity, specifically, Social Networking Site (SNS) users.

SNS have become an essential ingredient in the way we work, do business, and obtain and share information. Integrating daily life with technology has immense benefits but also influences our cognition and affect. For instance, research on the impact of SNS has revealed that when use becomes problematic and poorly controlled it results in elevated negative mood (Fumero, Marrero, Voltes, & Peñate, 2018; LaRose, Lin, & Eastin, 2003) and related distress (Shensa et al., 2017; Turel & Bechara, 2017). Moreover, an emerging body of evidence suggest that problematic SNS use is linked to heightened impulsivity (Chen, Lo, & Lin, 2017; Wilmer & Chein, 2016). Nevertheless, Griffiths (2009) notes that experiencing negative consequences in relation to SNS use is what separates elevated general use, from use which is problematic. Based on this research we conducted a third and final study to address thesis aim two, to examine whether a higher propensity towards impulsive behaviour and elevated symptoms of negative mood are associated with general or problematic SNS use.

5.2 Study design

The original design of study three included both trait and behavioural measures, following recommendations from Sharma, Markon, and Clark (2013) and Coffey (2015) mentioned in previous Chapters. The trait measure included was the UPPS-P (Whiteside & Lynam, 2001; Cyders et al. 2007), which assess five pathways to impulsive behaviour, including negative urgency, positive urgency, lack of perseverance, lack of premeditation and sensation seeking. The behavioural measures included were based on findings from our second study (Chapter Four). As such, we included the Stop Signal Task (SST), the strongest index of response interference from study two, and the Jumping to Conclusions beads Task (JTC) as a measure of information sampling. Based on recent findings on impulsivity and problematic technology use we also included a measure of delay discounting (Hayashi & Blessington, 2018; Hayashi, Miller, Foreman, & Wirth, 2016), and reversal learning as a proxy of compulsivity (Andreassen, 2015).

5.3 Data analysis considerations

During data collection, we observed that most participants successfully completed questionnaire-trait measures, but that there was a significant dropout for behavioural measures (45.68%). This is not uncommon in online studies (Zhou & Fishbach, 2016), and is probably due to the incentive offered and the length of the study. As a result, we ended up with $N = 159$ for trait measures and $N = 71$ for the behavioural tasks. Given this and considering that at least $N = 151$ participants were required to achieve power in the proposed models, (G*Power f 2 = .15, 90% power, and alpha < .05, 11 predictors), we decided to focus only on the trait dimensions when examining the relationship between impulsivity and SNS use in Chapter Six. The results of the behavioural measures are presented in Appendix A.

Chapter 6: Trait Impulsivity and Negative Mood States are Associated with Both General and Problematic Social Networking Site Use

Abstract

Existing research suggests problematic social network site (SNS) use is driven by impulsivity and negative mood states including depression, anxiety and stress. To explore this, we examined whether trait impulsivity and negative mood states were associated with two different levels of SNS use: general and problematic. Problematic SNS use, is use which negatively impacts daily functioning, whereas general use has no such negative impact. We administered three measures to assess SNS use: the frequency of social media–use scale, a modified version of the Social networking time-use scale and the Social Media Disorder Scale. The UPPS-P was used to measure trait impulsivity, and the depression, anxiety and stress scale (DASS21) to assess negative mood. These tasks were administered in 159 participants (female, *n* = 112) who were recruited from Facebook and Amazon Turk Prime. Multiple linear regression analysis revealed that negative mood and negative urgency were associated with problematic SNS use, whereas negative mood, age, sensation seeking, and positive urgency were associated with general use. These findings show that impulsivity and negative mood are differentially associated with general and problematic SNS use. This distinction may help determine those most at risk of developing dysfunctional SNS behaviours.

1. Introduction

Access to social networking sites (SNS), such as Facebook, Twitter, Instagram and Snapchat have radically amplified our ability to connect with people globally. This unprecedented ease of connecting has brought with it a steady rise in SNS use. There are now an estimated three billion active SNS users worldwide, equating to nearly 40% of the world's population (Kemp, 2018). This rise is also reflected in Australian daily use, it is estimated that on average, Australians spend one hour and 39 minutes on SNS every day (Kemp, 2018). Despite the benefits, including ease of social connection, our growing relationship with SNS is not without negative consequences. The continuous bombardment of SNS notifications and the immediacy with which we can act upon them, may alter our basic cognitive and affective functioning (Barr, Pennycook, Stolz, & Fugelsang, 2015), and research indicated that it is users who struggle to control their SNS use who are most at risk of problematic use.

SNS use becomes problematic when it is uncontrolled (Turel & Bechara, 2017), causes adverse effects on relationships (Griffiths, Kuss, & Demetrovics, 2014), and or impairments in psychological health and wellbeing (Shensa et al., 2017). Interacting with SNS for many is an ingrained habitual behaviour (Larose, Kim, & Peng, 2010), however problematic use should not be conflated with high levels of use, as excessive use does not necessarily equate to problematic use (Griffiths, 2009). Despite some users spending excessive amounts of time on SNS, not all experience a negative impact on their lives. It is the experience of negative consequences that Griffiths (2009) argues separates excessive general use from problematic use, prompting debate on whether problematic SNS use can be categorised as a behavioural addiction (Andreassen, 2015; Lee et al., 2012).

Emerging evidence suggests that problematic SNS use has characteristics similar to pathological gambling (Lee et al., 2012; Park et al., 2010), including an inability to control use and a growing motivation and tension to use (Andreassen, 2015). This lack of control and tension results in feelings of distress, discomfort and social or work difficulties (Andreassen, 2015; Cao, Su, Liu, & Gao, 2007; Chen, Lo, & Lin, 2017; Shensa et al., 2017). Although the classification of problematic SNS use as a behavioural addiction is not acknowledged within current diagnostic manuals, such as the DSM-5, researchers report a strong feature overlap between problematic SNS use and components of addiction, including preoccupation, mood modification, conflict, relapse and functional impairment (Andreassen, 2015; Chen et al., 2017; Lee et al., 2012). Like addiction, problematic internet use, including SNS, is associated with impulsivity (Lee et al., 2012).

Impulsivity, the predisposition to act on immediate urges (DeYoung, 2010), has a robust relationship with problematic technology use (Chen et al., 2017; Lee et al., 2012; Park et al., 2010; Wilmer & Chein, 2016). For instance, several studies have demonstrated that impulsivity increases concurrently with problematic SNS use (Cao et al., 2007; Lee et al., 2012; Park et al., 2010). With regards to trait impulsivity, problematic internet use is strongly associated with the cognitive, non-planning and motor subfactors of the Barratt Impulsivity scale, a measure of trait impulsivity (Lee et al., 2012). With evidence demonstrating that the motor impulsivity sub-factor predicts future problematic internet use (Chen et al., 2017). Furthermore, cognitive impulsivity, such as, response interference— the inability to supress a task irrelevant response— is elevated in problematic users (Chen et al., 2017). Collectively, research indicates that those displaying problematic internet use struggle to regulate behaviour (Caplan, 2010) and that impulsivity is a potential vulnerability marker for problematic use (Lee et al., 2012).

In addition to impulsivity, another risk factor is negative mood (LaRose, Lin, & Eastin, 2003). Negative mood, including depression, stress and anxiety, has been consistently associated with problematic technology use (LaRose et al., 2003; Lee et al., 2012; Lin, Wu, You, Hu, & Yen, 2018; Shensa et al., 2017). For instance, evidence from Andreassen (2015) indicates that the inability to access SNS results in feelings of stress, irritation and restlessness, while Lee et al. (2012) found elevated symptoms of anxiety and depression in those with internet addiction. Increased levels of subjective distress and psychiatric comorbidity have also been found in those suffering from internet addiction (Shapira, Goldsmith, Keck, Khosla & McElroy, 2000). Moreover, large scale studies (such as Banyai et al., 2017; Shensa et al., 2017) indicate that individuals experiencing more severe depression symptomology are at the highest risk of problematic SNS engagement (Banyai et al., 2017). A relationship which LaRose et al. (2003) suggests is causal, in that, using SNS to alleviate negative mood can result in use which becomes problematic.

As SNS use is rising (Kemp, 2018) it is imperative we understand what distinguishes general everyday use from use that becomes problematic. Empirical research has predominantly examined factors associated with problematic use in adolescent or college samples (Banyai et al., 2017; Chen et al., 2017); however, research is lacking on how individual differences in cognition and affect are associated with SNS use in a healthy adult sample. In addition, while trait impulsivity has been consistently linked to SNS use, it is unclear whether this relationship holds for the UPPS-P model of trait impulsivity. Moreover, research is yet to distinguish between general and problematic use when examining factors associated with problematic use. As such, this study aims to examine whether trait impulsivity, and negative mood states (depression, anxiety and stress) are associated with general and problematic SNS use. We hypothesise that trait impulsivity, specifically negative urgency, positive urgency, sensation seeking, premeditation and perseverance, as well as negative mood will be positively associated with problematic but not general SNS use.

2. Methods

2.1 Participants

The sample included 159 participants (Age, $M = 28.22$, $SD = 7.92$) that were recruited from advertisements placed on Facebook ($n = 92$) and an Amazon Turk Prime Panel ($n = 67$), an online participant database. The demographic data are summarised in Table 1. To be eligible for the study, participants had to be between 18 and 45 years, not currently diagnosed with a disability or mental illness and not taking psychotropic medication, as indicated by self-report.

Table 1: Summary of demographic variables ($N = 159$)

Measure	*n*	%
Gender		
Female	112	70.00
Male	45	28.10
Transgender	2	1.90
Education		
PhD/Doctorate	4	2.5
Masters	20	12.50
Bachelor's degree	56	35.00
Diploma	25	15.60
Certificate	19	11.90
Secondary school	35	22.50
Geographic location		
Australia	57	35.60
New Zealand	3	1.90
Asia	12	7.50
Africa	6	3.80
Europe	22	13.80
North America	55	34.4
South America	1	0.60
Other	3	2.50

2.2 Measures

These data were collected as part of a larger study on SNS use (see Chapter 5) that included trait and behavioural impulsivity. Behavioural measures were included in the study session, reported in Appendix A.

2.2.1 Trait impulsivity

The *UPPS-P Impulsive Behaviour Scale* (UPPS-P: Whiteside & Lynam, 2001; Cyders et al. 2007) is a 59-item inventory that assesses five distinct personality traits that lead to impulsive behaviour. All items are scored on a 4-point Likert scale ranging from (1) *Agree Strongly* to (4) *Disagree Strongly.* The UPPS-P assesses (1) Negative Urgency, which is the tendency to act on cues when experiencing negative affect (12 items, $\alpha = 0.87$);
(2) Perseverance (lack of), which is the inability to follow through on tasks (10 items, $\alpha = 0.85$); (3) Premeditation (lack of), which is the proclivity to act without contemplating potential consequences (11 items, $\alpha = 0.85$); (4) Sensation Seeking, which is the propensity to engage in high energy and thrill behaviours (12 items, $\alpha = 0.86$); and (5) Positive Urgency, which is the tendency to act on cues when experiencing positive affect (14 items, $\alpha = 0.93$) (reliability coefficients from Whiteside & Lynam, 2001). The UPPS-P produces both an overall impulsivity score, as well as five subfactor scores.

2.2.2 Negative mood states

The *Depression Anxiety and Stress Scale 21* (DASS21: Lovibond & Lovibond, 1995) assesses the negative emotional states of depression, anxiety and stress. This short version includes 21 items, seven per subscale of, (1) depression, which assesses hopelessness, low self-esteem, and low positive affect; (2) anxiety, which measures autonomic arousal, musculoskeletal symptoms, situational anxiety and subjective experience of anxious arousal;

and (3) stress, which gauges tension, agitation and negative affect. Respondents are instructed to indicate the presence of a symptom over the previous week on a 4-point scale, from (0) *did not apply to me at all over the last week* to (3) *applied to me very much over the last week*. The DASS21 is psychometrically sound (Antony, Bieling, Cox, Enns, & Swinson, 1998; Henry & Crawford, 2005). Evidence supports a general dimension of negative affect (Henry & Crawford, 2005; Le et al., 2017) that encompasses all three subscales. Thus, we calculated a composite score, taking the average score across each of the three subscales as a general measure of negative mood.

2.2.3 Social networking site engagement

The *Frequency of Social Media Use Scale* (FSMU) is a novel two-item scale that assesses the diversity of social media use. The first item asks respondents to indicate which of the 15 most popular SNS in Australia (Kemp, 2018) and the US (Pew Research Center, 2018), they use (e.g., Facebook, Twitter and Snapchat) and to rate how frequently they use them, from (1) *a few times a year* to (5) *multiple times a day*. The second item requires participants to indicate, as a percentage, the extent to which they access SNS on a phone, tablet or computer. The FSMU produces three indices: (1) an index of SNS diversity, calculated by adding how many unique platforms the user accesses; (2) an index of engagement, which reflects how frequently the platforms are accessed (sum of all scores positively scaled); and (3) a percentage index reflecting how users are accessing SNS (i.e., phone, tablet or computer).

2.2.4 General social networking site use

The *Modified Social Networking Time Use Scale* (SONTUS: Olufadi, 2016) assesses time spent on SNS across a range of everyday situations. We modified the original SONTUS to increase comparability and reduce conceptual overlap with the Social Media Disorder Scale (SMDS). The original SONTUS assesses SNS use across five domains: relaxation and free periods, academic related periods, public places, stress-related encounters, and motives to use. We removed the fourth subscale, 'stress-related encounters' as it overlaps with problematic use, assessed within the SMDS. The remaining four subscales included 23 items, which required participants to indicate how often they used SNS sites over the past month. Respondents rated their behaviour against statements such as, how often do you use SNS, *'when you are at home sitting idly'* on a 6-point Likert scale, ranging from (1) *Not applicable* to (6) *Multiple times a day*. The original SONTUS uses an 11-point Likert scale that is converted into four points during scoring. We modified the original scale to be consistent with the FSMU. Overall, the SONTUS demonstrates reliability (test-retest, r = .85) as well as structural and convergent validity (Sigerson & Cheng, 2018). We used the global score, calculated by adding all four domain scores, as a positively scaled measure of general SNS use.

2.2.5 Problematic social networking site use

The *Social Media Disorder Scale* (SMDS: van den Eijnden, Lemmens, & Valkenburg, 2016) is a brief tool that identifies problematic social media use. The SMDS includes nine yes-or-no-answer questions, such as have you '*felt bad when you could not use social media*'. This scale is psychometrically sound and has shown to be both sensitive and specific to problematic SNS use (van den Eijnden et al., 2016). The primary outcome is a global SMDS score calculated by summing all questions answered with 'yes'.

2.3 Procedures

Participants entered the study either via a Facebook advertisement or an Amazon Turk Prime Panel (an online participant database). Using the online survey platform Qualtrics, participants were first briefed and consented. Next, we collected demographic information on age, gender, education, current and past mental health, and disability. Questions regarding mental health included: diagnosis (if any), time since diagnosis (<12 months, 12–24 months and 2+ years), and current medications (if any). Questions regarding disability included: disability (if any), and the nature of the disability (if any). Participants first completed the three SNS use scales, FSMUS, SMDS and the SONTUS, respectively. Following this, participants completed the UPPS-P measure of trait impulsivity, followed by the DASS21 scale of depression, anxiety and stress. Participants who entered the study via Facebook were reimbursed for their time by going into a draw to win one of two $100 Coles Vouchers, whereas those who entered via Amazon Turk Prime were reimbursed US$1.75 each (amount predetermined by Amazon). The Monash Human Research Ethics Committee approved this study (MUHREC, 9061).

2.4 Statistical analysis

Data analysis was conducted using the Statistical Package for Social Sciences (SPSS V25). The dataset was examined for missing values, removing participants who did not complete all questionnaires. An iterative process was used to identify univariate outliers ($Z < 3.29$) and treated by Winsorizing, which assigns such values the highest possible cut-off score that is not an outlier (Field, 2013). All variables were examined for normal distributions with Kolmogorov Smirnov tests, and no transformations were deemed necessary.

To examine the association between trait impulsivity and SNS use we first conducted bivariate correlations, to assess the direction and strength of the relationship between predictors. Following this, we ran two separate multiple linear regression models. In each regression analysis we entered age and education (control variables), and negative mood and the five UPPS-P subfacets (interest variables). The dependent variable was the SONTUS global score in the first analysis, and the SMDS score in the second. Based on previous studies, assessing the relationship between impulsivity and internet addiction where effect sizes ranged from moderate (Cao et al., 2007; Zhang et al., 2015) to large (Lee et al., 2012), we expected to find a moderate effect size (Cohens $d \geq 0.3$ or $R^2 \geq .13$). A G*Power a priori power analysis with a medium effect size, $f^2 = .15$, 90% power, and alpha < .05, recommends a sample size of ≥ 135 with eight predictors, or ≥ 151 with 11 predictors. To reduce experiment-wise error produced by multiple analysis we included a composite score for the DASS21, resulting in a total of eight predictors.

3. Results

3.1 Descriptive statistics

Participants accessed SNS predominantly via their phones (61.43%) or computer (30.58%), rather than a tablet (8.09%). A diversity of SNS platforms were accessed, with majority of participants engaging with at least one SNS platform, once per day. No significant differences in gender were observed across either problematic or general SNS use. There were, however significant differences between recruitment methods. Sensation seeking, $t(158) = 2.43$, $p < .05$, and the SONTUS, equal variance not assumed, $t(104.21) = 5.59$, $p < .001$, were significantly higher in those recruited from Facebook as opposed to Turk Prime. However, participants recruited from Turk Prime were significantly older $t(157) = -5.48$, $p <$

.001 (full results in Table 6). The scores on the primary outcome measures are summarised in Table 2.

Table 2: Descriptive statistics for outcome variables (*N* = 159)

Measure	Min	Max	Mean	SD
Age	18.00	45.00	28.22	7.92
DASS21 Composite	.00	40.67	12.39	10.43
Positive urgency	1.00	4.00	2.11	.70
Negative urgency	1.17	4.00	2.53	.60
Premeditation	1.00	3.36	2.01	.48
Perseverance	1.00	3.30	2.10	.51
Sensation seeking	1.08	4.00	2.61	.65
SMDS	.00	9.00	2.35	2.12
SONTUS	2.00	138.00	65.43	34.00
FSMUS engagement	1.00	75.00	27.41	11.55
FSMUS diversity	1.00	16.00	7.91	3.15

3.2 Impulsivity, negative mood and general SNS use

The overall combination of the eight factors explained 34% of the variance, *adjusted* $R^2 = .34$, $F(8,150) = 11.11$, $p < .0001$. Age, negative mood, positive urgency and sensation seeking were all significant predictors, as per Table 3.

Table 3:Summary of the multiple regression statistics general SNS use (*N* = 159)

Predictor	B	SE(B)	β	*t*	*p*
Age	–1.16	0.31	–0.27	–3.76	.000
Education	0.73	1.54	0.03	0.47	.637
DASS21 Composite	0.58	0.26	0.18	2.22	.028
Positive Urgency	11.27	5.15	0.23	2.19	.030
Negative Urgency	2.96	6.11	0.05	0.48	.629
Premeditation	0.41	5.70	0.01	0.07	.943
Perseverance	–4.41	5.85	–0.07	–0.75	.453
Sensation Seeking	11.03	4.20	0.21	2.63	.009

3.3 Impulsivity, negative mood and problematic SNS use

Next, we assessed problematic SNS use, finding the factors explained 35% of the variance, *adjusted* $R^2 = .35$, $F(8,150) = 11.39$, $p < .001$; however, negative mood states and negative urgency were the only significant predictors (see Table 4).

Table 4: Multiple regression statistics for problematic SNS use ($N = 159$)

Predictor	B	SE(B)	β	*t*	*p*
Age	.01	.02	.02	.28	.776
Education	–.01	.10	–.01	–.08	.939
DASS21 Composite	.08	.02	.38	4.88	.000
Positive Urgency	–.34	.32	–.11	–1.07	.285
Negative Urgency	1.07	.38	.30	2.83	.005
Premeditation	–.49	.35	–.11	–1.40	.164
Perseverance	.55	.36	.13	1.53	.128
Sensation Seeking	.44	.26	.14	1.70	.091

4. Discussion

Supporting our hypothesis, trait impulsivity and negative mood states were both positively associated with problematic SNS use. Contrary to our expectations both variables were also linked to general SNS use, although different facets of trait impulsivity characterised general versus problematic use. General use was associated with elevated levels of sensation seeking and positive urgency, whereas problematic use was distinguished solely by elevated negative urgency. These findings support negative mood states as a key factor contributing to SNS use and suggests that different components of trait impulsivity influence SNS use.

Our findings regarding negative mood and problematic SNS use are supported by previous studies (Banyai et al., 2017; Fumero et al., 2018; LaRose et al., 2003; Shensa et al., 2017). Problematic SNS use has been identified as the predominant reason depression is associated with SNS use (Shensa et al., 2017); although, our results also indicate that negative mood is linked to general use, albeit to a lesser degree. A similar result was found by Shensa et al. (2017), who included an SNS frequency variable approximating general use as a covariate and found it was independently associated with depressive symptoms. Together these findings indicate that experiencing negative mood may perpetuate and, in turn, deepen SNS use until it becomes problematic, although longitudinal research is required to substantiate this. Further, the relationship between dysregulated SNS use and negative affect is mirrored in trait impulsivity.

Expanding on previous findings regarding trait impulsivity and internet addiction (Lee et al., 2012; Wilmer & Chein, 2016), we found negative urgency—the propensity to act impulsively when experiencing negative affect (Whiteside & Lynam, 2001)—was associated with problematic but not general SNS use. Similarly, Billieux et al. (2011) found that negative urgency was the only impulsivity subfacet to predict problematic use, albeit for massively multiplayer online role playing games, leading the authors to suggest that play may become an automatic habit to assist in the relief of negative affect. Overall, findings indicate that experiencing symptoms of depression, anxiety or stress in conjunction with the propensity to act impulsively when experiencing negative emotions, are associated with problematic SNS use and worsen on a relatively linear trajectory.

Contrary to prior research (Lin & Tsai, 2002; Navas, Torres, Candido, & Perales, 2014; Rahmani & Lavasani, 2011) our results indicated that both positive urgency and sensation seeking underpin general, not problematic SNS use, suggesting that non-disordered engagement is an unregulated reward or novelty seeking behaviour. One reason for this inconsistency is that Lin and Tsai (2002) and Rahmani and Lavasani (2011) used high school or college samples and sensation seeking is higher in young adults (Quinn & Harden, 2013;

Romer & Hennessy, 2007). Our findings also indicate that being younger is associated with general but not problematic use, which may partially explain why higher rates of sensation seeking are linked to general use.

Age has previously been associated with high levels of SNS use. For instance, Kemp (2018) reported that those between 18 and 34 years old account for 58% of Facebook users worldwide, while the Pew Research Center (2016) found that in North America, 88% of online 18 to 29 year old adults use Facebook, reflecting the increased readiness of young adults to accept and engage with new technology. Given that our sample was, on average, older than previous studies (e.g., Banyai et al., 2017; Shensa et al., 2017), it is noteworthy that age was positively associated with general but not problematic use, suggesting that individuals displaying a certain set of characteristics are at a higher risk of problematic use, regardless of their age.

Our findings must be considered within the context of several limitations. To reduce experiment-wise error and maintain adequate levels of statistical power, we calculated a composite score for negative mood, reflecting depression, anxiety and stress. Future research would benefit from assessing each discrete negative mood factor to enable a more accurate conceptualisation of the drivers of both general and problematic SNS use. Further, impulsivity is a heterogeneous construct, including both trait and behavioural components; however, this analysis only included a trait measure. Future research could include both trait and behavioural impulsivity to examine how the different components of impulsivity influence general and problematic use. Finally, we did not assess an individual's preference for online social interaction, which previous research suggests is a factor which motivates the use of online communication, specifically with regards to mood regulation (Caplan, 2010).

We examined the influence of cognition and affect, namely impulsivity and negative mood, on SNS use. We demonstrated that negative mood symptomology and trait impulsivity are key factors in SNS use. General SNS engagement was related to reward or novel stimulus seeking behaviour, whereas problematic use occurred concomitantly with negative urgency. Practically, our findings indicate that psychological interventions could be of practical utility in addressing problematic SNS use. Further longitudinal research is needed to explore how negative mood and trait impulsivity contribute to the development of problematic SNS use.

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Table 5: Bivariate correlations

Measure	1	2	3	4	5	6	7	8	9	10
1 Age	-									
2 Education	.19*	-								
3 DASS21 Composite	–.11	–.17*								
4 Positive Urgency	–.09	–.05	.49***							
5 Negative Urgency	–.15	–.16	.52***	.75***						
6 Premeditation	.09	.12	.01	–.01	–.02					
7 Perseverance	–.07	–.14	.27*	.22**	.35***	.50***				
8 Sensation Seeking	–.33***	.03	.08	.42***	.32***	–.08	–.13			
9 SMDS	–.12	–.14	.53***	.39***	.51***	–.05	.25**	.20*		
10 SONTUS	–.37***	–.05	.34***	.45***	.39***	–.07	.04	.44***	.40***	

Note: N = 159, * < .05, ** p < .01., *** p < .001.

Table 6: Independent samples t-tests comparing methods of recruitment

	Facebook		Turk Prime		95% CI Mean Difference			
Task	**M**	**SD**	**M**	**SD**		***t***	**df**	**Sig**
DASS21 composite	12.67	9.99	11.95	11.17	-2.63, 4.07	.424	158	.67
SONTUS	76.98	27.10	47.19	35.99	19.22, 40.35	5.591	104.21	.00
SMDS	2.51	1.95	2.10	2.34	-.26, 1.09	1.205	158	.23
Negative urgency	2.59	.59	2.45	.60	-.05, .34	1.501	158	.14
Premeditation	2.03	.44	1.97	.52	-.09, .22	.825	158	.41
Perseverance	2.15	.51	2.00	.52	-.01, .32	1.804	158	.07
Sensation seeking	2.71	.66	2.45	.61	.05, .46	2.431	158	.016
Positive urgency	2.11	.69	2.12	.72	-0.24, .21	-.171	158	.86
Age	25.72	7.44	32.23	7.02	-8.85, -4.16	-5.477	157	.00

Note: DASS21 composite, Depression, Anxiety Stress Scale average score; SONTUS, Social Networking Time Use Scale; SMDS, Social Media Disorder Scale.

Chapter 7: General Discussion

7.1 Introduction

This final chapter provides an integrated discussion of the main findings of this thesis in the context of the original research aims and previous research on the cognitive components of impulsivity and impulsivity and SNS use. Theoretical and practical implications are discussed, as well as the overall strengths and limitations of the thesis, followed by suggestions for future research and concluding remarks.

7.2 Summary of findings

The aims of this thesis were twofold: to assess a tripartite structure of cognitive impulsivity, including attention interference (AI), information sampling (IS), and response interference (RI), in healthy adults (see Chapters 3 and 4); and to examine if impulsivity and negative mood states (depression, anxiety and stress) contribute differently to general and problematic SNS use (see Chapter Six and Appendix A).

To address thesis aim one, we first developed novel behavioural tasks to measure AI and IS. The first empirical paper (Chapter 3) details the testing of these novel behavioural tasks. Within this study we also examined whether AI, IS and RI could differentiate between high and low levels of trait impulsivity. Findings indicated that the novel tasks failed to offer a significant improvement in validity over the existing tasks in assessing the relevant cognitive processes. Moreover, there was inadequate concordance between the novel and validated tasks and poor discrimination at the component level; that is, the tasks did not accurately reflect variations in individual performance. Furthermore, AI, IS and RI were not able to distinguish between low and high trait impulsivity.

In the second empirical chapter (Chapter 4) we sought to substantiate a tripartite model of impulsivity using a factor analysis of theory-driven impulsivity indices. Unexpectedly, we extracted a four-factor solution. The first and largest factor represented response interference, the second reflected response time across tasks, and two other components reflected a single behavioural task each. Despite each of our three impulsivity components being confirmed previously via several factor analyses (e.g., Caswell et al., 2015; MacKillop et al., 2016; Reynolds et al., 2006; Sharma et al., 2013), we were unable to confirm these components in our analysis. The indicator tasks did not appear to consistently and jointly measure their target constructs. These findings highlight the consistency with which similar outcome variables group together to unduly influence the components extracted. This is reflected in both multidimensional studies (Caswell et al., 2015; Cyders & Coskunpinar, 2012) and meta-analysis (Sharma et al., 2013).

To address thesis aim two, we investigated impulsivity in SNS users, an arguably impulsive population. Specifically, we examined whether trait impulsivity and negative mood were associated with general and problematic SNS use. The results of this examination are presented in empirical chapter three (Chapter 6). Contrary to expectations, findings demonstrated that trait impulsivity and negative mood were associated with both general and problematic SNS use, although distinct facets of trait impulsivity characterised general and problematic use. For instance, general SNS use was associated with elevated levels of sensation seeking and positive urgency, whereas elevated negative urgency was associated with problematic SNS use. Our findings suggest that elevated general use may be driven by the need to share positive emotion or to seek novel stimulus, whereas problematic use arises from the need to alleviate intense negative emotion. Moreover, experiencing symptoms of negative mood may impact the preference for online communication in both general and problematic SNS users.

Within study 3, we also examined cognitive impulsivity, including response interference and information sampling, as well as delay discounting and compulsivity in relation to general and problematic SNS use, the analysis for which is presented in Appendix A. We chose to analyse the behavioural data separately as there were significantly less complete cases for the laboratory tasks. An inadequate case to variable ratio, calculated a priori, meant that the inclusion of all variables within a single analysis would have resulted in an underpowered study. Findings indicate negative mood and response interference share a positive relationship with both general and problematic SNS use, while a lower discounting rate was positively associated with problematic SNS use. Compulsivity was not associated with SNS use at all. These findings should be considered with caution, as validation with a larger sample is required.

Taken together, the empirical findings presented in this thesis demonstrate that trait impulsivity is weakly related with cognitive impulsivity, and that tasks used in the assessment of cognitive impulsivity do not converge to a factor structure as would be predicted based on theoretical frameworks. This finding contrasts with previous literature, which has paired behavioural indicators with specific components of impulsivity. Furthermore, similar indices grouped together, indicating that the individual components extracted were more influenced by the overall assortment of tasks chosen, than the distinct underlying cognitive aspects of impulsivity they are purported to represent. This thesis also provides evidence that cognitive and trait impulsivity are positively associated with SNS use.

7.3 Theoretical and practical implications

The findings from empirical chapters one and two reported in this thesis have important practical implications for how we assess impulsivity. First, although it may be unreasonable to expect such disparate measures—which range from asking participants to refrain from pressing a button when presented with a non-target stimulus, to indicating agreement with statements such as, *"I have a reserved and cautious attitude toward life"*—to share a statistical relationship (Duckworth & Kern, 2011), both trait and cognitive impulsivity are associated with daily life impulsive behaviours (Sharma et al., 2013), internet addiction (Cao, Su, Liu, & Gao, 2007), and negative health behaviours, such as gambling disorder (Hodgins, & Holub, 2015). Therefore, a potential explanation for the lack of concordance between trait and cognitive measures, is that the construct variance of cognitive impulsivity is not adequately captured by a single behavioural task due to task impurity (Miyake & Friedman, 2012). Thus, a composite cognitive index may be able to overcome the method invariance between trait and behavioural measures and provide a more accurate representation of cognitive impulsivity (Sharma et al., 2013). Alternatively, Glicksohn et al. (2016) posit that impulsive individuals may not consistently perform impulsively on behavioural measures. Based on this theory, we might expect to see weak or at times no concordance between measurement types. As such, research on impulsivity should use both trait and cognitive measures when assessing impulsivity.

Second, our examination of the factorial interrelatedness of several cognitive tasks associated with AI, IS and RI, highlight how theories of impulsivity are constrained to the particular observations measured. This is problematic if your aim is to identify the underlying mechanisms of impulsivity because observations must be interpreted based on prior assumptions and theory (Kane, 2001), and there is no solid theoretical structure for cognitive impulsivity. Further evidence of this can be found in attempts to advance cognitive impulsivity theory over the past decade, which are mostly based on how a set of observations cluster. This thesis confirms what many researchers have already asserted, that the current task-based approach results in a constantly shifting theoretical structure which is unable to settle on a set of specified components. In an attempt to overcome this challenge, we first identified a potential structure based on a methodical review of the literature, however it is grounded in studies which themselves use observation or task based theories. In light of this we reiterate that the assessment of cognitive impulsivity requires a shift towards construct validation, and the use of multiple indices of performance, including trait and cognitive measures, to progress towards a coherent model of impulsivity more broadly.

The findings from empirical chapter three have important practical implications for how we identify and manage problematic SNS use. Specifically, our findings suggest that elevated symptoms of negative mood, trait impulsivity and response interference are potential risk factors for problematic SNS use. Considering how pervasive technology has become in our daily lives, determining risk factors predictive of problematic use is of growing importance, as early identification and treatment may serve to avert the negative consequences of problematic use. Negative consequences which include relationship difficulties (Griffiths, Kuss, & Demetrovics, 2014), impairment in psychological health and wellbeing (Shensa et al., 2017), and engagement in risky activities (Tsitsika et al., 2011). Furthermore, the identification of negative mood and negative urgency as factors associated with problematic SNS use, supports the potential utility of psychological interventions in treating problematic users. For example, cognitive behavioural therapy has already been used successfully to reduce time spent online, as well as depression and anxiety in individuals addicted to the internet (Winkler, Dörsing, Rief, Shen, & Glombiewski, 2013).

7.4 Thesis strengths

Previous research on the structure of impulsivity in healthy subjects has relied predominantly on undergraduate samples (Barnhart & Buelow, 2017; MacKillop et al., 2016; Stahl et al., 2014), limiting the generalisability of findings. This thesis extended research beyond undergraduate students, using progressive online recruitment methods to obtain samples from across Australia and the US, in two of three studies (see Chapters 4 and 6), extending the generalisability of findings.

Given that there has been considerable debate within the literature (Chamberlain & Fineberg, 2015; Coffey, 2015; Cyders, 2015), questioning the lack of consideration given to validity within the cognitive impulsivity literature and highlighting the need for specific validity research, a strength of this thesis was the attention given to the measurement properties of behavioural tasks currently used to assess impulsivity-related constructs (particularly in empirical Chapter one). Using predefined principles of incremental construct validity, we were able to identify specific weaknesses within current methodology, particularly for information sampling and attention interference. This thesis, while not directly assessing the validity of existing tasks, placed a strong focus on measurement issues and, through the findings presented in empirical Chapters two and three, highlight the need for specific validity studies.

There is a significant and growing body of research into varying forms of problematic technology use and psychological factors such as depression and impulsivity. These studies focus nearly exclusively on problematic, oftentimes labelled addicted use (Cao et al., 2007; Lee et al., 2012; Zhou, Zhu, Li, & Wang, 2014). To our knowledge, study 3, is the first to distinguish between general and problematic SNS use. This study is also one of the first to examine the association between different facets of the UPPS-P model of trait impulsivity and SNS use. Separating general from impaired use allowed for a more nuanced picture of the relationship between SNS use, impulsivity and negative mood, than is currently available.

7.5 Thesis limitations and future research directions

The findings of this thesis need to be considered within the context of the following limitations. First, all three studies included adequate but small samples given the statistical analysis used. Additionally, the samples in empirical Chapters three and six were gender imbalanced, both predominantly female, which limits the generalisability of the findings to males. Future studies in larger, gender balanced samples are required. Further, as we focused on only three cognitive components of impulsivity, our findings cannot speak to other unmeasured but related variables such as proactive interference—interruption from an irrelevant mental representation (Stahl et al., 2014). Moreover, we did not sample from all possible cognitive tasks associated with impulsivity; instead, we intentionally chose purported to produce indicators sensitive to attention interference, information sampling and response interference. The weakness inherent in using this approach is pre-structuring, where the type and mix of tasks heavily predetermine the factor structure (Block et al., 1995). To avoid pre-structuring, future research could take an exploratory approach using a diverse set of tasks associated with the measurement of the mental predecessors of impulsiveness.

The studies outlined in empirical chapter two and three used online recruitment and data collection techniques. This allowed us to collect a diverse sample, but also meant we were unable to fully control the experimental environment. Future research using online methods could investigate implementing software to increase experimental control, such as

Respondus, which limits screen use to a single window. Another weakness inherent in using online methods, despite data quality assurance procedures, was participant attrition. Attrition during Study 3 meant that the trait and behavioural data were unable to be assessed together. This is a weakness given the heterogeneous nature of impulsivity, as we were unable to determine how trait and behavioural impulsivity jointly influence SNS use. As such, future research should jointly assess how trait and behavioural measures of impulsivity differentially influence general and problematic use, as well as in those few extreme users who meet the criteria for SNS addiction.

7.6 Concluding remarks

This thesis examined the validity of AI, IS and RI as components of cognitive impulsivity. The work presented here illustrates that further validation of indices used to measure components of cognitive impulsivity is required. The limited purity of these indices, in conjunction with the specific assortment of indices chosen limits attempts to substantiate a theoretical model of cognitive impulsivity. Furthermore, this thesis reaffirms the relevance of both trait and behavioural impulsivity in our understanding of negative health behaviours, namely SNS use. In a practical sense, the findings suggest that interventions aimed at addressing negative mood and negative urgency in those who prefer online communication may be effective at discouraging problematic SNS use. Impulsivity remains an elusive construct to define and measure. Progress towards a unified theory will allow for a deeper understanding of the aetiology of impulse-based behavioural problems.

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Appendix A: Cognitive Impulsivity and Negative Mood are Associated with Both General and Problematic Social Networking Site Use

1. Introduction

Study 3 took a multidimensional approach to the assessment of impulsivity with the aim of determining if facets of trait impulsivity and components of cognitive impulsivity were associated with general and/or problematic SNS use. During the online recruitment processes selective attrition after the first section of the study, which included only self-report measures, meant there were significantly less complete datasets for the behavioural tasks. Despite switching the study sections midway through recruitment at the end of the data collection period, there was an inadequate number of complete cases (including both self-report and behavioural) to include all variables in the regression. As such, the self-report data was assessed separately, with a priori power calculations indicating an adequate case to variable ratio, whereas the sample including the behavioural data was identified as underpowered. Due to an inadequate sample size the behavioural analysis has been included here as an appendix, rather than an empirical paper.

1.1 Response interference

Emerging evidence indicates that cognitive impulsivity is associated with problematic technology use (Chen et al., 2017; Wilmer & Chein, 2016; Zhou, Zhou, & Zhu, 2016). For instance, problematic users exhibit elevated levels of response interference (Chen et al., 2017; Zhou et al., 2016; Zhou, Zhu, Li, & Wang, 2014), the inability to supress a task irrelevant response. Specifically, heightened response interference is linked to problematic internet use in college students (Chen et al., 2017). Dysfunctional internet users have also been found to exhibit similar levels of response interference to alcohol dependant patients (Zhou et al., 2014) and higher levels when compared to problematic gamblers (Zhou et al., 2016). Together, research suggests that the failure to regulate behaviour is strongly associated with problematic technology use.

1.2 Compulsivity

What may begin as impulsive behaviour, the urge to view a phone notification, can develop into a compulsion, the insistent need to view the notification (Andreassen, 2015). This insistent need or preoccupation is associated with compulsivity, actions which persist and have no obvious relationship to the task goal (Dalley, Everitt, & Robbins, 2011). When behaviour shifts from impulsive to compulsive, we would expect to see unfavourable consequences deepen in severity as the behaviour becomes increasingly uncontrolled (Andreassen, 2015). While impulsivity is implicated in the development of SNS addiction (Lee et al., 2012), compulsivity may be associated with the maintenance of this behaviour and contribute to anxiety surrounding use.

1.3 Information sampling

To our knowledge no study has examined SNS use and information sampling. Despite no empirical evidence of a relationship between SNS use and information sampling, evidence suggests that users often make decisions based on limited information when engaging with content. For instance, it is estimated that 59% of links shared on SNS's are not clicked on at all (Gabielkov, Ramachandran, Chaintreau, & Legout, 2016), indicating that users tend to engage with posts on SNS's based on limited information, such as the headline, rather than the content. Additionally, individuals respond significantly faster to Facebook stimuli (Turel, He, Xue, Xiao, & Bechara, 2014), which could be the result of users habitual and often reflexive engagement with (e.g., like, comment, and share) SNS content; although further research is required.

1.4 Delay discounting

Delay discounting is the tendency to choose smaller immediate over larger but delayed rewards (Wilmer & Chein, 2016). The classification of delay discounting as a state or trait component of impulsivity is contentious (Odum, 2011), and it has also been associated with problematic technology use (Wilmer & Chein, 2016); primarily, dysfunctional engagement with mobile phones. For instance, evidence from Wilmer and Chein (2016) indicates that delay discounting is associated with heavier mobile phone use. Moreover, delay discounting is a driver of inappropriate texting behaviour (Hayashi & Blessington, 2018; Hayashi, Miller, Foreman, & Wirth, 2016). Although studies demonstrate that delay discounting is associated with mobile phone use, this relationship is yet to be replicated in other mediums.

1.5 Aims and hypotheses

Studies have demonstrated that response interference is linked to problematic technology use (Zhou et al., 2016; Zhou, Zhu, Li, & Wang, 2014); however, no study to date has assessed whether other components of cognitive impulsivity, such as information sampling, are also associated with dysfunctional use. Moreover, despite being associated with mobile phone use and inappropriate texting behaviour (Hayashi & Blessington, 2018; Hayashi et al., 2016; Wilmer & Chein, 2016), delay discounting is yet to be explored within the context of SNS use. Similarly, there has been no investigation into compulsivity and SNS use, although Andreassen (2015) highlights the compulsive nature of SNS notification checking behaviour. As such, this analysis sought to examine how cognitive impulsivity, delay discounting, compulsivity and negative mood states contribute to general and problematic SNS use. We hypothesise that compulsivity, delay discounting, response interference, information sampling and negative mood will be positively associated with problematic but not general SNS use, and that performance will be worse on a GNG task in a SNS condition when compared to a control condition.

2. Methods

2.2 Participants

This sample is a subset of the sample described in Chapter 6. It includes 71 participants (Age, M = 30.93, SD = 7.06) recruited from Facebook (n=26) and an Amazon Turk Prime Panel (n=45), an online participant database. The demographic data is summarised in Table 1.

Table 1: Summary of demographic variables (*N* = 71)

Measure	***n***	**%**
Gender		
Female	45	63.40
Male	26	36.6
Education		
PhD/Doctorate	3	4.20
Masters	10	14.10
Bachelor's degree	31	43.70
Diploma	13	18.30
Certificate	4	5.60
Secondary school	10	14.10
Geographic location		
Australia	17	23.90
Asia	5	7.00
Africa	5	7.00
Europe	9	12.7
North America	33	46.5
Other	2	2.8

2.2 **Measure**s

This data was collected as part of a larger study on SNS use. As such, additional measures were included in the study session that are not reported. We chose one tasks to assess each of the hypothesised components of impulsivity; that is, information sampling, response interference and delay discounting, as well as one measure each to assess problematic SNS use, general SNS use, negative mood and compulsivity. The details for each task are outlined below.

2.2.1 *Response interference*

Social Media Go No-Go Task (based on Fillmore, 2003; Turel, He, Xue, Xiao, & Bechara, 2014)—This task assesses response interference across two conditions, one in which SNS cues are used and one using stimuli with little associative value (road signs). Participants are instructed to press the space bar when a Go stimulus is presented but refrain from pressing the space bar when they see a No-go stimulus. The Go and No-go stimulus switch between conditions one and two; that is, if the SNS icons were the Go stimuli in test bock one they become the No-go stimuli in block two and vice versa. Each trial begins with a red fixation cross (500 ms), followed by either the Go or No-go stimuli (500 ms), randomly generated from a pool of eight images (10 signs, 10 SNS icons). There are three blocks, including one practice block of 22 trials, 11 per condition (social media and traffic signs), followed by two test blocks, one per condition, consisting of 48 trials per block (75% Go trials and 25% No-go trials 25%). This task uses a variable inter-trial interval (1500, 2000, 2500, 3000 and 3500 ms). Indices include the false alarm rate (frequency of responding to no-go trials), conceptualised as a measure of response inhibition; accuracy on Go trials (hit rate); the sensitivity index (*d'*), which quantifies how readily an individual can distinguish between target (Go) and non-target (No-go) stimuli across trials; decision bias (*C*), the extent to which one response is more likely than another; and a composite measure of false alarms (the average across conditions).

2.2.2 Compulsivity

Probabilistic Reversal Learning Task (RLT: Swainson et al., 2000; Verdejo-Garcia et al., 2010)—This task assesses perseverative responding; that is, persisting with a previously but no longer rewarded response, a hallmark of compulsivity (Dalley et al., 2011). Participants are presented with two coloured squares and must select which of the two colours is correct. The task consists of 160 trials broken into four blocks with 40 trials each. The correct colour shifts across the four task blocks with the previously correct stimulus becoming incorrect during the next phase. Further, the reward is probabilistic. Within each phase the correct colour is only correct in majority of cases resulting in a reward of two points, while the other is incorrect, resulting in a penalty of two points. In phases 1 and 2 (trials 1–80), 70% of correct selections are rewarded and 70% of incorrect choices are penalised, resulting in 30% of all trials receiving false feedback. Phases 3 and 4 (trials 81–160) only differed from phases 1 and 2 with regards to the reward probability, with 60% of correct trials rewarded. The primary index is the total number of perseverative errors (across phases 2–4).

2.2.3 Delay discounting

Delay Discounting Task (DDT: Kirby, Petry, & Bickel, 1999)—The DDT assesses the extent to which an individual discounts the value of a reward as it becomes temporally distant. It is a 27-item questionnaire in which participants are presented with hypothetical monetary options—an amount to be received immediately and a larger amount to be received after a delay (e.g., *Would you prefer $100 today, or $101 in 300 days?*). This measure is highly valid and reliable (Kirby et al., 1999). The primary outcome index is the *k* value (calculated with, Kaplan, Lemley, Reed, & Jarmolowicz, 2014), which indicates how rapidly value is degraded for each participant, with larger values indicating elevated impulsivity.

2.2.4 Information sampling

Jumping to Conclusions Beads Task (JTC: Garety, Hemsley, & Wessely, 1991)—This is a probabilistic reasoning task that is sensitive to impulsive responding due to inadequate information sampling (Banca et al., 2016). Each trial begins with two jars (A and B) presented centrally on the screen, each with different ratios of red to blue beads (85:15 or 60:40). Participants are instructed that '*the computer will draw one bead at a time and always return the bead to the jar before it draws the next bead'*. The participant is tasked with deciding which jar the computer is drawing beads from. Participants can select as many beads as they want prior to choosing a jar. As the beads are selected they appear at the bottom of the screen in a sequence to remind the participants of the colour of each bead drawn so far. Feedback is provided at the end of every trial. This version employed two blocks: a practice block with five trials (probabilities of 85:15), and one test block with 15 trials (probabilities of 60:40). The primary outcome is the median number of beads drawn, an indication of how much information is sampled prior to decision making.

2.2.5 General SNS use

The *Modified Social Networking Time Use Scale* (SONTUS: Olufadi, 2016) assesses SNS use frequency across four domains individuals experience in their day to day lives: relaxation and free periods, academic related periods, public places and motives to use. Participants are asked to indicate how frequently they used SNS's over the past month to statements such as, *'when you are in bed about to sleep'* on a 6-point Likert scale, ranging from (1) *Not applicable* to (6) *Multiple times a day*. The primary index was a global score, which is the sum of all four domain scores, and is a positively scaled measure of general SNS use.

2.2.6 Problematic SNS use

The *Social Media Disorder Scale* (SMDS: van den Eijnden, Lemmens, & Valkenburg, 2016) is a brief nine-item tool that assesses problematic SNS use. A single global index is calculated by adding all items answered with 'yes'.

2.2.7 Negative mood states

The *Depression Anxiety and Stress Scale 21* (DASS21: Lovibond & Lovibond, 1995) measures negative emotional symptoms. The brief 21-item version includes three subscales (seven items each): depression, anxiety and stress. The DASS 21 produces three subscale scores, although evidence also supports a global score indicative of negative affect (Henry & Crawford, 2005; Le et al., 2017). We used a composite score, calculated by taking the average of all three subscales, as a general measure of negative mood.

2.3 Procedures

Participants are directed to the study either via an advertisement on Facebook or an Amazon Turk Prime Panel. First, participants are briefed and consented using the online survey platform Qualtrics. We then collected demographic data prior to participants completing both SNS use scales, and the DASS21 scale of negative mood. Following this, participants are redirected to Inquisit, where they are instructed to download the Millisecond Inquisit Web Player (version 5.0). The Web Player then runs each of the three behavioural tasks in a randomly generated order. After completion of the study, participants were reimbursed for their time. The Monash Human Research Ethics Committee approved this study (MUHREC, 9061).

2.4 Statistical analysis

Data was collated and analysed in the Statistical Package for Social Sciences (SPSS V24). We initially removed participants if their survey responses were incomplete. Similarly, responses were examined independently for each behavioural task and any incomplete cases were removed, followed by any participant who exhibited a pattern of responses indicative of either a failure to understand the task instructions or an inability to perform the task successfully. Next, we used an iterative process to identify univariate outliers ($Z < 3.29$), treated via Winsorizing, assigning it a lesser weight (Field, 2013). We then analysed the data for normality with Kolmogorov Smirnov tests, which indicated that all variables except age were non-normal; however, transformations did not normalise the distributions.

To examine the association between SNS use and different components of behavioural impulsivity, response interference, information sampling and delay discounting, as well as compulsivity and negative mood, we conducted bivariate correlations and two independent multiple linear regression models. In each regression analysis we entered age and education (controls), negative mood and the four behavioural variables. For response interference a composite false alarm rate was entered, which was the average across both conditions. The only difference between model one and two was the dependant variable, which we switched from the SONTUS global score in the first to the SMDS score in the second. Based on previous studies in which effect sizes ranged from moderate (Cao, Su, Liu, & Gao, 2007; Zhang et al., 2015) to large (Lee et al., 2012), we conducted an a priori power analysis in G*Power ($f^2 = .15$, 90% power, and $\alpha < .05$), which indicated a sample size of ≥ 130 was required with seven predictors.

To assess any differences between the SNS and control (road sign) GNG conditions we compared the means of each behavioural index, including, the hit rate, false alarm rate, sensitivity index (*d*') and decision bias (*C*). Prior to calculating *d*' and C we converted the hit and false alarm rate to *p* and then *z* values; however, as it is possible that a participant could detect all signals resulting in a hit rate of 1.00, or make no false alarms resulting in a false alarm rate of 0, we set the maximum value for $p = (N-1)/N$ and the minimum value at $p = 1/N$, where *N* is the number of trials used in the calculation of *p* (Stanislaw & Todorov, 1999). Further, as Levene's indicated that equal variance could not be assumed for any of the behavioural outcomes except decision bias for the control condition, the non-parametric Wilcox signed-rank tests was employed.

3. Results

3.1 Descriptive statistics

Participants predominantly accessed SNS's with their phones (51.57%) or computer (38.31%), instead of a tablet (10.12%). No significant gender differences were observed across problematic or general SNS use. There were a number of significant differences between recruitment methods. Sensation seeking, $t(69) = 2.29$, $p < .05$, and the SONTUS, $t(69) = 3.87$, $p < .001$, were significantly higher in those recruited from Facebook as opposed to Turk Prime. However, participants recruited from Turk Prime were significantly older $t(69) = -3.64$, $p < .01$, and discounting more steeply, equal variances not assumed, $t(68.75) = -2.48$, $p < .05$ (full results in Table 6). The primary outcome measures are summarised in Table 2.

Table 2: Descriptive statistics for outcome variables ($N = 71$)

Measure	Min	Max	Mean	SD
Age	19.00	50.00	30.93	7.06
DASS21 composite	.00	35.33	10.79	9.88
RLT perseverative err	.00	19.00	4.86	4.59
JTC median beads	2.00	51.00	10.61	14.02
Delay discounting *k*	.00	.20	.04	.06
SMDS	.00	6.00	1.90	1.91
SONTUS	2.00	138.00	53.30	35.70
GNG composite	.02	.85	.21	.15
GNG SNS				
HIT rate	.57	.97	.95	.07
False alarm rate	.02	.92	.17	.17
d'	.48	3.93	2.89	.76
C	–.61	1.64	.32	.37
GNG Ctrl				
HIT rate	.09	.97	.94	.12
False alarm rate	.02	.92	.25	.12
d'	–1.44	3.93	2.52	.18
C	–.62	1.19	.47	.33

3.2 Impulsivity, compulsivity, negative mood and general versus problematic SNS use

We initially ran bivariate correlations to determine the direction and strength of the relationship between predictors prior to running the regression analysis, summarised in Table 3.

Table 3: Bivariate correlations

Measure	1	2	3	4	5	6	7	8	9
1 Age									
2 Education	–.11								
3 DASS21 composite	–.13	–.09							
4 RLT perseverative err	–.05	.09	–.17						
5 JTC median beads	–.22	.15	–.22	.19					
6 Delay discounting k	.06	–.27*	.17	–.23	–.12				
7 SMDS	–.21	–.01	.50**	–.15	–.19	–.06	-		
8 SONTUS	–.44**	.26*	.40**	–.12	.00	–.10	.51**		
9 GNG composite	–.02	–.02	.26*	–.05	–.10	.29*	.29*	.27*	

Note: N = 71, *$p < .05$., ** $p < .01$.

Following this we assessed general SNS use, finding that the nine factors explained 38% of the variance, *adjusted* $R^2 = .38$, $F(7,63) = 6.99$, $p < .000$. Age, education, negative mood and false alarms were all significant predictors, as per Table 4.

Table 4: Summary of the multiple regression statistics general SNS use ($N = 71$)

Predictor	**B**	**SE(B)**	**β**	***t***	***p***
Age	–1.87	.50	–.37	–3.73	.000
Education	5.86	2.67	.22	2.19	.032
DASS21 Composite	1.14	.37	.32	3.07	.003
RLT perseverative err	–1.00	.77	–.13	–1.30	.198
JTC median beads	–.04	.26	–.01	–.14	.891
Delay discounting *k*	–101.10	63.90	–.17	–1.58	.119
GNG composite	52.97	24.12	.22	2.20	.032

Note: GNG composite is the average false alarm rate for both conditions

For problematic SNS use, the combination of factors explained 28% of the variance, *adjusted* $R^2 = .28$, $F(7,63) = 4.95$, $p < .000$. Within this model, negative mood, delay discounting and false alarms were all significant predictors, as per Table 5.

Table 5: Summary of the multiple regression statistics problematic SNS use ($N = 71$)

Predictor	**B**	**SE(B)**	**β**	***t***	***p***
Age	–.05	.03	–.17	–1.58	.119
Education	–.03	.15	–.02	–.20	.840
DASS21 Composite	.08	.02	.41	3.74	.000
RLT perseverative err	–.04	.04	–.10	–.96	.340
JTC median beads	–.02	.02	–.12	–1.08	.284
Delay discounting *k*	–7.41	3.67	–.23	–2.02	.048
GNG composite	2.83	1.38	.22	2.04	.045

Note: GNG composite is the average false alarm rate for both conditions

3.3 Response interference: SNS versus control condition

Decision bias was significantly greater in the SNS condition (M*dn* = .24), compared to the control (M*dn* = .49), $z = –3.48$, $p = .001$, $r = –.41$. Similarly, sensitivity was greater in the SNS condition (M*dn* = 2.92), compared to the control (M*dn* = 2.62), $z = –3.88$, $p < .001$, $r = –.46$. The reverse was true of the false alarm rate, with the SNS condition lower (M*dn* = .07), compared to the control (M*dn* = .23), $z = 3.64$, $p < .001$, $r = –.43$. The difference between hit rates for each condition was non-significant.

4 Discussion

We sought to examine whether response interference differed within an SNS context, as opposed to a control. Findings ran contrary to our prediction as impulsive responding was lower within the SNS condition. We also aimed to investigate whether cognition and affect is associated with different forms of SNS use. Specifically, to determine if impulsivity, including delay discounting response interference and information sampling, as well as compulsivity and negative mood are linked to problematic rather than general SNS use. Contrary to our expectations, general SNS use was characterised by being young, having a higher education, experiencing negative mood and elevated response interference, while problematic use was demarcated by negative mood, heightened response interference and lower levels of delay discounting. Our findings suggest that negative mood and components of impulsivity, but not compulsivity, are associated with both general and problematic SNS use.

Our findings regarding negative mood and problematic SNS use are consistent with previous studies (Banyai et al., 2017; Fumero et al., 2018; LaRose et al., 2003; Lin et al., 2018; Shensa et al., 2017); although, the link we found between negative mood and general use raises questions as to whether problematic use is the predominant reason depression is associated with SNS use, as suggested by Shensa et al. (2017). So, although findings indicate that experiencing negative mood could perpetuate and, in turn, deepen SNS use until it becomes problematic (Banyai et al., 2017; LaRose et al., 2003), this relationship may be more nuanced than we expected. For instance, Andreassen et al. (2016) found problematic SNS use was characterised by anxiety rather than depression; whereas, Rus and Tiemensma (2018) found that Facebook use prior to experiencing a stressor acted as a psychological buffer. Similar complexity appears between impulsivity and SNS use.

In examining response interference and SNS use we found that SNS cues alone did not alter the ability to inhibit a task irrelevant response, although the inability to regulate motor responses contributed to both elevated general and problematic SNS use. This is somewhat inconsistent with Turel et al. (2014), who observed normal inhibition system functioning via *f*MRI regardless of Facebook addiction severity. While both Zhou et al. (2016) and Zhou et al. (2014) found evidence of heightened response interference on a GNG task, their sample included only those meeting criteria for disordered internet use. Together, findings suggest that response interference is not altered by the presence of a SNS cue; however, the inability to inhibit an irrelevant response is a general characteristic of individuals with elevated and/or problematic SNS use, which may generalise to other behaviours. Future research may seek to examine the extent to which problematic SNS use co-occurs with other problem behaviours, such as alcohol use.

While there has been limited research into delay discounting and technology use, our results are inconsistent with previous studies (Hayashi & Blessington, 2018; Hayashi et al., 2016; Wilmer & Chein, 2016), as we found a negative relationship between problematic SNS use and the preference for immediate over larger delayed rewards; that is, problematic users discounted less. Despite finding a positive association between delay discounting and technology engagement, Wilmer and Chein (2016) concluded that poorly controlled impulses rather than reward seeking behaviour was the primary driver of technology habits. The discrepancy between current and earlier findings could, in part, be attributed to education and age, as discounting rates have been negatively associated with education (Reimers, Maylor, Stewart, & Chater, 2009; Wilson et al., 2015) and shown to increase with age (Liu et al., 2016). We acknowledge that differences in study design and statistical power may have contributed to the results.

Somewhat inconsistent with previous findings, being younger and educated were linked to elevated general but not problematic SNS use. For instance, Andreassen, Pallesen and Griffiths (2017) found those who were less educated reported greater symptoms of SNS addiction; however, age was negatively associated with problematic use. Conversely, Hardy and Castonguay (2018) found no relationship between SNS use and education. Further, while it is true that younger adults account for a higher proportion of social media users (Kemp, 2018) and report using a broader variety of social media platforms (Hardy & Castonguay, 2018), evidence suggests social media use in young adults (18–29 years) reduces anxiety (Hardy & Castonguay, 2018). Although we did not assess depression, anxiety and stress separately, age was not independently associated with negative mood. Thus, although negative mood and age were both linked with general SNS use, it may be that stress or depression is a more prominent factor for younger adults, while education a potential protective factor in the development of problematic SNS use.

Several limitations should be acknowledged, with important implications for future research. First, our sample was underpowered and predominantly female, reducing the generalisability of the results, particularly since previous studies have found gender differences (Andreassen et al., 2017; Hardy & Castonguay, 2018). Additionally, the data collected on SNS use was via self-report and individuals are not always accurate when it comes to evaluating their own technology use (Andrews, Ellis, Shaw, & Piwek, 2015). Future research would benefit from using an objective measure of SNS use, such as tracing minutes spent using or frequency of sessions. Further, because the sample included participants with low–medium levels of problematic SNS use symptoms, future research could examine those few extreme users that meet the criteria for SNS addiction.

This study examined the association between components of cognitive impulsivity, compulsivity, delay discounting, and negative mood with both general and problematic SNS use. Elevated response interference and negative mood both displayed a consistent relationship with SNS's, regardless of the type of use. Findings suggest that the inability to regulate behaviour may drive SNS use regardless of whether it is problematic, however further research in a larger sample is required. Future research could aim to examine how both cognitive and trait impulsivity together, contribute to SNS use.

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Table 6: Independent samples t-tests comparing methods of recruitment

	Facebook		Turk Prime		95% CI Mean Difference			
Task	**M**	**SD**	**M**	**SD**		***t***	**df**	**Sig**
DASS21 composite	10.38	8.72	11.02	10.58	-5.53, 4.25	-0.26	69	.795
GNG composite	0.20	0.12	0.22	0.17	-0.09, .058	-0.44	69	.661
Negative urgency	2.53	0.56	2.43	0.59	-0.18, .39	0.73	69	.465
Premeditation	2.07	0.50	1.93	0.53	-0.12, .39	1.07	69	.289
Perseverance	2.10	0.48	1.98	0.52	-0.13, .37	0.96	69	.341
Sensation seeking	2.79	0.61	2.45	0.59	0.04, .63	2.29	69	.025
Positive urgency	1.99	0.73	2.06	0.70	-0.42, 0.28	-0.43	69	.672
Delay discounting *k*	0.02	0.04	0.05	0.07	-0.06, -.01	-2.48	68.75	.016
JTC median beads	12.29	15.28	9.64	13.32	-4.27, 9.56	0.76	69	.448
RLT perseverative err	4.50	4.50	5.07	4.68	-2.83, 1,70	-0.50	69	.620
Age	27.23	5.79	33.07	6.89	-9.04, -2.64	-3.64	69	.001
SONTUS	73.00	28.13	41.91	34.87	15.07, 47.11	3.87	69	.000
SMDS	2.35	1.70	1.64	2.00	-0.23, 1.63	1.50	69	.138

Note: GNG composite is the average false alarm rate for both conditions. SONTUS, Social Networking Time Use Scale; SMDS, Social Media Disorder Scale.