



## Relationship between measures of impulsivity in opioid-dependent individuals



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### ABSTRACT

**Background:** Impulsivity is implicated as a contributing factor to ongoing heroin use. This study aimed to determine the inter-relatedness of a battery of self-reported and performance-based behavioural measures of impulsivity in opioid-dependent individuals.

**Methods:** Seventy-two participants on opioid substitution pharmacotherapy completed a battery of impulsivity measures. We analysed the correlations and factor structure of the impulsivity tasks.

**Results:** We observed correlations between self-report measures, but self-report measures were unrelated to the performance-based tasks. For the performance-based tasks, correlations were only observed between outcome measures of the same task, and between outcome measures of the impulsive decision-making tasks. Principal components analysis revealed five components that we labelled self-reported impulsivity, impulsive decision-making with learning, impulsive decision-making without learning, sensitivity index, and responding without consideration of consequences.

**Discussion:** This study reinforces the distinction between multiple facets of impulsivity. This may assist with comparisons between studies that use different measures of impulsivity, and to design improved treatment interventions that target specific aspects of impulsivity.

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### 1. Introduction

Initiation and continued use of heroin have both been linked to impulsive personality traits and behaviour (c.f. Bickel & Marsch, 2001; Dawe & Loxton, 2004; de Wit & Richards, 2004; Verdejo-Garcia, Lawrence, & Clark, 2008). Impulsivity refers to a tendency to engage in “actions that are poorly conceived, prematurely expressed, unduly risky or inappropriate to the situation, and often result in undesirable outcomes” (Evenden, 1999, p. 348). The factor structure of impulsivity has been investigated in healthy controls (e.g. Caswell, Bond, Duka, & Morgan, 2015; Cyders & Coskunpinar, 2011; Sharma, Kohl, Morgan, & Clark, 2013), but may not translate to people with high levels of impulsivity, i.e., drug dependent individuals (Meda et al., 2009). Moreover, patterns of impulsivity in opioid users differ from users of other substances (Loree, Lundahl, & Ledgerwood, 2014; Stevens et al., 2014). The factor structure of impulsivity in opioid dependence has not been comprehensively investigated (Lane, Cherek, Rhoades, Pietras, & Tcheremissine, 2003).

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Self-report questionnaires putatively assess trait impulsivity whereas performance-based tasks assess state impulsivity (Lane et al., 2003; Meda et al., 2009). The Barratt Impulsiveness Scale (BIS) is the most commonly used self-report impulsivity measure, and includes attentional, motor, and non-planning subscales (Stanford et al., 2009). In contrast, performance-based impulsivity measures vary across studies, but are broadly divided into measures of motor and cognitive impulsivity, measuring inhibition of pre-potent responses, and excessive reward sensitivity, respectively (Evenden, 1999; Lane et al., 2003; Reynolds, Ortengren, Richards, & De Wit, 2006). Cognitive impulsivity has been further divided into three types - disadvantageous decision-making (i.e., difficulty weighing options and taking appropriate risks based on available information); choice impulsivity (i.e., excessive discounting of delayed reinforcement); and reflection impulsivity (i.e., reduced tendency to ascertain information from the environment before decision-making) (Fineberg et al., 2014; Verdejo-Garcia et al., 2008). Also, based on suggestions from previous research (e.g., Bowden-Jones, McPhillips, Rogers, Hutton, & Joyce, 2005; Passetti et al., 2011), decision making can be divided into tasks that include or omit learning components.

The inter-relationships within the impulsivity construct can only be understood by examining a range of impulsivity measures in the same study.

No 'gold-standard' impulsivity battery exists. Whether tasks measuring various types cognitive impulsivity can be combined into higher order factors is unknown (Monterosso, Ehrman, Napier, O'Brien, & Childress, 2001), and most studies include too few impulsivity measures to permit comprehensive examinations of factor structure (e.g., Lane et al., 2003; Meda et al., 2009; Reynolds et al., 2006). Moreover, there is evidence that self-report measures tend to correlate, but not with performance-based measures, which themselves tend to be uncorrelated, and thus whether self-report and performance-based measures tap similar constructs is unknown (Cyders & Coskunpinar, 2011, 2012).

To our knowledge no study has compared impulsivity measures within opioid-dependent individuals using a comprehensive framework, although one previous study (Vassileva et al., 2014) examined individuals dependent on heroin and/or amphetamines. Thus, we examined the structure of the impulsivity construct in opioid dependent individuals. We administered a battery of self-report and multiple performance-based measures to examine whether simple component factors could be identified. We hypothesised strong correlations between the subscales of the self-report measure, but low correlations between the self-reported and performance-based measures, and between performance-based measures. We also hypothesised that principal components would substantiate discrete aspects of impulsivity.

## 2. Materials and methods

### 2.1. Participants

We recruited 72 (52 male and 20 female) participants aged 22–50 ( $M = 35.64$ ,  $SD = 5.99$ ), who met DSM-IV criteria for current opioid dependence and reported heroin as their primary substance abused. Participants were recruited for a larger study (author DL, principal investigator), through substitution maintenance pharmacotherapy prescribers and dispensers, and substance use treatment/outreach services in Melbourne. All participants were prescribed opioid substitution pharmacotherapy (62.5% methadone, 37.5% buprenorphine). Mean daily dose for methadone was 44.38 mg (range 4–100) and buprenorphine was 9.45 mg (range 0.1–26). Participants provided a urine sample to confirm self-reported recent use of illicit drugs and opioid substitution pharmacotherapy. Table 1 details drug use history and current drug dependences in the sample; each drug class (other than inhalants), had been used by majority of participants in their lifetime.

Exclusion criteria were current DSM-IV major depressive episode, or histories of a psychotic disorder, bipolar disorder, or neurological disease. Participants were: mainly daily nicotine smokers (82%),

**Table 1**  
Previous and current substance use and DSM-IV-TR dependence.

Substance	Substance use (%)			Dependence (%)	
	Lifetime	Past 12 months	Past month	Current	Past only <sup>a</sup>
Illicit opioids	100	100	50	100	0
Tobacco <sup>b</sup>	100	93	82	–	–
Alcohol <sup>b</sup>	–	–	55	7	31
Cannabis	100	72	40	14	38
Amphetamines <sup>c</sup>	99	53	19	0	47
Cocaine	85	16	1	0	14
Sedatives (illicit) <sup>d</sup>	78	66	18	7	22
Hallucinogens	85	15	4	0	13 <sup>e</sup>
Ecstasy <sup>c</sup>	88	13	1	–	–
Inhalants	38	4	0	0	3

$N = 72$ .

<sup>a</sup> Past-only dependence. i.e., total lifetime dependence is 7% current + 31% past = 38% lifetime dependence.

<sup>b</sup> Lifetime and past 12-month alcohol use, and tobacco dependence, were not measured.

<sup>c</sup> Comprising  $n = 12$  (17%) 1–2 days,  $n = 1$  (1%) 3 days, and  $n = 1$  (1%) 8 days.

<sup>d</sup> Comprising  $n = 9$  (13%) 1–2 days,  $n = 3$  (4%) 3–4 days, and  $n = 1$  (1%) 6 days.

<sup>e</sup> The SCID classifies ecstasy as a hallucinogen, hence dependence for ecstasy and other hallucinogens is combined.

unemployed (54% unemployed, 28% students/part-time work, 11% fulltime work, 7% home duties), had a mean of 11.9 years of education ( $SD = 2.5$ ) and average predicted IQ ( $M = 104.5$ ,  $SD = 9.5$ ). Aside from nicotine, most participants (76%) were currently dependent only on opioids. Nineteen percent reported one, and 4% reported two additional drug dependencies. Eight percent met criteria for current PTSD, and 18% met criteria for opioid-induced mood disorder. Seventeen percent were prescribed anti-depressants, although none met criteria for current major depressive episode. Levels of opioid withdrawal symptoms on the Short Opiate Withdrawal Scale (Gossop, 1990) were low ( $M = 0.64$ ,  $SD = 0.61$ ).

### 2.2. Measures

#### 2.2.1. Impulsivity measures

A Go/No-Go Task (GNG) task designed to measure motor impulsivity, based on Fillmore, Rush, and Hays (2006), was administered using Inquisit 3 (2012). For each trial, a cue preceded either a 'go' target or 'no go' target. Participants were required to respond as quickly as possible to the 'go' targets and withhold their response to 'no go' targets. The 'go' cue preceded the 'go' target on 80% of trials and the 'no go' cue preceded the 'go' target on 20% of the trials (reverse for 'no go' targets). In total, 250 targets were presented, and task performance was measured by reaction time and  $d'$  which is a sensitivity index of signal to noise ratio.

The Information Sampling Task (IST; Clark, Robbins, Ersche, & Sahakian, 2006), used to measure reflection impulsivity, was administered using Inquisit 3 (2012). For each trial, participants open sequential boxes in a  $5 \times 5$  grid and had to decide, in as few moves as possible, which of two colours was in the majority of boxes. In the first condition (fixed win, FW), participants won or lost 100 points regardless of number of boxes opened. For the second condition (decreased win, DW), participants started with 250 points, and the winnings decreased by 10 points with each box opened. Condition order was randomised and ten trials were presented for each condition. Task performance was measured by the probability of being correct (Prob Correct; Clark et al., 2006) for FW and DW conditions.

We used a computerised Iowa Gambling Task (IGT) to measure decision making based on learning, based on Bechara, Damasio, Damasio, and Anderson (1994). Participants were provided with \$20 of virtual money and asked to maximise profit by selecting cards from one of four decks (A, B, C, D). Unbeknownst to participants at the start, two decks resulted in a \$1.00 win/loss that varied between \$1 and \$12.50, whereas the other two decks resulted in a \$0.50c win/loss that varied between \$0 and \$2.50. On average, after 10 selections, two decks were disadvantageous as they resulted in an expected total loss of approximately \$2.50 whereas the other two decks were advantageous as they resulted in an expected total gain of approximately \$2.50. Participants selected 150 cards, and the net score (proportion of advantageous vs. non-advantageous choices) was computed for 6 blocks, with 25 choices in each block. Based on previous research (e.g., Gansler et al., 2011), we created separate net scores for blocks\_1–2 ('learning' blocks) and blocks\_3–6 ('performance' blocks).

The Cambridge Gambling Task (CGT), administered using the CANTAB platform, is a decision-making task not based on learning. Participants viewed ten boxes, in various proportions of red/blue, with a hidden token under one box, and were required to indicate which colour box the token was under. Participants were then offered a series of bets (presented as points to be won/lost) – firstly the increasing bet condition (where bets offered were presented in ascending order), followed by a decreasing bet condition, with two blocks of ten trials for each condition. Task performance was measured by deliberation time, and a measure of decision quality (number of bets made on the choice with highest win probability).

The Monetary Choice Questionnaire (MCQ) is a computerised measure of temporal impulsivity, commonly referred to as 'delay

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