A PSYCHOMETRIC AND BEHAVIOURAL ANALYSIS OF MOBILE GAMBLING

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PUBLICATIONS

Peer reviewed manuscripts that have been produced in the process of the research conducted as part of this PhD, and the results of extracts of which have been included in this thesis.

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Non-peer reviewed work that has been produced that directly relates to the content of this thesis

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ABSTRACT

The British population are increasingly using mobile devices (e.g. smartphones, tablets) to gamble. The empirical work in this thesis looks at how the interaction of gambling's schedule of reinforcement and mobile device behaviours accelerate the acquisition of learned maladaptive behaviours. The first four chapters report psychometric modelling of gambling prevalence data to understand problem gambling further and identify key indicators relevant to associative processes in gambling behaviour. Chapter 2 reports a taxometric analysis of problem gambling assessment data to test whether these screens measure a dimensional or latent class model, finding stronger support for the latter. However, this only identified a small taxon consisting of around 5% of gamblers endorsing more than one problem gambling symptom. Chapter 3 reports the use of latent class analysis to examine distinct subtypes of responding to different screens, findings a common three-class model that showed signs of a mixed latent structure: the same taxon as Chapter 2 was observed, but the three classes showed little overlap in symptom count. Chapter 4 reports further work modelling the sociodemographic characteristics of these different subgroups. Together the data from these chapters were used help to identify indicators of those most likely to a) be most susceptible to gambling harm and b) common to all problem gamblers. In Chapter 5 a Monte Carlo analysis was conducted to understand the efficacy of taxometric procedures on binary variables, before replicating the taxometric analysis reported in Chapter 2 using dichotomous variables and extending the work to the South Oaks Gambling Screen. The indicators derived from these chapters were then used in laboratory and field studies to study mobile gambling

behaviour. The laboratory study in Chapter 6 manipulated two behavioural processes, trial spacing and partial reinforcement, that are relevant to mobile gambling behaviour, showing how a mobile-like schedule is related to increased perseverance and loss-chasing. The same paradigm was used to deliver an experiment on participants' mobile phones in a field environment in Chapter 7. They further demonstrate that a mobile style schedule of reinforcement is associated with considerable persistence in the face of mounting losses, as participants continued to persevere in the face of losses despite a free choice to cease playing. Finally in the discussion I apply the key themes of the thesis to in-play betting, a form of play that has been heavily promoted alongside mobile gambling, and to an understanding of behavioural addictions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 -

GENERAL INTRODUCTION[1]

1.1 Introduction

The introduction of technologies such as the internet and smartphones into the consumer market has often changed the ways in which people work, communicate and play. These changes also engender the potential to profoundly alter human thought and behaviour. The expansion of the Internet in the 1990's opened up a plethora of opportunities for people to go online and engage with a range of content and multimedia. Much of this has been positive; it has become easier to access information now than at any point in history. Such developments might entail changes in the way we learn, think or behave; it has been claimed that the proliferation of technologies such as smartphones or search engines has distributed functions across multiple devices that would previously have been executed by our cognitive processes (Barr, Pennycook, Stolz, & Fugelsang, 2015; Sparrow, Liu, & Wegner, 2011). These changes might make tasks easier or more enjoyable, or make certain activities available to people who could not access them in the past. Some of these changes, it has been contended, might be negative. With increased ease of access, it has been argued that increased availability of certain forms of content may be harmful or addictive to the wider population. The most

[1] Parts of sections 1.2 and 1.4 have been adapted from James, O'Malley & Tunney (in press), "Understanding the psychology of mobile gambling: a behavioural synthesis" at *British Journal of Psychology*.

prominent of these addictive behaviours is gambling[2]. Recent changes to the diagnostic manual for American psychiatrists (American Psychiatric Association, 2013) have cemented the consensus that gambling is addictive in a similar manner to substance based addiction disorders. A considerable research effort has been undertaken to examine whether gambling via the Internet is more harmful than other forms of play (Gainsbury, Wood, Russell, Hing, & Blaszczynski, 2012b; Wardle, Moody, Griffiths, Orford, & Volberg, 2011a). This has continued to the present, despite the growth of Internet gambling perhaps becoming less spectacular than thought around the turn of the millennium (Griffiths, 2003).

The past seven to eight years have seen a remarkable growth in the ownership of smartphones, mobile phones that are capable of a range of functions and include multiple sensors within the device. Content is typically delivered to smartphones using specially designed websites or applications users download onto their phones. Gambling is one of the forms of media that has become available and popular in a mobile format. Data from the gambling industry and The Gambling Commission suggests that there has been a growth in mobile gambling that has met the promise that online gambling once offered (The Gambling Commission, 2016a). However, perhaps in part because of slower than anticipated growth of online gambling, little consideration has

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[2] Activities such as video gaming or online pornography are potential candidates for this mantle, but the question as to whether pornography is addictive is still highly contested. Considerations concerning this and other behaviours are returned to in 8.3 (General Discussion).

been given to mobile gambling in spite of nearly a decade of increasing smartphone proliferation. It is unclear whether mobile gambling should be seen as synonymous or distinctive from other forms of gambling that use the internet. It is also unclear whether, if mobile gambling is distinctive, the idiosyncratic features of mobile gambling might nudge users towards excessive or addictive gambling, or whether they are attractive to people who might already have gambling problems or are at risk of them. In determining the likely nature of the association between mobile gambling and problem gambling, it is necessary to determine whether mobile and other internet gambling should be considered as synonymous or separate. The introduction outlines many of the issues in this area, and considers the case for treating mobile gambling as distinctive. This covers both the environmental aspects of mobile gambling (e.g. context of use, type of game) and the more psychological considerations that are the main focus of this thesis (i.e. app use, associative learning).

This thesis explores the possible effects that mobile gambling as an emerging technology might have on mobile gamblers and the wider public. The central focus of the experimental work in this thesis is to test whether the combination of gambling behaviour and the unique features of interaction with a mobile device, combined with an approach informed by the psychology of learning, suggest that mobile gambling will mediate the acquisition of learned behaviour. All contemporary models of problem, pathological or disordered gambling include a behavioural or associative component (section 1.5a), with the most prominent claiming that one of the causal pathways to problem gambling is purely associative (Blaszczynski & Nower, 2002). This means that the transition from recreational to problem gambling is likely to be different on a mobile device to other forms of gambling (section 1.4b).

This general introduction begins by outlining online gambling, first by providing a more in-depth definition of what mobile gambling is for the purpose of the remainder of this thesis (section 1.2a), and outlining the literature on the relationship between online and problem gambling, mostly focusing on environmental factors such as availability or accessibility (section 1.2b). This then continues by outlining existing methodological and conceptual limitations in this literature, arguing that accounts purely focusing on availability or accessibility are more difficult to quantitative substantiate than retail gambling, and that the relationship with problem gambling is either unclear or indirect. The introduction then continues by outlining the state of gambling in the United Kingdom as many of the wider impacts of mobile gambling are more germane to be experienced here first than worldwide (section 1.3). A more satisfying account of the effects of mobile gambling is therefore more likely to come from a behavioural analysis of mobile gambling, and the changes to gambling behaviour that emerge from mobile phone usage (sections 1.4a, 1.4b). The introduction then outlines many of the issues that must be account for when considering mobile as distinctive or similar to other online forms of play, exploring contextual and technological factors that distinguish mobile gambling alongside how mobile gambling is presented to the public (sections 1.4c, 1.4d, 1.4e, 1.4f, 1.4g). The introduction continues by introducing problem gambling (section 1.5), and how prominent models of gambling highlight the importance of behaviour in the acquisition and maintenance of problem gambling behaviours (section 1.5b), and how these can be used to address the thesis question. Finally the overall structure of the thesis is outlined and an overview of the empirical work contained herein (section 1.6).

1.2 Online gambling

1.2.a Mobile Gambling

Mobile gambling includes multiple ways in which gambling can be accessed. This can be via a bespoke app, a website optimised for mobile gambling, gambling over the phone or via text message. Mobile gambling and mobile video gaming increasingly overlap with one another, as many free-to-play games include gambling games as a secondary form of play such as a mini-game within a larger game. These typically involve users being awarded a free play on a gambling game after a certain amount of time has elapsed, offering a non-monetary in-game reward. Users can often purchase further plays using a secondary currency obtained within the game or real money. Although not the focus of this thesis directly, as the status of these activities as 'gambling' remains uncertain in a regulatory and legislative context (The Gambling Commission, 2015), many of the considerations here will be of relevance. The online gambling literature has examined some of this under the term 'social gambling', which Parke, Wardle, Rigbye, and Parke (2012) note cover a range of services that may differ considerably between websites or applications. In a briefing document produced by The Gambling Commission (2015), the UK gambling regulator refers to social gambling as covering games that include free gambling elements, and takes a 'watching brief' on social gaming. This is because the overwhelming majority (c. 85%) of social gaming users do not spend money on their app (Parke et al., 2012). However, The Gambling Commission note that further evidence is required as it is unclear whether there is a relationship with harmful behaviours, whether some users display signs of problem gambling like behaviours on these games or whether social gamblers migrate to real money gambling.

Gainsbury, Hing, Delfabbro, and King (2014) propose a taxonomy of online gambling and games that separates different activities based on whether payment is required or optional, whether the game is chance or skilful, the platform the game is played upon and the centrality of the gambling theme to the game. In this taxonomy, 'online gambling' refers not only to 'internet gambling' (i.e. spending money on gambling for the chance of a monetary reward) but also a wider range of activities such as social casino games, practice games, gambling video games and competitions or tournaments based on gambling games (e.g. poker). In the context of this taxonomy, this review can be seen to examine whether the grouping Gainsbury et al. (2014) classifies as 'internet gambling' should include a further distinction between mobile and other internet gamblers. When mobile gambling has been discussed in research, it has been often been included under the aegis of 'internet gambling' (Gainsbury et al., 2014; Gainsbury et al., 2012b; Kairouz, Paradis, & Nadeau, 2011; Phillips, Ogeil, & Blaszczynski, 2012; Williams, Wood, & Parke, 2012b; Yani-de-Soriano, Javed, & Yousafzai, 2012), without consideration given to potential differences in platform and user behaviour. Some studies have discussed wider differences but this has not been typical of the literature (Gainsbury, 2011; Gainsbury, Liu, Russell, & Teichert, 2016). The principal concern of this review is to consider whether the way in which gamblers interact with gambling on mobile phones is broadly synonymous with other internet gambling, or whether it has sufficiently distinctive features that might entail different considerations for individuals, practitioners and policy makers. There is already some evidence to suggest that mobile gambling is associated with an elevated risk of problem gambling (Gainsbury et al., 2016), based on self report data from gamblers across a range of different devices.

1.2.b Internet Gambling

Gambling using the internet has been viable since the mid 1990's (Griffiths, 1999). A literature exists concerning whether internet gambling entails a distinctive risk of problem gambling to users. Immediate explanations for this have focussed on factors such as increased availability and accessibility (Gainsbury et al., 2012b). Models of problem gambling commonly hypothesize that these form part of the initial step in the development of problem gambling, in which recreational gambling transitions towards mounting harm or the development of an addictive behaviour (Blaszczynski & Nower, 2002; Sharpe, 2002). From this, it follows that by making gambling more available, or shifting the landscape of the gambling environment towards games that are easier to access should entail an increase in the prevalence of problem gambling. Much of this research has relied on self-report data to test whether internet gamblers show a higher problem gambling prevalence (Shaffer, Peller, LaPlante, Nelson, & LaBrie, 2010), and behavioural evidence has provided mixed findings to support these predictions (LaPlante & Shaffer, 2007; Shaffer & Martin, 2011). A number of studies have concluded that internet gambling has a higher risk of problem gambling (Griffiths, Wardle, Orford, Sproston, & Erens, 2008; McBride & Derevensky, 2009; Petry, 2006; Wood & Williams, 2007; Wood & Williams, 2011), with survey data suggesting that in relation to other forms of gambling, problem gamblers are substantially overrepresented among the population of internet gamblers. It has also been argued that problem gamblers on the internet might experience different types of harm to in-person gamblers (Gainsbury, Russell, Hing, Wood, & Blaszczynski, 2013). These findings have three important caveats that have queried whether internet gambling poses a direct causal risk factor for problem gambling, but instead forms part of a constellation of risk factors found in high frequency gamblers (Gainsbury, 2015).

The first challenges the nature of the association between availability or accessibility and problem gambling. LaPlante and Shaffer (2007) studied data from a combination of gambling prevalence surveys, regional estimates of exposure, longitudinal research and self-exclusion rates to examine whether populations adapt to changing circumstances. These circumstances might include the implementation of liberalising gambling legislation or an increase in the number of opportunities to gamble. They found there was an increase in the prevalence of problem gambling in the short and medium term, but not the long term suggesting support for an adaptation hypothesis where the risk of problem gambling attenuates over time. More generally, they concluded that the relationship between these environmental factors and problem gambling was related to other social factors rather than a direct relationship. However, further research has suggested that the ability of gamblers to adapt to changing circumstance depends upon their involvement with gambling. LaPlante, Schumann, LaBrie, and Shaffer (2008) found that adaptation differed as a function of involvement, with more involved gamblers showing less adaptation to novel gambling (i.e. did not show a reduction in gambling) amongst a sample of gamblers in the period shortly after they subscribed to an online betting website.

There is also the question of what is meant by availability: LaPlante and Shaffer (2007) primarily considered availability on a population-wide level. Multiple studies have also looked at the link between geographic proximity of gambling establishments and problem gambling. These found that individuals living closer to casinos have a greater risk of problem gambling, and the density of casinos is positively associated with the risk of problem gambling (Slutske, Deutsch, Statham, & Martin, 2015; St-Pierre, Walker, Derevensky, & Gupta, 2014; Welte, Barnes, Tidwell, Hoffman, & Wieczorek, 2015). Similar findings have been identified with fixed odds betting terminals in bookmakers, which are the UK analogue of electronic gaming machines in other jurisdictions (Wardle, Keily, Astbury, & Reith, 2012b). Further studies have found that modelling for electronic gaming machine density removes most of the effect of availability on gambling and problem gambling (Slutske et al., 2015). In the wider addiction literature there is a clear behavioural rationale that incidental environmental cues are associated with the activation of drug based addictive behaviours (Crombag, Bossert, Koya, & Shaham, 2008; Hogarth, Dickinson, & Duka, 2009). For example, many individuals with a substance use disorder experience feelings of craving in locations where they previously purchased or used a drug. However, the relationship between availability and internet gambling is unclear. The means to gamble (i.e. an internet connected device) is ubiquitously available, more so than any other form of gambling, yet population-wide engagement in jurisdictions where there are few restrictions to internet gambling is relatively low (Wardle et al., 2011a). This is despite several forms of internet gambling being embedded in the public consciousness (e.g. online poker). The semi-permanence of gambling related cues, such as the presence of a bookmaker or casino might be more salient than an online advert or email that can be closed or deleted at will.

The second is that comparisons of problem gambling prevalence between internet and non-internet gamblers have generally failed to consider the importance of involvement, and analyses that adjust for this have tended not to demonstrate similar effects. It has been argued this might be due to the methodological approaches typically used in the internet gambling literature. Shaffer et al. (2010) found that prior internet gambling research, in a systematic search of the literature, was either primarily commentary, or the data collected was self-report/survey data. This led them to call for further research using behavioural data from internet gamblers, of which several analyses have been conducted before and since (e.g. Braverman, LaBrie, & Shaffer, 2011; Gray, LaPlante, & Shaffer, 2012; Xuan & Shaffer, 2009). Although problem gambling prevalence is higher amongst gamblers who play on the internet, it is argued that this might be because these gamblers are seeking as many means to gamble as possible, and so is a consequence of harmful play in a multitude of contexts and environments rather than being caused by internet gambling. Studies that have attempted to control for involvement have generally failed to find an increased risk of gambling problems amongst internet gamblers (Afifi, LaPlante, Taillieu, Dowd, &

Shaffer, 2014; LaPlante, Nelson, & Gray, 2014). In a similar vein, studies using survey data that compared internet, retail and mixed gamblers found that risks of problem gambling were present in mixed use but not online-only gamblers suggesting again the role of involvement in online gambling harm (Gainsbury, Russell, Blaszczynski, & Hing, 2015; Wardle et al., 2011a). Latent class analyses of gamblers and internet gamblers specifically (Lloyd et al., 2010; Wardle et al., 2014) have strongly suggested that there are several different subtypes of gambler on the basis of the games they play, and that increased risk measured by internet gambling studies in fact comprise a group of multimodal, multi-game gamblers. Along similar lines, studies comparing subtypes of problem gambling derived from latent class analysis found that intermediate and high severity gamblers did not differ their probability of engaging in internet gambling with no difference in internet sports betting, an activity that is pertinent to mobile gambling as the findings in Chapter 3 will examine.

The third consideration is that is unclear that the structural features of internet gambling are particularly different from forms of play in a bookmaker or casino, which might explain why the relationship between internet and problem gambling is mixed. Most contemporary gaming machines are computerised, and so are likely to have similar software to that running on an internet gambling site, attenuating the behavioural differences between the two types of gambling (Floyd, Whelan, & Meyers, 2006). Differences between the two are therefore likely to focus more on contextual factors or the medium on which it is delivered. On this, recent commentaries in the field of 'internet addiction' cast doubt on the latter, arguing that the addictiveness of the internet as a medium is conceptually unsound (Starcevic, 2013). However, it has been speculated that in some cases the use of the internet might moderate the relationship between the individual and a potentially addictive behaviour (Starcevic & Aboujaoude, 2016).

In summary, it is clear that internet gamblers are overrepresented amongst problem gamblers and there is a basis to suggest the same might occur with mobile gambling. What is unclear is why: is it because the means to do so are highly available, in an environment that is more likely than not to leave gamblers isolated? Alternatively, studies that have attempted to control for gamblers' levels of involvement with gambling have found some types of game (EGM and 'live action' or 'in-play' gambling) are associated with problems but not internet gambling as a whole (Afifi et al., 2014; Gray et al., 2012; Hing, Russell, Vitartas, & Lamont, 2015). This perspective implies problem gamblers diversify the range of games they play in, and internet gambling is one means among many; given the relatively low uptake of internet gambling, this suggests the risk associated with internet gambling is not distinctive from other forms of play. Regardless, while accessibility and involvement are important components in gambling and problem gambling, and the near constant presence of mobile phones suggests this is an important area to consider as mobile gambling grows, it is at present unlikely to provide a more satisfying answer than the present literature on internet gambling. It is therefore of greater utility to look at the next stage, the role of behaviour.

1.3 The British gambling market

Britain has one of the least regulated gambling markets in the world. Gambling is legal and most forms of gambling are legal to consume in the United Kingdom. With particular regards to internet gambling, it has one of the least restrictive regulatory regimes in the world. In comparison, online gambling or betting is illegal in several countries (the United States, Japan, India) and is heavily restricted to a certain number of operators in many European countries and worldwide. Additionally, a number of countries with highly developed gambling markets, such as Canada and Australia, have restrictions on certain gambling activities. In Canada, online betting is legally restricted to licensed regional operators who are only allowed to offer parlay bets to gamblers, and cannot offer wagers on the outcome of a single sports event. Parlay bets, known as accumulator bets in the UK, involve wagering on the cumulative probability of a series of sporting outcomes occurring (i.e. betting on five teams each winning the match they play in). Typically the amount wagered is small on very small odds of winning. In Australia, there are restrictions on in-play betting, a form of play where bettors can wager on any number of outcomes within an event. For example within a football match in the UK, bookmakers will often offer outcomes on, say, the next goal, throw-in, booking and so on and so forth. Although in both instances the public, who instead gamble with unlicensed operators, largely ignores these restrictions; these restrictions do not apply in the UK.

It has been estimated that between seventy and eighty per cent of the British population will have gambled in the previous year (Wardle et al., 2011b; Wardle et al., 2014), and around forty to fifty per cent in previous four weeks (The Gambling Commission, 2016a). The overall trend is that engagement with gambling is gradually falling, both in annual and monthly estimates of prevalence. For the annual data this might be a artefact of the change from these questions being probed in a health versus a gambling survey (Williams & Volberg, 2010). This appears to be in large due to a fall in engagement with the National Lottery, the most popular form of play. This is in part because The National Lottery increased stake size in 2014. The granular panel data collected by the Gambling Commission suggests that the National Lottery dominates gambling activity in the UK. Although between two-fifths and one half of the population are estimated to have gambled in any given month, the prevalence of any non-lottery game rarely exceeds one in ten. The only exception to this is scratchcards, which are operated and promoted by the National Lottery, which frequently sit either side of ten per cent prevalence.

The British gambling regulator, as part of their continuing work in monitoring gambling engagement, has commissioned two rolling surveys ofgambling engagement. (The Gambling Commission, 2016a). The first measures overall gambling participation (conducted via telephone) and the second probes in-depth the behaviours and engagement of online gamblers (conducted online). These are conducted by Populus, a well known polling company who weight the data to the British population. Rolling averages from the former suggest that around 15 to 16 per cent of the British population has gambled online in the previous four weeks. The data from the latter suggests around a third of online gamblers have used a mobile device to gamble over that time period.

Thus extrapolating from this, caveats around representativeness and margins of error aside, it is likely the case that around five or six per cent of the population will have gambled using a smartphone or tablet in the past four weeks. A closer examination of this data suggests that there are considerable differences between younger and older adults: among over-55's just under 15% of online play is conducted via mobile or tablet, with a split of between 3 and 4 to 1 in favour of tablet over mobile. This reflects demographic differences in rates of smartphone ownership. Over 65's particularly show low rates of engagement, with overall rates of online gambling much lower (< 10%) than other age groups. Among the younger age groups, not only are rates of online gambling much higher (typically between 14 and 22%), but rates of mobile gambling are much as well: 44% among 18-24 year olds, 50% among 25-34's, 40% among 35-44's and 28% among 45-54's. In these groups smartphone gambling is also more common than gambling via a tablet; there is more than a 2:1 ratio among under 35's, 28% versus 20% for 35-44 year olds and around parity for 45-54's. While there are potentially issues concerning generalizability, particularly for the online gambling survey, cases are weighted in both surveys against another random probability sample of the general population (The National Readership Survey) on a range of demographic variables. The general indication from these data, despite a number of caveats, is that mobile gambling has rapidly emerged as a common form of play in the British gambling market. This is likely to continue as smartphone ownership continues to increase.

The regulatory context in which mobile gambling has been introduced in the UK is one that makes it ideal to study mobile gambling. If any problems: legislative, regulatory, public health or psychological, emerge from mobile gambling, the uniquely unrestricted environment in which mobile gambling operates in the UK is likely to be the first place these are identified. Moreover, the extant data suggest there has been considerable growth in mobile gambling, and that a substantial portion of the population, in the context of overall engagement with non-lottery gambling, are engaging with it. Additionally mobile gambling is very well advertised (see section 1.4d), which means that public awareness of mobile gambling is also very high.

1.4 Is mobile gambling distinctive from other online gambling?

This section outlines some of the key issues that mobile gambling might make itself distinguishable from other internet and online gambling, or where there is clear evidence of similarities. This section primarily focuses on how individuals use their phones, and the likely impact this will have based on a behavioural analysis of gambling. The section goes onto to consider differences in the context of use, how mobile gambling is advertised and the type of games played on phones, the hardware differences between mobile and other internet gambling, and the role of social gaming/gambling that is particularly prevalent on mobile. Each of these incrementally suggests differences between mobile and internet gambling that are worth attention and in many cases further research. The thesis itself primarily restricts itself to the first three of these issues.

1.4.a App Use Behaviours

A literature investigating smartphone app use has suggested that mobile phone users engage with their device in a manner that may be conductive to the conditioning of habitual or problematic behaviours. Mobile phone users tend to engage with apps in a similar manner, using a small number of apps on a very frequent basis. Most users download apps on a frequent basis although this varies by age (Ofcom, 2014), use a moderate range of these on a quarterly basis (The Nielsen Company, 2014b) and much more restricted number of these on a regular basis (The Nielsen Company, 2014b; Walker, 2012). The way in which users engage with these apps once downloaded appears to be similar across users. Studies have demonstrated that users engage with mobile phone apps in excess of one hour per day (Bohmer, Hecht, Schoning, Kruger, & Bauer, 2011) and increasing (The Nielsen Company, 2014a), but only use these apps for approximately one to two minutes per session (Bohmer et al., 2011; Tossell, Kortum, Rahmati, Shepard, & Zhong, 2012). Furthermore, in using applications over these time, the behaviour appears to be habitual or 'checking' in nature (Oulasvirta, Rattenbury, Ma, & Raita, 2012). Much has been made of this finding in regard to the potential for harmful mobile phone related behaviours (Lee, Chang, Lin, & Cheng, 2014; van Deursen, Bolle, Hegner, & Kommers, 2015). These checking behaviours generally focussed on a single application, but this was associated with engagement with other apps on their phone, such that users engaged with sequences of apps in a regular fashion. Combined, this suggests that users engage with a small set of apps on a frequent basis, on which users will regularly play for a small period of time many times a day. What this means is that while in many cases the software used on mobile versus other online gambling is largely similar (see section

1.4.e), the behaviours people engage in when interacting with gambling are quite different. As the next section demonstrates, this is likely to have a dramatic effect on learning processes.

1.4.b Behavioural mechanisms

Gambling is a behaviour that operates on a 'random ratio' (RR) schedule of reinforcement; this means the desired reinforcer (e.g. winning, money, physiological arousal) occurs on average after a pre-specified number of gambles, but that the number of intervening trials between wins may vary, such as in the fixed-odds scenarios that comprise many games of chance. The random ratio is similar to the variable ratio schedule of reinforcement. This schedule of reinforcement has long been demonstrated to rapidly produce a frequent level of gambling that is difficult to suppress (Dickerson, 1984; Skinner, 1972), and has been found to take longer to extinguish in high frequency gamblers (Horsley, Osborne, Norman, & Wells, 2012), showing deficits in partial reinforcement that demonstrate themselves in greater perseverative gambling not unlike loss-chasing. There is already some evidence that longer delays between gambles contributes to continued play, in the form of lottery games (Griffiths & Auer, 2013) – gambling prevalence research has consistently found that lottery games are amongst the most popular with the general public (Sproston, Erens, & Orford, 2000; Wardle et al., 2011b), and often have large latencies between gambles.

This schedule of reinforcement appears to be particularly relevant for certain types of game, such as slot machines and electronic gaming machines and fixed odds betting terminals. In addition, research in betting has identified the importance of timing in the form of the fixed interval (FI) schedule. Dickerson (1979) noted that a 'late betting' effect was observed in high frequency gamblers. This was interpreted in terms of physiological arousal, which is a core element of cognitive-behavioural approaches to problem gambling (Coventry & Brown, 1993; Sharpe, 2002). In addition to being present on a FI basis, physiological arousal is also present in a more frequent RR schedule, partially independent of the outcome of a near miss (Reid, 1986) or losses disguised as wins (Dixon, Harrigan, Sandhu, Collins, & Fugelsang, 2010). These both produce high levels of arousal that appear to stimulate continued gambling. These have been typically studied in simulated slot machine games as the sequential stopping of slot reels produces strong feelings of anticipation. Economic analyses of online betting data in Italy, although not considering a behavioural explanation, found a similar effect to late betting with data from over a million bets; performance was worse when bets were made closer to the beginning of an event (Innocenti, Nannicini, & Ricciuti, 2014). Theories of problem gambling such as the Pathways Model (Blaszczynski & Nower, 2002) claim that extensive exposure to these processes and the development of maladaptive conditioned behaviours and cognitive biases underpin the transition between recreational and problem gambling.

One of the central features of mobile app use in general is the role of intermittent periods of engagement with an app. Mobile phone users interact with their phone on a frequent, habitual and intermittent basis (Oulasvirta et al., 2012). Such a schedule of reinforcement in the context of gambling has the potential for the development of harmful behaviours. In the associative learning literature, there is a body of research on the effects of inter trial interval, or the gap between two reinforcements, on learned behaviours (Barela, 1999; Bouton, Woods, & Todd, 2014; Gallistel & Gibbon, 2000; Moody, Sunsay, & Bouton, 2006; Sunsay & Bouton, 2008), which suggests that distinct psychological processes might contribute to mobile gambling. This research has amply demonstrated that longer intermissions between reinforcing events (i.e. gambles, wins in the context of gambling) produces faster acquisition of conditioned behaviours. There is already evidence within the gambling literature to suggest that this prediction is already partially realised; Blaszczynski, Cowley, Anthony, and Hinsley (2015) found that craving to gamble increased in line with inter-session interval on a simulated slot machine game. While they provided an explanation based on theories of behavioural completion, this finding can be adequately described with an associative learning based account. This stands in contrast with a wider literature on breaks in play, although Blaszczynski et al. (2015) note these include additional interventions that require gamblers to think about their play and it may be the content of these messages that drive reappraisal of gambling behaviour. Furthermore, in studying the role of inter trial intervals in gambling behaviour, the experiment that will be reported in Chapter 6 found that perseverative gambling during extinction in a simulated slot machine game was affected by the amount of inter trial interval participants were exposed to; longer inter trial intervals were associated with gambling in the face of continued losses, particular at lower rates of reinforcement. The implications of this are clear. Given that associative processes are thought to be instrumental in the development of problem gambling, this suggests that the acquisition of harmful gambling behaviours will be accelerated in mobile gamblers relative to other gamblers. This strongly suggests there is reason to identify mobile gambling as separate from other interactive gambling technologies.

This also has important qualifications for many responsible gambling interventions. Many of these approaches or interventions aim to reduce problematic gambling behaviour by breaking up individuals' play alongside messages about the risks of gambling. It might be the case that further consideration ought to be taken in tailoring responsible gambling strategies, particularly with a technology where typical user behaviour and often (particularly in the case of video games) the developer's intention is to force latencies between uses to extend play. It may be the case that current responsible gambling strategies may be less efficacious with mobile gambling technologies.

The role of 'snacking' like behaviours in mobile gambling is that a 'snack' like or intermittent schedule of reinforcement might lead to users acquiring gambling behaviours (including harmful behaviours if contemporary models of problem gambling are supported) more rapidly than other forms of gambling. It is presently disputed whether this also affects the suppression or extinction of learned behaviours (Bouton et al., 2014; Gallistel & Gibbon, 2000) in the same manner, although there is increasing evidence to support this (Bouton et al., 2014; Moody et al., 2006).

In addition to the behavioural processes maintaining and reinforcing gambling behaviour there are mechanisms governing the distribution of responses to different forms of gambling play. One example of this is the matching law (Herrnstein, 1974) and its generalisation (Baum, 1974), which attempts to describe how organisms distribute responding to multiple concurrent ratio or interval schedules. There is a literature on response allocation in concurrent slot machines, but findings in this area have been mixed; a number of studies (Coates & Blaszczynski, 2014; Daly et al., 2014; Dixon, Fugelsang, MacLaren, & Harrigan, 2013a; Dixon, MacLin, & Daugherty, 2006; Dymond, McCann, Griffiths, Cox, & Crocker, 2012; Zlomke & Dixon, 2006) found evidence consistent with matching, but there is also evidence gamblers undermatch, showing greater (or in some cases, total) equivalence between machines that diverge either in rate of return to player or rate of reinforcement on a ratio schedule (Coates & Blaszczynski, 2013; Daly et al., 2014; Lucas & Singh, 2012; Weatherly, Thompson, Hodny, Meier, & Dixon, 2009). In addition, matching is highly susceptible to being overridden by contextual cues (Nastally, Dixon, & Jackson, 2010; Zlomke & Dixon, 2006) although this appears to weaken with extended exposure to the contingencies of a machine (Hoon & Dymond, 2013). Furthermore there are some situations, such as on multiple line slot machines where the rate of reinforcement can be (and is) controlled by the player while the rate of return remains the same (MacLaren, 2015).

There have also been analyses of pools betting that suggest in betting on the outcome of college basketball games people probability match, making predictions based on past frequencies and overestimating the probability of upsets (McCrea & Hirt, 2009). This pattern of behaviour, specifically a greater resistance towards maximising when asked to predict a guaranteed outcome between two choices with different rates of reinforcement, has been found to be more common among problem gamblers (Gaissmaier, Wilke, Scheibehenne, McCanney, & Barrett, 2016). Although frequently attributed to the matching law, this is actually a violation of this principle; when presented with a choice where an outcome is guaranteed, the matching law predicts the selection of the choice with the highest rate of reinforcement (Herrnstein & Loveland, 1975; Shanks, Tunney, & McCarthy, 2002). While evidence on this is sparse, this may be common to a number of different types of betting behaviour, not just pools but accumulator betting and standard betting. Adherence and divergence from the matching law may be one of the factors that separates betting from games of chance.

As discussed earlier, a consensus has emerged in the internet gambling literature that broadly suggests the importance of involvement rather than any specific effect of the platform, the type of games played online or availability/accessibility. The behavioural processes outlined in this section cannot be readily explained by involvement as these affect a different stage of the transition from recreational to problematic gambling as predicted by contemporary models (Blaszczynski & Nower, 2002; Sharpe, 2002). The remainder of this review will outline the context in which mobile gambling is played, focusing on the sensing capabilities of smartphones versus other remote gambling hardware, app use behaviour in general, where mobile gambling is played, the games that are played and the restrictions that are placed on accessing mobile gambling.

1.4.c Context of Use

Internet gambling is much more constrained in the context in which a device can be used than mobile gambling. This is illustrated when considering the advertisements that are used to promote gambling apps, although rigorous research on the content of gambling advertising in the UK is relatively limited (Binde, 2014). Many of these are presented in social environments, such as at pubs or as an adjunct to sporting events, during sports programmes, or at a sporting event (Parke, Harris, Parke, Rigbye, & Blaszczynski, 2014). Unlike other gambling technologies, mobile gambling allows users to gamble at these locations. Other literature that has considered mobile gambling has suggested that it may be engaged with as an adjunct to everyday activities, such as travelling or watching television. Griffiths (2007) notes that mobile gambling occurs in different contexts to online gambling, and in contexts that are more amenable to gambling, which suggests that mobile gambling might be a more enjoyable experience. Indicators from gambling operators and consultants (Ladbrokes, 2015; Pietkanien, 2014) suggest that the operators are finding that whilst shop and mobile betting do not appear to overlap at present, this does not necessarily appear to be the case between desktop and mobile gambling. An obvious explanation for this is that the context in which mobile gambling can be engaged is more similar to in-person gambling, and is less constrained by having to be on a computer and so users are migrating from desktop to smartphones. In contrast, the research on online gambling conducted as the first and second generations of smartphones came on the market indicated that the vast majority of users gambled from home (97%), with very little engagement in other locations (McBride & Derevensky, 2009). The other prevailing responses, all engaged in by less than 15% of users, primarily focus on using PC's in other locations (e.g. at work). It should be noted that this did include mobile phones, which 2.3% of the sample had used to gamble. Recent data from The Gambling Commission (2016a) suggests that while the most common place to gamble on the internet is at home (97% of gamblers played at home), younger gamblers (<35's) are increasingly gambling while commuting, at sports events or in social environments (e.g. pubs). Context of use is important when contrasting mobile and retail gambling as one of the potentially attractive features of both mobile and online gambling is the private nature of online/mobile gambling, and that retail gambling locations may have a tendency to discourage some potential gamblers because of the negative societal connotations associated with them (Gainsbury et al., 2012b).

Another reason why mobile and retail gambling operations may not overlap is the demographic profile of mobile gamblers. Comments from gambling industry executives to the Culture, Media and Sport Select Committee (2012) in the UK indicated mobile gambling operators believe that mobile gamblers are younger and may not previously have interacted with gambling before. Similarly, Gainsbury, Russell, and Blaszczynski (2012a) found that university students were more likely to gamble using a smartphone. This has until recently been borne out in the demographic profiles of smartphone owners (Ofcom, 2015) but this is now changing as older adults are increasingly purchasing smartphones. The attraction of mobile gambling to this audience is also relevant to its relationship with problem gambling, as problem gambling is more common in younger gamblers despite a lower prevalence of gambling (Wardle et al., 2011b).

1.4.d Gambling Advertising and Types of Play

UK operators frequently advertise mobile apps alongside in-play betting, a form of betting where wagers can be made on various outcomes during a sporting events, and typically where the odds rapidly change over relatively short periods of time. It is important to note that marketing of mobile gambling frequently presents in-play gambling as a normative mobile gambling game. The effect of gambling advertising on attitudes and behaviour has similarly been well recognized (Binde, 2014; Derevensky, Sklar, Gupta, & Messerlian, 2009; Parke et al., 2014). In a similar manner to how social norms approaches attempt to recalibrate perceptions about overestimated unhealthy behaviours, the advertising for mobile gambling frequently emphasises an association with in-play gambling, an activity that is known to have an increased risk of harm. The advertising for mobile gambling frequently emphasises an association with in-play (or 'live action') betting, an activity that is known to have an increased risk of harm.

Mobile gambling has traditionally had a heavier emphasis on sports betting than other forms of gambling (Griffiths, 2007). However, there is evidence that the predominance of betting within the mobile market is changing, with the annual reports of major UK gambling operators reporting increased investment in casino style games as mobile technologies allow an aesthetic experience similar to other internet gambling (Ladbrokes, 2015;

William Hill, 2015). Betting remains the main source of revenue for operators and this is continuing to increase; the 2014 World Cup was heralded as a ‘mobile tournament’ operators in the UK as gamblers increasingly used their mobile phones to wager (Ladbrokes, 2015), likely helped in part by the evening kick-off of many games.

There is limited data on the types of games played on mobile. Much of the data concerns ‘remote’ gambling, a composite term for all internet gambling. However, from comparing what evidence is available, there are some broad trends that can be gleaned. A report by H2 Capital (2013) indicates that the majority of online gambling (defined by gross win) comprises online sports betting, making up just over 50% of the market. However, a report commissioned by HM Revenues & Customs (Frontier Economics, 2014), suggests that remote gaming (i.e. casino games) rather than betting makes up the majority of revenue in the UK market. Similarly, data from a report on online gambling in the European internal market (The European Commission, 2012) shows that while betting enjoys a plurality of market share (32%) in the largest legal market for online gambling, it is closely followed by casino gaming (22%) and poker (21%). For mobile gambling, figures from the major UK operators where show a very strong bias toward betting. In the annual reports and financial returns of these companies, the proportion of revenues obtained from sports and other betting exceed 60% of total mobile profit. However, it should be noted that for the major operators for which data is available (Betfair, 2015; Ladbrokes, 2015; Paddy Power, 2015; William Hill, 2015), all bar one of these are major retail bookmakers in the UK (the other is a betting market). However, these also report some of their fastest increases in revenue for their mobile casino operations. While betting appears to be the predominant form of mobile gambling, there appears to be a shift toward casino style games.

Research on in-play betting has identified this form of gambling as being a particular risk factor for problem gambling behaviours (Brosowski, Meyer, & Hayer, 2012). LaPlante et al. (2014) analysed data from European internet gamblers, finding that use of in-play betting was associated with problematic and harmful behaviour when controlling for involvement. However, this also highlights that in-play betting is available on internet gambling websites as well. The causal mechanism behind this association with problem gambling is unknown, and it has been speculated that either the potentially continuous schedule of gambling or the shorter delay between wager, outcome and reward might drive this risk. It is also unclear whether in-play, like mobile or online, has a causal link with problem gambling, or if it is particularly attractive to individuals who are problem gamblers or are prone to developing addictive behaviours. Behaviourally in-play offers a large array of opportunities to gamble within a single sporting event, alongside a highly variable rate of reinforcement. Given in-play bettors showed a lower net loss than other forms of betting in this study, this might be due to in-play having a higher win rate, or the success of lower odds bets. The former might indicate that in-play gambling encourages players, particularly gamblers transitioning from other forms of gambling, to 'accelerate' their responding (i.e. by gambling more) in line with the law of effect (Herrnstein, 1970). Alternatively, models of addiction and problem gambling in reinforcement learning highlight how statistically unexpected wins are likely to create a 'state-splitting' effect that would lead to gambling that is very difficult to extinguish (Redish, Jensen, Johnson, & Kurth-Nelson, 2007). Although there is an association between this form of play, prevalent on mobile phones, and problem gambling when controlling for involvement, in-depth research on in-play betting is sparse.

1.4.e Sensing

Smartphones differ markedly from many computers in the range of sensors that are built into each device. The majority of online gambling is conducted via keyboard and mouse/trackpad. Some websites might include functionality for webcams to increase the social experience (e.g. for internet poker), but the range of interactions tends to be rather limited. A large array of sensors were built into smartphones from the earliest generations of smartphone (Lane et al., 2010), that can potentially be used to deliver a unique gambling experience over and above other online gambling. Until the more recent generations of smartphone, the graphical and processing limitations of smart and mobile phones meant that the rich gambling environments necessary for some types of gaming were not possible (Griffiths, 2007). The range of sensors included in most contemporary smartphones, alongside more sophisticated hardware, potentially enables a personalized gambling experience that is more enjoyable than traditionally online offerings. However, an important caveat to consider is whether this potential corresponds to substantially different gambling experiences. The evidence at present suggests not. A weakness of current offerings has been identified by a report conducted by Deloitte (Pietkanien, 2014), which found that some of the weaknesses in the present mobile applications focussed on user friendliness and user experience.

Their analysis of mobile products indicated a gap for further innovation, including examples of usability and sensing that might maximise the user experience. This strongly suggests that although the mobile gambling experience can differ from online gambling, this currently remains a potential rather than an actual difference. However, as the report does identify this as a future market gap, it is possible future growth in the mobile gambling market may be driven by applications that take advantage of these, and drive further differences between mobile and internet gambling.

1.4.f Legislative restrictions

Unlike internet gambling, it is easier to restrict mobile gambling, particularly via app use. Because the majority of apps are downloaded via two app stores, and these can restrict content based on location, it is more difficult to circumvent restrictions on gambling apps than a PC or laptop. As an example of legal restrictions, gambling apps are restricted in America as online gambling is severely restricted following the Unlawful Internet Gambling Enforcement Act 2006, and so most are unavailable on the US version of the iOS App Store (social gambling games are available). Furthermore, the availability of gambling apps on Android phones is more limited than iOS as these apps are banned on the Google Play Store. However, gambling apps can still be installed onto devices, and some major UK operators have Android offerings. However, given the potential role of availability, this restriction may be of considerable importance. Google Play does allow free-to-play casino gambling apps on their store, in which further credits or other items can be bought with real money in-game, but do not award real money. The Apple App

Store allows real money gambling (although the app must be free to purchase) for betting, casino and other gambling games in a number of jurisdictions, including the UK, Ireland and Australia. Other apps differ by jurisdiction. For instance major betting operators have a different app available in Australia where in-play betting is currently restricted (William Hill, 2015).

1.4.g Social gambling and simulated gambling (or pseudo-gambling) in mobile video gaming

Many mobile video games (i.e. not gambling games) include gambling elements within them. Gambling mechanisms are frequently used as a means of income in the free-to-play model of games. With many of these, players are given the opportunity, either after logging in for a number of consecutive days or spending an amount of a secondary currency earned through extended play or bought with money, to play a gambling game. These are frequently advertised as a chance to win a rare in game item or similar collectible. These almost exclusively operate as games of chance, with mechanisms similar to a scratchcard or slot machine operating on a fixed odds basis. A multitude of concerns can be found with this type of model. The Gambling Commission notes the presence of three potential risks: problem gambling like risks (i.e. excessive, harmful play), transitional risks (encouraging real gambling) and consumer protection risks. Research looking at the transitional risks of these games does suggest that some users transition to real money gambling (Kim, Wohl, Salmon, Gupta, & Derevensky, 2014), including among adolescent populations who form a particular risk group for problem gambling (King, Delfabbro, Kaptsis, & Zwaans, 2014) and simulated gambling within this appears to predict problem gambling severity. More widely, for many massively multiplayer or mobile gambles, the former of which has been the subject of concern in the context of Internet Gaming Disorder (Petry & O'Brien, 2013), many of the features of play operate on random-ratio schedules of reinforcement that are analogous to those found in gambling. Although a behavioural account of Internet Gaming Disorder is still forthcoming, one would presume that there is a similar behavioural basis to gambling, given that much of the basis for considering disordered internet use is derived from gambling as a behavioural addiction. Although many of these issues will be discussed in further detail in the General Discussion in light of the findings of the findings of this thesis, it is worth stating in advance that from a behavioural perspective these are likely to have more similarities than differences with gambling, and mobile gambling in particular.

1.5 Problem Gambling

While it is interest in of itself to understand how mobile gambling appears to be distinctive from other forms of gambling, this also has impact to wider society because gambling itself is an addictive behaviour, with significant, additional public health implications that are often understated. Like alcohol, where it has been observed that the majority of consumption is clustered in around a quarter of the population (Sheron & Gilmore, 2016), the majority of gambling expenditure (and thus gross gaming yield for the industry) is derived from a relatively small part of the population, more so than alcohol as a smaller section of the population gamble frequently (Orford, Wardle, & Griffiths, 2013). While it is frequently argued that gambling is a safe, recreational activity for the overwhelming proportion of the population given rates of problem gambling beneath one per cent (Wardle et al., 2011b; Wardle et al., 2014), it is unclear whether a comparison against any form of past year gambling participation is the appropriate reference point from which to draw conclusions about the risks of gambling. A significant proportion of the 50-78% of the population that gamble only do so very infrequently (i.e. betting on the Grand National) or limit their activities to the National Lottery, a game that is thought to have very minor risks of harm in isolation (Griffiths & Auer, 2013).

The potential distinctiveness of mobile gambling might be because it is more addictive, or that is more attractive to people with an underlying predisposition to addictive behaviours or already have an addiction to gambling. The literature explored in section 1.2b already suggests that this is thought to be the case for online gambling. This section will provide a broad outline of problem and addictive gambling that will be explored in further depth across the thesis, particularly in the forthcoming four empirical chapters. While there is some common ground between different perspectives on what is meant by the term 'problem gambling', substantial divisions emerge on central theoretical assumptions, and the need for further analyses of gambling data is warranted. The analyses reported in this thesis are designed to work towards the identification of markers of problem gambling that can be studied in the context of mobile gambling.

The DSM-5 (American Psychiatric Association, 2013) included Gambling Disorder in the category of 'Addictions and Related Disorders' in its latest revision. Disordered Gambling is the sole behavioural addiction included in the DSM at present. Previously classified as an impulse control disorder, Gambling Disorder is measured using nine diagnostic criteria. These probe a range of problematic gambling behaviours, such as loss-chasing, preoccupation, using gambling to deal with negative emotions, lack of success at cutting down or controlling gambling, and risking important life opportunities because of one's gambling behaviour. The standard model of Pathological Gambling, implicitly endorsed within the DSM and synonymous with a disease model, is that pathological gambling is a categorical typified by a loss of control of the gambler's interaction with gambling (Rosecrance, 1985a, 1985b).

The alternative approach to conceptualising gambling focuses on the harm problem gambling causes to the gambler and those around him. This approach broadly argues that a singular focus on indicators of addiction inadequately captures the consequences of gambling. While addictive gambling is likely to be part of the harm caused by gambling, it is far from the only measurement of interest. Proponents of a harm based approach to problem gambling generally conceptualise it as a latent continuum, with pathological or addictive gambling at the end point of a distribution of some sort. In terms of assessing problem gambling, these perspectives tend to argue that cut-off's on these assessments represent heuristically useful, but ultimately arbitrary cutting points, rather than a genuine distinction between people requiring intervention and not.

The key question, and the one the following chapter is devoted towards answering, is which of these constructs assessments of problem and pathological gambling appear to be measuring. Although the DSM is presumed to measure a categorical construct, psychometric modelling of Pathological Gambling criteria data suggest this is more complex (Strong & Kahler, 2007). In addition, the other predominant measurement of problem gambling, the Problem Gambling Severity Index (Ferris & Wynne, 2001), is explicitly designed to measure a continuum of harm. Psychometric analyses have suggested that a dimensional model fits this questionnaire well, but analyses have also suggested that the latent structure measured by the PGSI is more complex than it appears at face value (Kincaid et al., 2013).

The final sections of this introduction more formally outlines theoretical research on models of problem gambling, before explaining the structure of this thesis, and the empirical work that is covered herein.

1.5.a Models of problem gambling

There are two predominant models of problem gambling in the literature (Hodgins, Stea, & Grant, 2011). These have a number of commonalities but one of the models claims there are multiple distinct causes in the transition from recreational to problem gambling. In the large part, both of these have very similar theoretical antecedents as well. In terms of this thesis, it is important to be aware that both consider the importance of the gambling environment as an initial step of one's exposure to gambling, before considering the role of conditioning and behaviour in gambling.

Both models attempt to capture the distinction made by Jacobs (1986) between positive and negative reinforcement triggered gambling behaviour.

The former is driven by sensation-seeking and risk-taking personality traits, typically observed in a preference towards games with high levels of excitement such as betting. The latter however is driven by the instrumental use of gambling to control negative states and emotions, most commonly using highly repetitive forms of play such as slot or electronic gaming machines. Both also place considerable importance on the role of classical and operant conditioning. The latter emerges from Skinner's (1953) analysis of slot machines in terms of their schedule of reinforcement. The importance of classical conditioning has been highlighted in a number of instances, including in the role of near misses (Reid, 1986), the role of arousal in the development of addictive gambling behaviour (Brown, 1987) and in gambling cues and stimuli more generally (Sharpe & Tarrier, 1992).

The cognitive behavioural model of problem gambling (Sharpe, 2002) is a (primarily) unitary model of problem gambling that covers the entire range of psychological factors in the development of problem gambling. Starting from predisposing vulnerabilities, including attitudes, impulsivity and biological vulnerabilities in terms of dysfunction in neurotransmitter systems which may express themselves in forms such as depression or OCD, it is argued that some individuals are likely to have a predisposition toward gambling and some gambling problematically. Next, exposure to gambling experiences in general and specific types of experience as part of one's sociodemographic background or personal interests in particular will moderate the likelihood of engagement with gambling. Alongside this early experiences of gambling are thought to have a stronger impact on one's future interactions with gambling (Redish et al., 2007), as well as the physiological (i.e. arousal), cognitive (illusory control, gambler's fallacy) and behavioural (exposure to a schedule of reinforcement) aspects of gambling. In addition to the psychophysiological processes engaged by gambling, the model argues that different individual differences will drive betting and slot machine or electronic gaming interactions; sensation-seeking for the former and disordered mood for the latter. This mirrors the distinction made by Jacobs (1986) between positive and negative reinforcement drivers of gambling behaviour. Finally the model predicts, once gambling is instantiated and reinforced, there is a positive feedback loop in which states and gambling cues trigger gambling related arousal, these cue gambling related associations and urges to gamble, which are opposed by coping skills mediated by individual differences, state effects and other psychological processes (e.g. conditioning). Through continued engagement in this cycle, alongside mounting gambling related consequences or harms, indicators of problem and pathological gambling are likely to emerge.

The Pathways Model of problem gambling (Blaszczynski & Nower, 2002) argues that a unitary model of problem gambling misses that there are a number of distinct subtypes of problem or pathological gambler. The model argues there are three subtypes of problem gambler, defined by the presence or absence of premorbid mood disorder or impulsive personality traits with a common set of behavioural and cognitive processes. The first pathway comprises 'behaviourally conditioned' problem gamblers. These gamblers appear to transition from recreational to problem gambling purely on account of a series of behavioural (i.e. classical and operant conditioning) and cognitive (decision-making biases such as the illusion of control or the gambler's fallacy, attentional biases etc.) processes, which are shared across all three pathways. It is further argued these gamblers show the lowest levels of problem gambling severity, transitioning in and out of control over their gambling behaviour and are explicitly assumed to form a continuum with recreational gamblers. The second pathway of 'emotionally vulnerable' problem gamblers emerge from the presence of a series of risk-taking constructs that appear to be related to disordered mood, if not depression or anxiety directly. This includes boredom proneness, which appears to be related to related to disordered mood but not impulsivity, whereas boredom susceptibility is a facet of sensation seeking (Mercer-Lynn, Flora, Fahlman, & Eastwood, 2013). Finally there is a subtype of 'antisocial impulsivist' problem gamblers. These are thought to show the highest level of problem severity, and for whom the most severe gambling indicators (e.g. committing crimes to fund gambling) are endorsed, and the personality traits that appear to drive problem gambling represent a polymorphous risk of addictive behaviour in general.

In terms of the categorical/dimensional debate outlined in section 1.5 and central to Chapter 2, neither model strongly predicts either way. Sharpe's model is explicitly agnostic about whether problem gamblers are quantitative or qualitative distinct from recreational play. However, it suggests the incremental importance of a range of causal factors, which is typically standard of a dimensional model of psychopathology. The Pathways Model explicitly predicts the presence of a number of latent classes in problem gambling data, but also suggests that some gamblers are on a continuum with non-problem gambling. This implies a mixed latent structure.

It is also worth bearing in mind that a focus on problem gambling will miss some of the impact mobile gambling has on individual behaviour and on wider society. Whilst the latter is outside of the scope of this thesis, it should be noted in the case of the Pathways Model that behaviourally conditioned problem gambling is thought to be on a continuum with recreational play. What this means is that if mobile gambling has an effect on associative processes, any changes in problem gambling is likely due to a shift in the distribution of problem gambling indicators and reflective of a much wider scale change.

1.6 Structure of the thesis

The empirical research conducted in the course of writing this thesis broadly divides into different types of research activity. The first of these primarily consists of psychometric modelling of publically available, nationally representative survey data to further understand problem gambling and determine a clearer frame of reference for judging whether mobile gambling is likely to attract or create problem gamblers. This work is then taken forward to the more standard experimental psychology activities in the later chapters of the thesis, where indicators of different aspects of problem gambling are behaviourally modelled in the laboratory before being translated onto participants' mobile phones.

The psychometric work consists broadly of four different research activities. It begins by working towards a tractable definition of problem gambling, given the conceptual confusion in the literature (identified in section

1.5). Chapter 2 reports the findings of a taxometric analysis of problem gambling assessment data from the British Gambling Prevalence Survey 2010. Taxometric analysis tests whether a latent construct is best fit by a dimensional or latent class model; in the case of problem gambling, this means whether problem gambling is categorical or continuous. Further research in Chapters 3 and 4 uses a wider range of nationally representative data, building on the findings in Chapter 2 by using latent class modelling to understand different subtypes of gambler, their demographic backgrounds and the different behaviours they engage in. Different latent class models were estimated across different assessments and timeframes to examine the stability of these models. These subtypes were then used to look engagement in a range of different gambling behaviours (including online gambling, sports and online sports betting of particular relevant to mobile play), and differences in demographic profiles between the different groups. The last of the psychometric work, reported in Chapter 5, consists of additional taxometric modelling to systematically explore the ability of taxometric approaches to identify latent structure in dichotomous variables. This has relevance to the work in Chapters 2 and 3 given the place of gambling and addictions in the wider debate concerning how mental disorders should be labelled and perceived, but also the disputed literature specifically in the field of addiction and how an understanding of the methodological caveats associated with binary variables can help address some of the debates present in the current literature. In addition to that, the data used for the psychometric modelling Chapters 2, 3 and 4 is used to replicate the findings of Chapter 2 using an approach more congruent with the DSM than the continuous variables reported in that chapter (and used in Chapter 4), and extending it to the South Oaks Gambling Screen, a commonly used assessment in experimental research and analysed in Chapter 3. The output of the analysis also identifies patterns of endorsement for different indicators of problem and pathological gambling.

The research on online gambling, as has been shown in this chapter has shown that it is attractive to problem gamblers. For mobile the issues considered in this introduction suggest a separate case ought to be made. The laboratory and field work in the latter half of the thesis takes indicators derived from the psychometric work, and models relevant behaviours (timing, loss-chasing) in the laboratory. This is designed to test whether the behavioural profile distinctive of mobile gambling has a particular association with problematic gambling behaviours. The sixth chapter outlines a laboratory experiment in which participants were exposed to different slot machines. These machines differed in the latency between gambles and payoff rate. After a certain period of engagement participants were exposed to a sequence of continued losses and their behaviour in extinction was measured, alongside individual difference measures of impulsivity, depression and illusory control. The seventh chapter then tests the findings of these studies in a field environment, with the design of a mobile gambling application that was tested in two phases. These chapters report and analyse the data from approximately forty five thousand individual gambles, alongside detailed psychometric data. Finally the general discussion broadly focuses on two areas where the approaches and findings from the thesis might be maximally effective. The discussion begins by reviewing the evidence on the subtyping of gambling and problem gambling, including the work added by this thesis, before applying it alongside the approaches taken in Chapter 6 and 7 to in-play betting. The second is to discuss the implications these findings might have for behavioural addictions, as many activities might follow a similar pattern of excess and harm, but it is argued a behavioural analysis of this is warranted.

CHAPTER 2 -

THE LATENT STRUCTURE OF PROBLEM GAMBLING: A TAXOMETRIC ANALYSIS[1]

2.1 Overview

Before testing whether mobile gambling is associated with creating further gambling problems for existing gamblers or creating new problem gamblers, further analyses of gambling data are required. The contested literature on problem gambling necessitates testing whether additional analyses of problem gambling data can be used to further understand 'problem gambling'. As introduced in Section 1.5 there is a nascent debate concerning whether problem gambling is best conceptualised as a categorical or continuous construct. While the shift towards the latter has come to dominate thinking about psychopathology as of late, there is evidence to suggest that addictions better fit a categorical model and this may be the case for behavioural addictions i.e. problem gambling. This chapter reports a secondary analysis of British

[1] Much of the content in this chapter has been published as James, O'Malley & Tunney (2014) "On the latent structure of problem gambling: A taxometric analysis" in *Addiction*. The description of the taxometric method in Section 2.2.b has been taken from James, Dubey, Smith, Ropar & Tunney (2016) "The latent structure of autistic traits: a taxometric, latent class and latent profile investigation" at *Journal of Autism and Developmental Disorders*.

problem gambling assessment data, utilising taxometric analysis to test whether the latent construct measured by two problem gambling assessment is best represented as categorical or continuous. Data was taken from an adaptation of the DSM-IV Pathological Gambling criteria and the Problem Gambling Severity Index, which probe two prevalent models of problematic or pathological gambling. Although it is widely assumed one measures a dimension, and that the other has been empirically shown to do so despite being designed with a categorical model in mind, taxometric analyses found both measure a high severity latent category or taxon. A further analysis of the total scores on both measures demonstrated identical findings, although caution must be taken with the results, as these data were less suitable for taxometric analysis. The results strongly suggest that there is a taxon within problem gamblers, similar to other addictions.

2.2 Introduction

2.2.a Perspectives on problem gambling

As Section 1.5 of the introduction noted, a longstanding debate concerns the latent structure of problem gambling (Svetieva & Walker, 2008). Two perspectives have emerged, one arguing that problem gambling is defined by a categorical division between gamblers and problem gamblers, typified by loss of control over gambling, the other that problem gambling is at the extreme of a continuum of harm and that problem gambling assessments form a useful but arbitrary cutting point. This debate is central to research on the theory and measurement of problem gambling and its relationship to other addictions. In this chapter this question is addressed by conducting a taxometric analysis of two measures of problem gambling recorded in the British Gambling Prevalence Survey 2010 (BGPS 2010) (Wardle et al., 2011b): The Problem Gambling Severity Index (PGSI) (Ferris & Wynne, 2001) and a measure adapted from the DSM-IV Pathological Gambling criteria (American Psychiatric Association, 2000; Wardle et al., 2011b).

Although the introduction outlined a broad definition of problem gambling, 'problem gambling' has come to correspond to an array of different constructs depending on the context in which it is used. Although different research emphasises different aspects within problem gambling, one of the most debated considerations is whether problem gambling is best modelled as a discrete category (i.e. addicted versus non-addicted gamblers) or as a continuum that is distributed across the population. This mirrors an extensive debate in psychiatry concerning the latent structure of a range of psychopathologies. The DSM has traditionally framed psychiatric disorders as being discrete entities, categorising people as having a disorder or not. Increasingly taxometric analysis has been used to adjudge whether assessments of mental disorder more closely fit a dimension (latent factor) or categorical (latent class) model.

As noted above there are two different conceptualizations of problem gambling (Svetieva & Walker, 2008). The first defines problem gambling as an addiction disorder and a manifestation of pathological gambling. Pathological gambling is defined by this approach as a loss of control over gambling behaviour (Rosecrance, 1985a, 1985b). This category of theory includes models that emphasise causal roles for biological, psychological and social factors, in addition to loss of control in the development of problem gambling. For example the Pathways Model (Blaszczynski & Nower, 2002) proposes three distinct aetiologies of problem gambling. These pathways assume that problem gambling is caused by behavioural conditioning, life stressors, or impulsive/antisocial personality traits, the latter two underpinned by associative learning (i.e. classical and operant conditioning) and mounting cognitive biases, leading to a loss of control over gambling behaviour prior to the onset of pathological gambling. This model has strong empirical support, with several studies confirming three kinds of problem gambler (Milosevic & Ledgerwood, 2010; Nower, Martins, Lin, & Blanco, 2013). Although the Pathways Model is not purely an addiction-based theory, it does claim that a defining feature of problem gambling is a loss of control of gambling behaviour, that problem gambling is a categorical disorder and that different pathways are qualitatively distinct from one another. The model also claims that behaviourally conditioned gamblers, unlike the other two pathways, can return to controlled gambling. These claims imply the presence of a problem gambling taxon (Rosecrance, 1985a, 1985b) or qualitatively distinct category.

An alternative approach to problem gambling focuses on the individual harm that problem gambling causes and the wider impact of gambling on others and society (Neal, Delfabbro, & O'Neil, 2005). Although addictive gambling may be an important issue in this framework, this approach claims that the demarcation of problem gambling is excessive gambling behaviour (Svetieva & Walker, 2008). Excessive gambling is defined as the continuation of gambling beyond the limits an individual’s circumstances allow. In contrast to the Pathways Model, this conceptualization assumes that problem gambling is identified as a threshold along a dimension that includes non-problematic recreational gambling.

Much of the theoretical research has stressed the need to move from categorical to dimensional models of problem gambling. Although it is necessary to identify cutting points to screen individuals that need intervention, central to this approach is the assumption that these cutting points are subjective, and may ultimately differ based on the need of individual or of the society in which they live (e.g. funding for gambling interventions, legality of gambling, the gambler's relationships with loved ones or employers). Contemporary measurements of problem gambling, such as the Problem Gambling Severity Index, have been designed with this view in mind.

At first glance, research on the measurement of problem gambling reflects the same differences that exist in the theoretical literature. However, measures of problem gambling appear to exclusively measure an addiction construct (Orford, Wardle, Griffiths, Sproston, & Erens, 2010; Strong & Kahler, 2007; Svetieva & Walker, 2008). The Problem Gambling Severity Index (PGSI) is the most common population-wide assessment of problem gambling (Williams, Volberg, & Stevens, 2012a). The PGSI is designed to classify four levels of problem gambling severity along a dimension of harm (Ferris & Wynne, 2001). Although the use of a measure that hypothesizes a dimensional structure to make a categorical distinction isn't problematic if that distinction is meaningful (Ruscio, Haslam, & Ruscio, 2006), the use of the PGSI has produced difficulties in the problem gambling prevalence literature as there has been a failure to find a consensus on the appropriate threshold to discriminate between recreational and problem gamblers and the validity of the

PGSI categories (Currie, Casey, & Hodgins, 2010; Currie, Hodgins, & Casey, 2013; Gambino, 2012, 2014; Kincaid et al., 2013; Walker & Blaszczynski, 2011; Williams et al., 2012a). This debate arises because some items used in the PGSI to measure problem gambling as a dimensional construct are adapted from Pathological Gambling instruments such as the South Oaks Gambling Scale (Lesieur & Blume, 1987) and DSM-IV (American Psychiatric Association, 2000; Svetieva & Walker, 2008).

2.2.b Taxometric analysis

Taxometric analysis is a statistical approach designed to test whether a latent variable, measured by a number of ordinal or continuous observed variables, is categorical or continuous. Studies have demonstrated that taxometric analysis is better at discriminating latent structure relative to other psychometric techniques (McGrath & Walters, 2012), such as latent class modelling, provided that the assumptions of taxometric analysis are met. Haslam, Holland & Kuppens (2012), in reviewing the literature, found that the overwhelming majority of psychopathologies show a dimensional latent structure. However, three types of disorders: addictions, schizotypy and ASD were identified as potentially yielding taxa.

In taxometrics cases are assigned or not to a putative latent class, or taxon, on the basis of a cut-off, diagnosis, or base rate. Cases are then ordered along one of the indicators (the *input*), dividing them into ‘windows’ or ‘cuts’ and then a statistical operation is performed on another variable/couplets of variables/remaining indicators (the *output*). Different taxometric procedures provide non-redundant information on the latent structure of the variable of interest (Ruscio et al., 2006). Plotting the output of taxometric analysis may reveal discontinuities that suggest a taxon, typically represented by a distinct peak along the *x* axis. This however varies by levels of indicator validity, nuisance covariance, skew, kurtosis etc. Interpretation of taxometric findings typically include comparisons of bootstrapped datasets with idealised categorical and dimensional structures and comparing the disparity between the idealised and actual data to provide a quantitative index of fit between the two competing models (Haslam et al., 2012).

Prior to Ruscio, Ruscio, and Keane (2004), taxometrics was primarily conducted using visual analyses of taxometric plots (see section 2.2b for further details on interpretation). This typically meant visually analysing taxometric plots, looking either for a distinct peak in the graph or visual similarity to plots produced by Monte Carlo studies of taxometric analysis. Subsequent re-analysis of highly skewed data using quantitative indices such as the CCFI revealed in many cases data that were being interpreted as identifying a small latent taxon were instead a better fit of a dimensional or latent factor model. It has been noted across the literature by Haslam et al. (2012) that the use of quantitative indices has increased the proportion of non-taxonic findings in the literature.

Taxometric analysis has three key assumptions. The first is that putative indicators show substantial differences between a proposed taxon and non-taxon (or complement), quantified using the standardised between-groups effect size Cohen's *d* that ought to exceed 1.25 (Meehl, 1995) Indicators entered into taxometric analyses should show little *nuisance covariance*, meaning they are relatively uncorrelated (mean $r < 0.3$) among taxon and non-taxon cases (Ruscio et al., 2006). Finally both the overall dataset and the proposed taxon should contain enough cases. A minimum sample size of 300 is recommended for taxometric analysis, and taxon base rate should be at least 5% of the total sample and preferably 10% (Walters & Ruscio, 2009).

2.2.c The latent structure of psychopathologies

A recent review of the taxometric literature across a range of types of psychopathology highlights a number of interesting observations (Haslam et al., 2012). The first is that the vast majority of types of disorder appear to have a dimensional structure; very few psychopathologies are categorical in nature. Moreover the trend is that increasingly taxometric analysis are finding support for dimensional models in mental disorders, particularly with the use of quantitative indices of model fit. The nascent exceptions to these were schizotypy, autistic spectrum disorder and addictions.

Focusing on addictions, meta analytic research has indicated that dependence disorders represent one of the few fruitful candidates for the presence of categories in the latent structure of mental disorders. Addictions represent a particularly interesting area for the presence of taxa. The other areas Haslam et al. (2012) identify as potentially yielding taxa: schizotypy or autism spectrum disorder, have very strong genetic or developmental elements. While addictions have a similar component, with the importance of early exposure to alcohol or substances in adolescence being a strong predictor of future problem severity, addictions are particularly interesting as the other taxonic disorder emerge at birth or very early in life; addictions in contrast tend to begin development in adolescence or early adulthood, but can emerge across the lifespan. The Pathways Model appears to predict that the most severe cases of problem gambling emerge through the emotionally vulnerable and antisocial impulsivist pathways. The former is thought by some to consist of older gamblers, including a larger number of females and older adults than other problem gambling groups. Whether a potential taxon that might be identified in this analysis applies to these gamblers is unclear, but raises interesting considerations concerning potential members of a problem gambling taxon.

Understanding whether problem gambling has a categorical or dimensional structure is particularly important with the inclusion of Gambling Disorder in the DSM-5 as a behavioural addiction. This has been justified on the basis that behavioural, neural and genetic markers in pathological gamblers are similar to other addictions (Denis, Fatséas, & Auriacombe, 2012; Petry et al., 2014). However, one property that has not been tested is whether problem gambling has a similar latent structure to other addictions. Meta-analytic studies using taxometric analysis (a method to test whether the latent structure of a variable is categorical or dimensional) specifically identify addictions as one of the few psychopathologies that may be categorical (Haslam et al., 2012). Studies looking at the subtyping of problem gamblers have consistently found three subtypes of problem gambler (Milosevic & Ledgerwood, 2010; Nower et al., 2013). Studies in this area have increasingly used latent class modeling to identify distinct groups of gambler. Despite considerable debate about the nature of problem gambling, few studies have been conducted using appropriate statistical methods to test whether problem gambling is categorical.

However, numerous studies using a variety of analytic methods including some taxometric analyses have also found evidence that addictive disorders are best described as dimensional. Some of these have used latent class and latent mixture methods (Baillie & Teesson, 2010), in addition to methods that presuppose the presence of a latent factor (Strong & Kahler, 2007). Some taxometric analyses looking at several substance abuse disorders (Denson & Earleywine, 2006; Ginestet, Mitchell, & Wellman, 2008; Slade, Grove, & Teesson, 2009) have found evidence that disputes the presence of a taxon. Moreover a latent class analysis of British gamblers as part of the British Gambling Prevalence Survey 2007 indicated the presence of several latent classes ordered along symptom severity (McBride, Adamson, & Shevlin, 2010). However there are methodological considerations with each of these that require further attention. In particular the taxometric studies make considerable use of dichotomous indicators, analysed using a summed input approach that has come under scrutiny (Walters & Ruscio, 2009)[2]. Item response and latent class modeling also presuppose a latent structure, and in cases where differential responding between classes is ambiguous latent class analysis may equivocally support a categorical or dimensional interpretation.

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[2] Additionally the empirical work in Chapter 5 directly tests the ability of this type of analysis to discriminate competing latent structures for the first time. In short, while it performs better than standard taxometric approaches, there is a substantial false error rate associated with the failure of these methods to identify a latent taxon.

Two previous studies have conducted taxometric analyses on gambling. The first examined whether excessive internet sports gamblers formed a taxon (Braverman et al., 2011). Data were collected from actual internet gambling behaviour over several years. The analysis was carried out on three behavioural measures of involvement (money wagered, money lost and number of bets). Unfortunately for the purposes measures of problem gambling were not taken and the results from this study were inconclusive in discriminating between models. The second study examined whether problem gamblers formed a taxon on the basis of PGSI scores (Kincaid et al., 2013). PGSI items were analysed from respondents who scored greater than zero in the South African National Urban Prevalence Study of Gambling Behaviour (Ross et al., 2013). The taxometric analyses on these data indicated a categorical structure, and stronger support was found when the analysis was restricted to items testing a loss of control. However, the PGSI may not be the best measure to detect a problem gambling taxon because it contains fewer items relating to loss of control (Kincaid et al., 2013). The DSM has a greater number of items relating to a loss of control but to date, no such analysis has been conducted.

2.2.d The present study

To this end, and to determine whether problem gambling has a categorical or dimensional structure, taxometric analyses was conducted on the data from two problem gambling measures collected in the BGPS 2010 (PGSI and an adapted version of the DSM- IV Pathological Gambling criteria) (Wardle et al., 2011b). There are two benefits of using this dataset. First, as a general population dataset it contains the entire range of responses for both measures. Second, the DSM measure was collected in both continuous and dichotomous formats. Taxometric analyses typically require a variable to have at least 4 rank ordered categories in order to be suitable for analysis (Walters & Ruscio, 2009). Although the logic of the DSM-IV assumes a categorical structure, previous analyses have found that the DSM-IV construct of Pathological Gambling may be dimensional (Orford et al., 2010; Strong & Kahler, 2007). This interpretation may be an artefact of the analytic techniques these studies have used (e.g. factor analysis, Rasch models). Taxometric analyses do not make this assumption and can discriminate between latent variables that have categorical or dimensional structures. It was hypothesized that taxometric analyses of both the PGSI and DSM-IV would find evidence for a categorical structure similar to other addictions.

2.3 Methods

2.3.a Sample

Data for this analysis was taken from the British Gambling Prevalence Survey 2010 (BGPS 2010), a nationally representative sample of the UK population. The data is publicly available from the UK Data Archive (National Centre for Social Research, 2011).

The BGPS data collection consisted of a computer-aided self-interview conducted by the National Centre for Social Research (National Centre for Social Research, 2011; Wardle et al., 2011b). Almost 8000 ($n = 7756$) respondents completed the survey (response rate = 47%). Participants were sampled randomly from 391 postcodes, which were selected from a stratified probability sample. Data were analysed from participants who scored one or more on either the PGSI ($n = 569$) or the DSM ($n = 1387$) measures, based on previous taxometric analyses of problem gambling screens (Kincaid et al., 2013). Both measures assessed problem gambling prevalence over the past year. One case was removed prior to analysis, as it did not contain a full set of responses. The BGPS estimated the 2009 problem gambling prevalence in the United Kingdom to be 0.9% (DSM-IV-based measure) and 0.7% (PGSI). Distributional information about the data is included in Table 1.

Table 1

Means and standard deviations for the items on both problem gambling screens; responses on all items ranged from 0 to 3.

Item	Average	*S.D.*
Problem Gambling Severity Index		
1 – Excessive betting	0.53	0.719
2 – Tolerance	0.21	0.514
3 – Loss chasing	0.67	0.684
4 – Borrowed money to gamble	0.15	0.476
5 – Felt had a gambling problem	0.24	0.589
6 –Been told had a gambling problem	0.19	0.529
7 – Gambling related guilt	0.32	0.628
8 – Health problems, stress/anxiety	0.19	0.559
9 – Financial problems	0.39	0.673
Adapted DSM-IV Pathological Gambling Criteria		
1 – Loss chasing	0.56	0.788
2 – Preoccupation	0.94	0.665
3 – Tolerance	0.27	0.586
4 – Irritability when cutting down	0.15	0.508
5 – Gambled to escape	0.19	0.525
6 – Lied about gambling	0.12	0.433
7 – Difficulties controlling gambling	0.15	0.514
8 – Committed crime to fund gambling	0.02	0.285
9 – Risked important opportunity	0.03	0.253
10 – Borrowed money for gambling	0.05	0.281

The PGSI consists of nine questions that are scored from 0 to 3. Participants were classified as problem gamblers if they scored 8 or higher (Ferris & Wynne, 2001; Wardle et al., 2011b). The PGSI has strong internal consistency ($\alpha = 0.9$) (Orford et al., 2010). The classification accuracy of the PGSI has been studied alongside multiple measures and has been demonstrated to have adequate classification accuracy with the present problem gambling criteria (positive predictive value = 89.86%, negative predictive value = 92%, sensitivity = 44.42%, specificity = 99.22% (Williams & Volberg, 2010)).

The authors of the BGPS used a modified version of the DSM-IV pathological gambling criteria (Fisher, 1996; Sproston et al., 2000; Wardle et al., 2011b; Wardle et al., 2007). Instead of scoring the presence or absence of a symptom, the respondents rated each item on a 4-point scale of the frequency each symptom occurred (0 being 'never' and 3 'very often'). Also a lower threshold was used to classify problem gamblers (3) than the DSM-IV criteria (5). The authors of the BGPS justified this threshold (Orford et al., 2010) on the basis that a lower threshold is better at classifying these groups (Stinchfield, 2002; Stinchfield, Govoni, & Frisch, 2005). The adapted DSM-IV criteria show adequate internal consistency ($\alpha = 0.73$ (Orford et al., 2010) and $\alpha = 0.76$ (Orford, Sproston, & Erens, 2003)).

2.3.b Analytic Procedure

MAMBAC (mean above minus below a cut) (Meehl & Yonce, 1994) and MAXSLOPE (maximum slope) (Grove, 2004) analyses were carried out on the PGSI indicator variables. MAMBAC, MAXCOV (maximum covariance) (Meehl, 1973) and MAXEIG (maximum eigenvalue) (Waller & Meehl, 1998) analyses were conducted on the adapted DSM-IV items.

Taxometric analyses require an input variable and output variables. Across all taxometric analyses cases are rank-ordered by one of the variables selected for analysis (the input variable), which forms the ***x***-axis of taxometric plots (Figs 1-3). In MAMBAC analyses a series of cuts (preferably 50 (Walters & Ruscio, 2010)) are applied evenly across the other variable (the output variable). At each cut a mean difference, defined as the mean above minus the mean below, is computed and plotted as the ***y***-axis. The MAMBAC procedure is iterated through each potential input–output combination. MAXCOV analyses portions the input variable into a number of ‘windows’ or subsamples (Walters & Ruscio, 2009) as the input and the covariance between couplets of output variables at each window is plotted as the output variable. MAXEIG operates in a similar fashion to MAXCOV, except that the largest eigenvalue from two or more output variables is plotted (Walters & Ruscio, 2009). MAXSLOPE uses a slightly different approach, plotting a smoothed non-linear regression curve, and is conducted on two indicator variables. Categorical taxometric plots are generally peaked, whereas dimensional plots are flat (Ruscio et al., 2006).

For each analysis the observed data were compared against 200 samples of bootstrapped comparison data. Comparison data can discriminate between structures when the data are highly skewed (Ruscio et al., 2004). The bootstrapped data had the same distributional statistics as the data set, but half the samples had an idealized dimensional or a categorical structure. From this, the root mean squared residual (RMSR) was computed as an index of fit between the bootstrapped and observed data, and an index of the latent structure was derived by dividing the RMSR for the dimensional data by the sum of the RMSRs for the categorical and dimensional data. This produced a comparison curve fit index (CCFI (Ruscio et al., 2006)) between 0 and 1. Indices closer to 1 indicate a categorical structure and smaller indices a dimensional structure. A CCFI of 0.5 indicates support for neither structure. CCFIs between 0.4 and 0.6 are inconclusive (Ruscio et al., 2006).

For both MAMBAC analyses, 50 evenly spaced cuts were made in the output variable, with the first and last cuts specified as the 10 cases reserved at either extreme, based on studies using bootstrapped data (Walters & Ruscio, 2010). For MAXCOV and MAXEIG analyses, the output variables were divided into 50 windows. All the taxometric analyses were carried out using an R script developed by Ruscio (Ruscio, 2013).

2.4 Results

Cases were classified as problem or non-problem gambler based on each measure's classification criteria. A number of assumptions concerning the data should be met before taxometric analyses are conducted. The first recommends the base rate, or the proportion of cases in the whole sample assigned to the putative taxon should be ≥10% (Meehl, 1999) or 5% (Ruscio et al., 2006; Walters & Ruscio, 2009). The PGSI base rate (0.086) is sufficient, but the DSM-IV rate (0.046) is smaller than the recommended heuristic. The second requirement is for a large between-groups effect size between the putative taxon and non-taxon members of Cohen's $d > 1.25$ (Meehl, 1999; Ruscio et al., 2006). All the items meet this assumption (Tables 2 and 3). The third assumption is that there is little nuisance covariance, which refers to the correlations between indicator variables within the taxon and non-taxon groups. A correlation of $\boldsymbol{r} < 0.3$ has been recommended previously, and that the correlation between items across the whole sample is greater than the correlation between items in the taxon (Ruscio et al., 2006). Neither of the measures met this assumption, so composite indicator variables were constructed by summing scores across groups of items. Generalized least-squares factor analyses were carried out on the scores of taxon members to determine which items should be combined. The factor loadings and the composite indicator variables are included in Tables 4 and 5. The factor loadings for the PGSI are straightforward (Table 4). The loadings from the adapted DSM measure revealed a three-factor solution (Table 5). Two items loaded onto a first factor, and a further three items cross-loaded onto this factor and a second factor. Three items loaded onto a third factor. Two other items did not load onto any of the factors and were included as indicators separately. All these items have a sufficiently large between-groups effect size to be appropriate to detect the presence of a taxon (Tables 6 and 7). With the exception of two pairs of indicators, all the items met this assumption (Table 7).

Table 2

Indicator validity and skew measures for individual items on the PGSI.

Item	Cohen's *d*	Skew
1. How often have you bet more than you can afford to	2.331	1.477
2. How often have you needed to gamble with larger amounts of money to get the same feeling of excitement?	1.894	2.843
3. How often have you gone back another day to try to win back the money you lost?	1.576	1.026
4. How often have you borrowed money or sold anything to get money to gamble?	2.192	4.034
5. How often have you felt you might have a problem	3.779	2.952
6. How often have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?	2.946	3.387
7. How often have you felt guilty about gambling, or what happens when you gamble?	1.893	2.237
8. How often has your gambling caused you any health problems, including stress or anxiety?	2.545	3.550
9. How often has gambling caused any financial problems for you or your household?	1.917	1.978

Table 3

Indicator validity and skew measures for individual items on the DSM-IV assessment.

Item	Cohen's *d*	Skew
1. In the last 12 months, how often do you go back another day to win back money you lost?	1.805	1.416
2. In the last 12 months, how often have you found yourself thinking about gambling (that is reliving past gambling experiences, planning the next time you will play or thinking of ways to get money to gamble)?	1.779	0.743
3. In the last 12 months, have you needed to gamble with more and more money to get the excitement you were looking for?	2.784	-0.266
4. In the last 12 months, have you felt restless or irritable when trying to cut down gambling?	3.259	-0.246
5. In the last 12 months, have you gambled to escape from problems or when you are feeling depressed, anxious or bad about yourself?	3.792	3.387
6. In the last 12 months, have you lied to family, to others, to hide the extent of your gambling?	3.780	4.325
7. In the last 12 months, have made unsuccessful attempts to control, cut back or stop gambling?	2.593	3.975
8. In the last 12 months, have you committed a crime in order to finance gambling or pay gambling debts?	2.109	11.538
9. In the last 12 months, have you risked or lost an important relationship, job, educational or work opportunity because of gambling?	2.390	9.370
10. In the last 12 months, have you asked others to provide money to help with a desperate financial situation caused by gambling?	2.666	7.227

Table 4

Factor loadings and indicator names from generalized least squares factor analysis on PGSI taxon members.

PGSI Item Number and Content	Factor 1	Factor 2
Indicator 1		
1. How often have you bet more than you could afford to lose?	.274	**.801**
2. How often have you needed to gamble with larger amounts of money to get the same feeling of excitement?	.170	**.602**
3. How often have you gone back another day to try to win back the money you lost?	.305	**.595**
Indicator 2		
4. How often have you borrowed money or sold anything to get money to gamble?	**.545**	.100
5. How often have you felt that you might have a problem with gambling?	**.719**	.140
6. How often have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?	**.726**	-.011
7. How often have you felt guilty about gambling or what happens when you gamble?	**.594**	-.279
8. How often has your gambling caused you any health problems, including stress or anxiety?	**.950**	-.147
9. How often has gambling caused any financial problems for you or your household?	**.682**	.210

Note: Factor loadings greater than 0.4 are highlighted in bold.

Table 5

Factor loadings and indicator names from generalized least squares factor analysis on DSM-IV taxon members.

DSM-IV Item Number and Content	Factor 1	Factor 2	Factor 3
Indicator 1	.202	-.083	**.449**
1. In the last 12 months, how often do you go back another day to win back money you lost?			
2. In the last 12 months, how often have you found yourself thinking about gambling (that is reliving past gambling experiences, planning the next time you will play, or thinking of ways to get money to gamble)?	.005	.064	**.657**
3. In the last 12 months, have you needed to gamble with more and more money to get the excitement you are looking for?	.237	.266	**.534**
Indicator 2			
4. In the last 12 months, have you felt restless or irritable when trying to cut down gambling?	.318	.231	.385
Indicator 3			
5. In the last 12 months, have you gambled to escape from problems or when you are feeling depressed, anxious or bad about yourself?	.263	.107	.231
Indicator 4			
6. In the last 12 months, have you lied to family, to others, to hide the extent of your gambling?	**.941**	-.222	-.039
7. In the last 12 months, have you made unsuccessful attempts to control, cut back or stop gambling?	**.516**	-.065	.280
Indicator 5			
8. In the last 12 months, have you committed a crime in order to finance gambling or pay gambling debts?	.356	**.648**	-.165
9. In the last 12 months, have you risked or lost an important relationship, job, educational or work opportunity because of gambling?	**.434**	**.788**	-.049
10. In the last 12 months, have you asked others to provide money to help with a desperate financial situation cause by gambling?	**.552**	**.445**	-.008

Note: Factor loadings greater than 0.4 are highlighted in bold.

Table 6

Indicator validity and skew measures for composite indicator variables for the PGSI and adapted DSM-IV criteria, and the nuisance covariance for the PGSI measure.

Indicator	Cohen's *d*	Skew
Problem Gambling Severity Index		
1 (PGSI Items 1-3)	3.008	2.424
2 (PGSI Items 4-9)	4.388	3.411
Adapted DSM-IV Pathological Gambling Criteria		
1 (DSM Items 1-3)	3.635	2.125
2 (DSM Item 4)	3.806	3.830
3 (DSM Item 5)	3.791	3.385
4 (DSM Items 6-7)	3.868	3.993
5 (DSM Items 8-10)	2.985	8.930
	r	
PGSI Indicators 1 & 2 – Whole Sample Covariance	0.555	
PGSI Indicators 1 & 2 – Taxon Nuisance Covariance	0.288	
PGSI Indicators 1 & 2 – Non-taxon Nuisance Covariance	-0.054	

Table 7

Inter-indicator correlations for the DSM-IV assessment

Whole sample

	1	2	3	4	5
1	-				
2	0.517	-			
3	0.437	0.505	-		
4	0.484	0.560	0.517	-	
5	0.352	0.452	0.407	0.473	-

Taxon

	1	2	3	4	5
1	-				
2	**0.375**	-			
3	0.227	0.192	-		
4	0.255	0.278	0.229	-	
5	0.148	0.300	0.170	**0.330**	-

Non-taxon members

	1	2	3	4	5
1	-				
2	0.189	-			
3	0.063	0.190	-		
4	0.147	0.273	0.191	-	
5	-0.009	0.062	0.069	0.075	-

Note. The correlations that exceed the recommended nuisance covariance threshold of $r < .3$ are highlighted in bold.

2.4.a PGSI

Both the MAMBAC and MAXSLOPE analyses indicated support for a categorical structure. Although neither set of comparison data was a close fit to the observed data in the MAXSLOPE analysis (Figure 1), the observed data are within the range of the categorical bootstrapped data. A CCFI = 0.633 indicated support for a categorical structure. The MAMBAC analysis (Figure 1) shows stronger support in the same direction; the bootstrapped dimensional data is a poor fit of the averaged MAMBAC curve from the observed data, and a CCFI of 0.756 indicated strong support for a categorical interpretation.

2.4.b DSM-IV Pathological Gambling Criteria

The mean MAMBAC, MAXEIG and MAXCOV curves show a distinct peak on the right side of the x-axis that is characteristic of a taxon. Closer consideration of the bootstrapped data reveals that both categorical and dimensional data sets produce similar curves. Consequently, CCFIs were used to discriminate between these interpretations. The MAMBAC analysis (Figure 2) strongly supports a categorical structure, with the exception that analyses conducted on the first indicator were inconsistent. The computed CCFI across all curves was 0.717, indicating support for a categorical interpretation. The MAXCOV and MAXEIG comparison curves (Figure 2) demonstrate that the categorical comparison data is calibrated closely with the observed data. The CCFIs also support this observation, with both (MAXEIG = 0.756, MAXCOV = 0.811) indicating strong support for a categorical interpretation.

2.4.c Combined Indicators

However, these analyses preclude us from making strong claims about the presence of a problem gambling taxon. To follow this up, MAMBAC and MAXSLOPE analyses were conducted on the total scores of the PGSI and adapted DSM-IV criteria ($n = 1486$). Cases were assigned to the putative taxon if they were classified as a problem gambler by either measure ($n = 78$). It is noted, however, that the two measures are highly correlated [$r = 0.736$ (whole sample), 0.453 (taxon), 0.38 (non-taxon)], so it is recommended that this analysis is taken with extreme caution. Meehl has noted previously that high nuisance ($r > 0.3$) covariance should be tolerable as long as correlations are similar across both groups (Meehl, 1995). The analysis reveals very similar results to the analyses of the individual measures; the data provide stronger support for a categorical interpretation (MAMBAC CCFI = 0.628, MAXSLOPE CCFI = 0.567, Figure 3). In Figure 3 the MAXSLOPE curve has been included as well as the comparison curve because the comparison curve is very difficult to interpret due to the range of the comparison data.

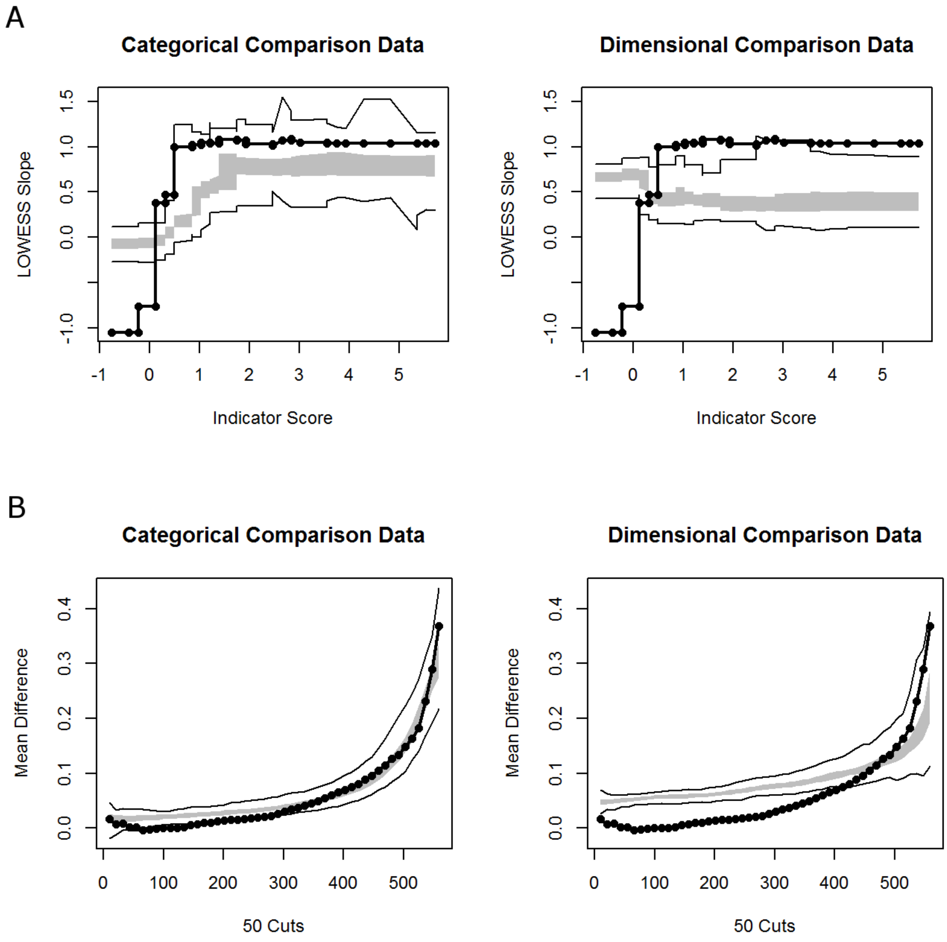

Figure 1

Categorical and dimensional comparison data compared against the observed data points for the PGSI MAXSLOPE (Graph A, CCFI = 0.633) and MAMBAC (Graph B, CCFI = 0.756) analyses. The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAXSLOPE curve from the actual data observed.

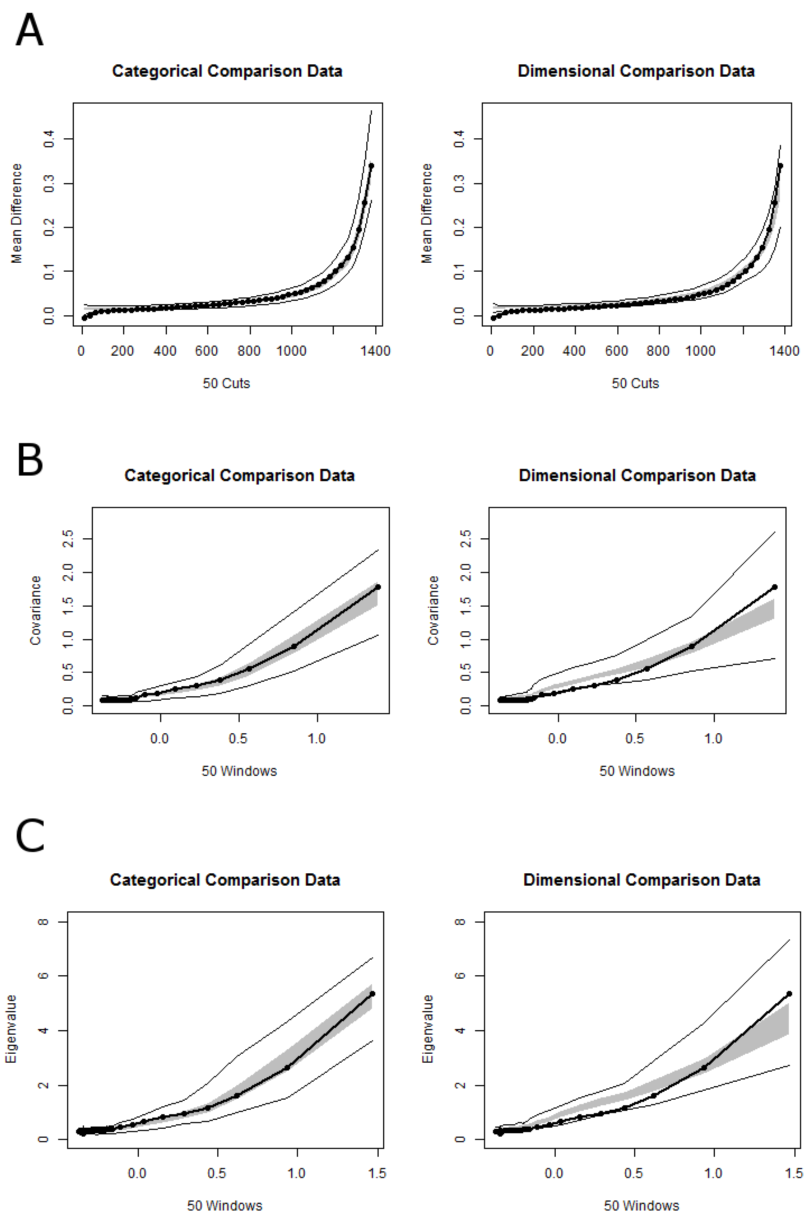

Figure 2

Categorical and dimensional comparison data compared against the observed data points for the DSM-IV MAMBAC (Graph A, CCFI = 0.717), MAXCOV (Graph B, CCFI = 0.811) and MAXEIG (Graph C, CCFI = 0.756) analyses. The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAMBAC curve from the actual data observed.

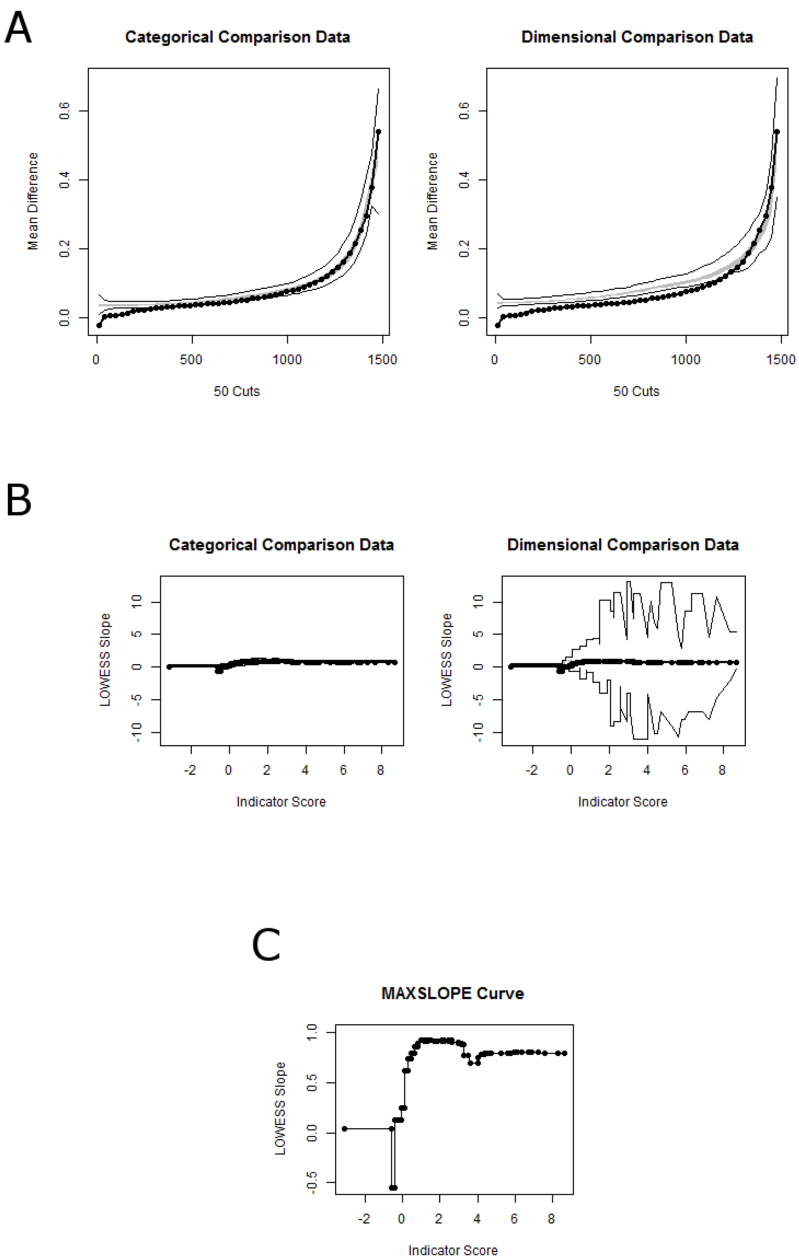

Figure 3

Categorical and dimensional comparison data compared against the observed data points for the DSM-IV and PGSI MAMBAC (Graph A, CCFI = 0.628) and MAXSLOPE (Graph B, CCFI = 0.567). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAMBAC curve from the actual data observed. The MAXSLOPE curve (Graph C) without comparison data because of the range of dimensional comparison data observed.

2.5 Discussion

The taxometric analysis of the PGSI and a measured derived from the DSM-IV Pathological Gambling criteria from the BGPS 2010 indicated that problem gambling as measured by these instruments is categorical. Specifically, the PGSI analysis located a division that calibrates well to the cut-off for problem gambler in the PGSI (8+) and supports the assumptions underlying the Pathways Model, particularly the claim that there is a distinct group of problem gamblers characterised by a loss of control over their gambling (Blaszczynski & Nower, 2002; Rosecrance, 1985a, 1985b). Follow up analyses comparing across both scales supported this, further finding support for the presence of a categorical latent structure.

The PGSI was developed and is used on the assumption that it is measuring a dimension of harm-centred problem gambling. This analysis shows that this assumption is flawed. The PGSI data from the BGPS demonstrates that the construct the PGSI is measuring is categorical, resembling a pathological model. Criticisms have previously been raised that the use of the PGSI is flawed because it is atheoretical (Svetieva & Walker, 2008). Although such a claim is beyond the scope of this analysis, the PGSI does appear to measure a construct that probes aspects of the pathological model (Rosecrance, 1985a, 1985b). Given the poor performance of DSM-IV derived items related to losing control, it seems to be the case that the PGSI is a more conceptually coherent measure of the construct that the DSM-IV is intended to measure. In addition to the claims that problem gambling is a categorical disorder and is demarcated by a loss of control of gambling behaviour, there are three other claims. The remaining claims are that problem gambling is a single phenomenon, compulsive gambling is a permanent and irreversible disorder, and that the disorder progresses through a series of stages. The progression of gambling behaviour begins with a transition from recreational to excessive gambling, followed by the appearance of cognitive biases and overconfidence. This in turn progresses changes in perceptions of value of money, then chasing losses, followed by the consequences of problem gambling, then a 'rock bottom' stage when treatment is sought. Although two of these claims, that problem gambling is a single phenomenon and irreversible are not empirically supported, the remaining claim is tested by the DSM-IV measure.

An indicator composed of items measuring a loss of control was also created for the adapted DSM-IV criteria (Indicator 1). In contrast to the PGSI, the results from this indicator variable were inconsistent. The observed difference between the PGSI and DSM constructs relating to a loss of control appears to be because the first two items on the DSM- IV measure are frequently endorsed and do not discriminate between problem and non-problem gamblers (Orford et al., 2010; Strong & Kahler, 2007). Previous latent class analyses of this data have suggested that endorsement rates for these items are similar for pathological and non-clinical gamblers who show sub clinically significant levels of disordered gambling.

The close similarity between the comparison curves on the analyses of the DSM-IV based measure should be noted. Although the CCFIs are suitably large to endorse a categorical interpretation, indices obtained from the analysis belie the similarity between the two sets of bootstrapped data (Figure 2). Although the DSM indicators are skewed, comparison data have proved highly capable of discriminating between dimensional and categorical structures in data that are substantially skewed (Ruscio & Marcus, 2007; Ruscio et al., 2004); the comparison data here strongly support a categorical conclusion.

In relation to other addiction disorders, the analysis provides further justification for the re-categorization of problem gambling as an addiction disorder in the *DSM-V*. Not only does problem gambling share strong similarities to substance use disorders (Denis et al., 2012), but problem gamblers appear to form a taxon like other addictions. One implication is the need to carry out further psychometric assessments of both the PGSI and DSM-derived measures of problem gambling. Previous analyses used methods that are based on the assumption that the latent variable that is being measured is dimensional (Orford et al., 2010; Strong & Kahler, 2007). This taxometric analysis of the BGPS demonstrates that this assumption is flawed. As such, the key implication is that different psychometric analyses, with different assumptions about latent models (such as latent profile analysis) are more appropriate for the psychometric evaluation of these measures.

In relation to treatment and intervention, it should be noted that some non-taxon members exceed the cutoff for Pathological Gambling in the DSM-IV, and a larger proportion are likely to do so for Gambling Disorder in the DSM-5; numerous cases would meet the criteria for requiring further intervention without being a taxon member on the basis of the identified taxon base rate. An argument has previously been made that focusing only upon the most psychometrically valid indicators of Gambling Disorder might miss clinically important concerns with gambling (Bowden-Jones, 2013), and this should be taken into account in terms of interpreting these findings.

2.5.a Limitations

There are some important limitations to consider with this analysis. The first is that the some of the parameters of the data are less than ideal for taxometric analysis, although at the same time far more suitable for taxometrics than the vast majority of other gambling prevalence datasets. While they have a large between-group separation and low nuisance covariance, they do show very substantial skew and the base rate is lower than the 10% typically recommended in the literature. However the analysis predominantly is interpreted on the basis of the CCFI, which has been demonstrated before to detect taxa at very small base rates and distinguish between structures with highly skewed data (Ruscio & Marcus, 2007; Ruscio et al., 2004) thus mitigating some of the associated caveats.

It would be beneficial to analyse other DSM datasets, however few are suitable because the DSM is usually measured dichotomously and may be unsuitable for taxometric analyses. This issue is addressed further in Chapter 4 where the ability of taxometric analysis to discriminate between latent structures in binary data is systematically examined. Further analyses also do not resolve the underlying problem that response rates for at least two DSM items are relatively high in both problem and non-problem gamblers alike. Moreover, the response rates for three additional items that form the fifth DSM indicator (see Table 2) are higher in severe problem gamblers and are highly positively skewed. However, a limitation of this analysis is that sampling the general population means the base rate of problem gambling is low and cross-validation with a clinical sample may be beneficial. Also, it appears that self-report measures of the DSM (such as the one used here) may have a different factor structure to interview/clinician-based assessments (Stinchfield et al., 2005). Taxometric analyses are optimal in samples where the proportion of category to non category members is 50:50, although meaningful taxa can be identified with a base rate of 5% (as in this analysis) (Ruscio & Marcus, 2007). An alternative way of overcoming these difficulties, and one that is explored in the following chapter, is the use of latent class analysis to overcome these difficulties, and in the case of the PGSI model the categorical latent structure that this analysis and others appear to identify. Many of the issues in question are less important for latent class than taxometric analysis, and the findings of this chapter pave the way for latent class modeling of problem gambling data. Additionally, because the taxon base rate is very low, it might be the case that there are additional latent classes present in problem gambling data. Therefore latent class modeling has additional utility over and above the methodological limitations of taxometrics.

2.6 Conclusions

A taxometric analysis was carried out on two problem gambling screens from the BGPS 2010, the PGSI and items from the DSM-IV Pathological Gambling criteria, as there was strong evidence in both theoretical and empirical research in problem gambling to hypothesize the presence of a taxon. The taxometric analyses demonstrated that the construct both scales probe is categorical in nature. The findings of this analysis have implications for the future measurement of problem gambling, and the psychometric methods used on these assessments. The findings also have implications for the classification of problem gambling as a behavioural addiction, demonstrating further empirical evidence that problem gambling shares a similar latent structure to other addiction disorders.

As noted in the final paragraph of the discussion (Section 2.5), these findings necessitate additional modeling of problem gambling data to understand the taxon identified in this chapter. In the next chapter a series of latent class analyses in British gambling data are reported to further explore the nature of the differences between different subtypes of gambler. This is designed to further hone down the indicators that will be the focus of the experimental research in the latter half of the thesis.

CHAPTER 3 -

LOSS OF CONTROL AND SEVERITY IN SUBTYPES OF PROBLEM GAMBLING[1]

3.1 Overview

The previous chapter indicated the presence of a taxon within problem gambling assessment data. To understand this further, this chapter reports a series of seventeen latent class analyses of problem gambling data from each nationally representative British survey of health and gambling behaviours that contains problem gambling assessment data. This allows further examination of the consistency of the class structure of problem gambling across time and measurement. Latent class analysis also provides an additional complimentary analysis, which tests for the presence of the taxon located in the previous chapter. The results overwhelmingly supported a three-class structure over different time-points encompassing substantial changes in the British gambling market, and different measurements of problem gambling. The overall structure of these was consistent: there was a high severity class that strongly resembled the taxon previously identified in overall prevalence and membership. In addition there was a group of gamblers who endorsed minimal

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[1] Analyses from this chapter have been published as James, O'Malley & Tunney (2016) "Loss of control as a discriminating factor between different levels of problem gambling severity" in *Journal of Gambling Studies*.

problem behaviours, and an intermediate group that heavily endorsed items probing loss-chasing and preoccupation. These groups strongly differed on severity, as overall problem gambling screen scores showed minimal overlap. At the same time, the intermediate and high severity groups showed strong differences on items relating to loss of control. This suggests that problem gambling has a mixed latent structure. However, one measurement (the DSM criteria using the scoring method included in the original survey analysis) failed to produce consistent results across time over many indicators.

3.2 Introduction

One of the debates in defining disordered gambling is whether disordered gamblers form the extreme of a continuum of severity, or whether there are qualitative differences between disordered and non-disordered gamblers. Studies of disordered gambling using taxometric analysis have identified a qualitatively distinct latent class of gamblers showing very high problem severity. The findings in Chapter 2 found much strong support for a taxon comprising a small number of severe problem gamblers, complementing findings in other studies (Kincaid et al., 2013). While these identify a latent taxon, taxometric modelling can only provide some information about the latent structure of problem gambling, and further psychometric modelling reported in this Chapter complements this work. Widely supported models of gambling disorder, such as the Pathways Model (Blaszczynski & Nower, 2002), hypothesize the presence of latent classes amongst problem and pathological gamblers (Blaszczynski, 2000). Other studies utilising latent class analysis (LCA) to determine the number of discrete subtypes have demonstrated mixed findings. LCA studies of pathological gambling have consistently found three or four subtypes of gambler. Some studies have concluded that there are quantitative and qualitative differences between latent classes (Nower et al., 2013; Xian et al., 2008), and others have emphasized that the ordering of the subtypes are evidence for a dimension (Carragher & McWilliams, 2011; McBride et al., 2010). Although arguing that the evidence was stronger for a dimension of severity, these haven't excluded the possibility of qualitative differences amongst gambling subtypes (McBride et al., 2010). The latent classes were similar across studies, comprising one group displaying no/minimal symptoms, a group showing moderate probability of symptom endorsement, and a group that exceeded the DSM cutoff for Pathological Gambling. Other analyses of prominent gambling assessments support a continuum of severity (Miller, Currie, Hodgins, & Casey, 2013; Strong & Kahler, 2007), but these use analytic methods that already assume a latent dimension is being measured. To examine this further, this report describes the findings of seventeen LCAs across five different surveys of the British population over a fifteen-year period, using four assessments measuring problem and pathological gambling constructs.

Between 1999 and 2012, five nationally representative British and English surveys included assessments of disordered gambling. Three of these (the British Gambling Prevalence Survey (BGPS) (Sproston et al., 2000; Wardle et al., 2011b; Wardle et al., 2007) surveyed gambling behaviours, attitudes and GD prevalence in the UK, and was conducted by the National Centre for Social Research. The initial BGPS (Sproston et al., 2000) assessed gambling in Britain following substantial changes in the gambling market (i.e. introduction of the National Lottery, scratchcards, internet gambling), and in anticipation of liberalized gambling legislation. The BGPS 2007 provided a baseline measurement of gambling in the UK prior to the implementation of the 2005 Gambling Act, and in light of changes since 1999. The BGPS 2010 intended to assess the impact of the Gambling Act introduced in September 2007. Measures of disordered gambling were included in three other surveys, commissioned by the Health and Social Care Information Centre or the Scottish Government; the Adult Psychiatric Morbidity Survey 2007 (APMS 2007) (McManus, Meltzer, Brugha, Bebbington, & Jenkins, 2009; Wardle, D'Souza, & Farrell, 2012a), the Health Survey for England 2012 (HSE 2012) (Craig & Mindell, 2013; Wardle & Seabury, 2013), and the Scottish Health Survey (SHS 2012) (Rutherford, Hinchliffe, & Sharp, 2013a, 2013b; Wardle, 2013).

This period is one in which the potential for gambling-related harm increased following one of the two major phases of deregulation in the British gambling market, the other being the legalisation of off-course gambling in the mid to late 1960's (Orford, 2010). During this period, electronic gaming machines (or FOBT's) were legalised for use in high street bookmakers, online gambling emerged, and regulations on gambling advertisement were relaxed. It also covers a period in which the number of bookmakers increased considerably, following a decrease in the early to mid-1990's (Snowdon, 2013). Analysis of BGPS 2007 and 2010 data showed a significant increase in problem gambling between 2007 and 2010 (Wardle et al., 2011b) using a measurement derived from the DSM-IV Pathological Gambling criteria, albeit with strong caveats attached. Not least because the rate of disordered gambling is small, the observed increase prevalence amounts to less than twenty individuals.

The surveys included four assessments of disordered gambling. The first two were derived from the DSM-IV Pathological Gambling criteria (American Psychiatric Association, 2000). In four of the surveys participants were given an adaption of the ten criteria, eliciting endorsement of a four-point scale of frequency (Fisher, 1996), subsequently dichotomized as present or absent. For the first seven criteria, indicators were scored as present if endorsed at the two highest levels of frequency. For the final three items, responses other than ‘never’ was scored as present (Sproston et al., 2000). However, this differs from the logic of the DSM as individuals displaying disordered gambling behaviours might not be categorised as showing a specific symptom. Other analyses of BGPS data (McBride et al., 2010) have addressed this by re-dichotomizing the data on present/absence, present defined as a score greater than 0. In the APMS, respondents were asked to respond yes/no if they engaged in each of the ten criteria at any point over the previous 12 months.

In addition, the Problem Gambling Severity Index (PGSI) was included in four surveys (BGPS 2007/2010 and HSE/SHS 2012). The PGSI is the predominant contemporary population assessment of problem gambling (Williams et al., 2012a). It is assumed to measure a continuum of harm (Ferris & Wynne, 2001; Miller et al., 2013), but has been shown to measure latent categories (Kincaid et al., 2013). The findings from Chapter 2 show that taxon and non-taxon members separate more noticeably on items related to a loss of control. The PGSI is partly derived from the DSM-IV Pathological Gambling criteria and the South Oaks Gambling Screen (SOGS) (Stinchfield, 2002; Svetieva & Walker, 2008), a pathological gambling assessment derived from the DSM-III criteria (Lesieur & Blume, 1987), and administered in the BGPS 1999. The once popular SOGS has declined in use because it has been found to produce inflated pathological gambling estimates (Sproston et al., 2000; Stinchfield, 2002). The questionnaire content, focusing on the financial consequences of gambling, has been criticised as not comprehensively measuring a pathological gambling model (Stinchfield, 2002). However, the SOGS is still frequently used as a screen in experimental research. While it has been argued that these assessments might converge on the same construct (Svetieva & Walker, 2008), this has not been directly tested. The PGSI and SOGS have not previously been analysed using LCA.

The aims of this study are fourfold. First, LCA's of PGSI and DSM-IV data are warranted as both measure latent categories and might measure different constructs; the analyses contained in Chapter 2 and other studies (Kincaid et al., 2013; Wardle et al., 2011b) identify considerable differences in responding on these screens, even to items with similar or identical content. Second, this report aims to establish whether the latent structure of gambling disorder is consistent across time, as availability and accessibility are key components of many disordered gambling theories (Blaszczynski & Nower, 2002). Also, LCAs comparing different DSM-IV assessments are useful to test whether screens that have elicited indicators in a different manner to the DSM retain a similar structure. Moreover, many of these assessments subtype gamblers (SOGS/PGSI), an approach taken by the DSM-5, or researchers often subtype sub-clinical gamblers (DSM-IV), and it is of interest to assess the validity of these distinctions.

3.3 Method

3.3.a Sample

The five surveys sampled 48,777 respondents. However, respondents were excluded if data was missing, or did not complete an assessment as they were under 16 or hadn't gambled in the previous year, leaving 27,219 participants (see Table 8 for full details about the sample). The anonymised survey data for these analyses was downloaded from the UK Data Archive (National Centre for Social Research, 2008, 2010, 2011; National Centre for Social Research & University College London. Department of Epidemiology and Public Health, 2014; Scottish Centre for Social Research and NatCen Social Research & Survey Research Centre, 2015). Interviewers employed by NatCen collected the data for each survey. The study lead researchers, prior to data collection, briefed the interviewers. They were given training on the questionnaire content, and instructed on the administration of the project and fieldwork protocol (Sproston, Errens & Orford, 2000; Wardle et al., 2011). After the sampling was carried out (see below), selected households were sent an advance letter informing them about the survey, and that they would be interviewed face to face for data collection (for the 2010 iteration the survey was administrated with computer assistance).

The BGPS 1999 (Sproston et al., 2000) was a nationally representative survey of the British general population aged 16 or older. The survey sampled

7,680 respondents from a random sample of 7,000 UK postcodes (response rate = 65%). The survey found that 72% of the sample had gambled in the previous year. 5,289 respondents, 95% of past-year gamblers, fully completed at least one pathological gambling assessment (DSM-IV ordinal response, SOGS).

The BGPS 2007 (Wardle et al., 2007) sampled 9,003 respondents from a stratified sample of 10,114 addresses taken from the UK Postcode Address File, with the sample stratified by Government Office Region, socio-economic status and ethnicity. The response rate was 52%, and 68.4% of the population gambled in the previous year. In total 5,635 respondents, 91.4% of past-year gamblers, fully completed a problem (PGSI) or pathological (DSM-IV ordinal) gambling assessment.

The APMS 2007 (McManus et al., 2009; Wardle et al., 2012a) was the third in a series of surveys investigating psychiatric disorders, conducted by NatCen in collaboration with the University of Leicester, on behalf of HSCIC. This survey sampled 7,403 respondents from a representative English sample (response rate of 57%). Households were randomly selected from a stratified sample of English postcodes. One person was randomly selected from each household to complete the survey. The prevalence of past year gambling was 65.9%, and a total of 3,568 respondents (73% of gamblers) fully completed the DSM-IV Pathological Gambling criteria based (yes/no) assessment included in this survey.

The BGPS 2010 (Wardle et al., 2011b) was a nationally representative sample of British households, conducted by NatCen on behalf of the Gambling

Commission. A total of 7,756 respondents completed the survey, with households being randomly sampled from a stratified sample (stratified by the same variables as the BGPS 2007) of 391 postcode sectors. The response rate was 47%, 73% gambled over the previous year, and 5,706 respondents fully completed a problem (PGSI) or pathological (DSM-IV ordinal) gambling assessment.

A module of gambling and PG questions was included in the HSE (Craig & Mindell, 2013; Wardle & Seabury, 2013) and the SHS (Rutherford et al., 2013a; Wardle, 2013) 2012. This data was drawn from a combined and reweighted sample based on a secondary analysis conducted by NatCen (Wardle et al., 2014). In total 16,935 respondents (10,333 English, 6,602 Scottish) completed the health surveys. In total 13,106 were asked about their recent gambling behaviour (8,291 England, 4,815 Scotland). 65% had gambled in the previous 12 months. Of those, 7,021 (4,290 England, 2,731 Scotland) fully completed a problem (PGSI) or pathological (DSM-IV ordinal) gambling assessment.

Table 8

Descriptive statistics for each of the problem gambling assessments, from each sample (weighted).

Sample	N	% > 0 on screen	% lower PG threshold	% higher PG threshold	Cronbach's α
BGPS 1999	**7,680 (5,543 – 72%)**				
DSM – BGPS	5,253	4.80%	0.78%	0.38%	0.77
DSM – > 1	5,253	21.05%	3.24%	1.29%	0.72
DSM – Polytomous	5,253	21.05%	N/A	N/A	0.78
SOGS	5,010	13.25%	13.25%	1.22%	0.79
BGPS 2007	**9,003 (6,085 – 67.58%)**				
DSM – BGPS	5,412	7.96%	0.92%	0.46%	0.71
DSM – > 1	5,412	22.12%	4.03%	1.33%	0.72
DSM – Polytomous	5,412	22.12%	N/A	N/A	0.77
PGSI	5,486	10.63%	2.97%	0.80%	0.9
APMS 2007	**7,393 (4,826 –65.76%)**				
DSM – Yes/No	3,628	5.79%	1.19%	0.55%	0.81
BGPS 2010	**7,756 (5,665 – 73.04%)**				
DSM – BGPS	5,651	6.81%	1.26%	0.6%	0.78
DSM – > 0	5,651	25.92%	5.24%	2.04%	0.75
DSM – Polytomous	5,651	25.92%	N/A	N/A	0.81
PGSI	5,657	11.05%	3.45%	1.01%	0.9
HSE & SHS 2012	**13,106 (7,506– 64.98%)**				
DSM – BGPS	6,753	4.59%	0.59%	0.24%	0.79
DSM – > 0	6,753	19.62%	2.93%	1.14%	0.75
DSM – Polytomous	6,753	19.62%	N/A	N/A	0.81
PGSI	6,787	7.16%	2.11%	0.47%	0.91

Note for Table 8: The PGSI cutoffs reported here are 3+ and 8+ (Ferris & Wynne, 2001).The DSM cutoffs reported are 3+, based on the BGPS report and 5+, based on the cutoff for Pathological Gambling (American Psychiatric Association, 2000; Sproston et al., 2000). For the SOGS, the cutoff's are 1-4 for 'gambling problems', 5+ for 'probable pathological gambler'(Lesieur & Blume, 1987).

3.3.b Measures

Gambling disorder was assessed via four methods: two DSM-IV Pathological Gambling based screens, PGSI and SOGS. The DSM measure included in the BGPS elicited each criterion on a 4-point scale of frequency. Latent class analyses were on this data in three formats (ordinal data, dichotomised using BGPS approach, dichotomised based on present/absent). The assessments are reported in full in the Appendix of the thesis.

All five surveys included a measure based on the DSM-IV Pathological Gambling criteria, which assesses the presence of ten symptoms, classified as present/absent based on past year prevalence. Respondents endorsing five or more symptoms were classified as a pathological gambler. The DSM-5 (American Psychiatric Association, 2013) uses a cutoff of four for Gambling Disorder. The BGPS reports use a cutoff of three to measure sub-clinical PG (Orford et al., 2010). For four of the surveys (BGPS series, HSE/SHS 2012), a questionnaire designed by Fisher (1996), and validated prior to the administration of the BGPS 1999 (Sproston et al., 2000) was used, with items probing each criteria elicited on a four point scale of frequency. In the APMS 2007, respondents were asked yes/no if they engaged in the behaviour covered by each criteria.

The PGSI (Ferris & Wynne, 2001) is a nine-item assessment of problem gambling, designed to measure a continuum of gambling harm, elicited on a four-point scale of past-year frequency. The PGSI was administered in the BGPS 2007, 2010 and HSE/SHS 2012 surveys. The PGSI is a comparatively superior assessment of problem gambling (McMillen & Wenzel, 2006). The PGSI discriminates four levels of problem gambling severity; non problem gambler (0), low risk problem gambler (1-2), moderate risk problem gambler (3-7) and problem gambler (8+). However, the validity of the intermediate interpretive categories used in the measure has been questioned (Currie et al., 2013), and the appropriate cutoff score to determine which individuals are of interest (Walker & Blaszczynski, 2011). Several items in the PGSI are derived from the DSM-IV Pathological Gambling criteria or the SOGS.

The SOGS is a 16-item questionnaire derived from the DSM-III Pathological Gambling criteria (Stinchfield, 2002). SOGS scores can range from 0 to 20[2], probing numerous problem and pathological gambling behaviours, including loss-chasing, guilt from gambling, lying to, receiving criticism from, and arguing with people close to the respondent about their gambling. Half of the SOGS items pertain to borrowing money, selling items or taking loans/credit out to fund gambling. A score of 0 is classified as non-pathological gambling, between 1-4 as having some problems with gambling, and 5 or more as a probable pathological gambler. The SOGS was adapted for the BGPS 1999 to measure past year, rather than lifetime, pathological gambling (Sproston et al., 2000).

3.3.c Analytic Procedure

LCA was conducted on each disordered gambling screen from each survey, on each case where a completed assessment was present. The indicators included

[2] Item 16 has 11 sub-items. Items 1, 2, 3, 12, 16j and 16k aren't counted towards the SOGS score.

for each analysis were the individual questions from each screen. The analysis was conducted using MPlus 6.1.3 (Muthén & Muthén, 1998-2011). One through six-class models were compared in each analysis. LCAs were adjusted for survey weight (which differed depending on the sample[3]), clustering and stratification[4]. Interpretation of competing latent class models was conducted using multiple indices of fit. A number of different indices of fit can be used to determine which latent class model is appropriate, as there is no objective method for determining a latent class model to adopt. These include the Akaike Information Criterion (AIC) (Akaike, 1974), Bayesian Information Criterion (BIC) (Schwarz, 1978), Sample-Size Adjusted BIC (SSABIC) (Sclove, 1987), and adjusted likelihood ratio tests (LRT) (Lo, Mendell, & Rubin, 2001). Lower information criteria indicate superior model fit. LRT's test the likelihood that a *k*-class model is a better fit of the data compared to a *k-1* class model, and reports a *p* value. If the *p* value is not significant, it is not possible to reject the *k-1* class model (Muthén & Muthén, 1998-2011). Greatest weight was given to BIC, as previous studies have indicated its effectiveness at discriminating between latent class models (Nylund, Asparouhov, & Muthén, 2007). Some methods appear to be more efficacious than others, but these appear to interact with a number of factors, with sample size for example an important consideration in determining whether to place greater weight on BIC or AIC. A number of studies have supported the use of a bootstrap variant of the likelihood ratio test (Nylund et al., 2007), but this test

[3] Please see supplementary information for details on sampling.

[4] The BGPS 1999 data was weighted and adjusted for clustering; no stratification variable was included in the dataset.

cannot be calculated for latent class models that account for complex sampling methods, such as the latent class models described in this report. The proportion of cases assigned to each latent class was determined based on the estimated model. In addition, the probability of endorsement for each level of each indicator for each latent class was calculated, and the posterior probability that each case assigned to a specified latent class.

Local independence was initially tested by assessing the chi-square for the overall model. It has previously been suggested that this is the most appropriate test for violations of local independence (Asparouhov, 2015). A significant result indicates residual dependence between indicators at the level of the latent class or classes. In these situations looking at the bivariate residuals is advised to direct where local independence should be relaxed.

3.4 Results

The results section addresses a number of potential considerations. The first section gives an overview of the output of the LCAs, identifying the pattern of the similarities across analyses, and the profile of gamblers that fall into the different latent classes. The following section covers several indices of fit that may be used to justify selecting a specific latent class model. After this a high level overview of the level of consistency between different LCAs is reported. In light of these findings, consideration is then given to differences in demographic profiles and gambling behaviours, as research has tended to identify that the most severe disordered gamblers form different demographic profiles and engage in a range of addictive behaviours such as drinking and smoking. This is also informative to the literature concerning whether specific types of gambling game are linked with problematic behaviours. Finally more detailed results are provided for each of the measurements used in the surveys covered in this analysis. For the DSM-IV based measure used in the gambling prevalence and health surveys, this contrasts between different methods of elicitation identified by the study authors and in the literature.

Fifteen of seventeen LCAs supported a three-class model. A summary table of 2-4 class models is reported in Table 9, which reports the full details of key indices of fit for the estimated models. The tables reporting all of the indices of fit collected are reported in Appendix 2. The three classes were consistent across measures: one class comprising 90-95% of the sample showed minimal probability of endorsing any disordered gambling indicator, a second had a high probability of endorsing preoccupation and loss-chasing indicators, and a third had a high probability of endorsing many indicators. Response probabilities, standard errors for these, and the proportion of individuals assigned to each class for the estimated models are reported in the aforementioned sections of this chapter. These indicated that differences between the second and third classes were primarily on items related to loss of control, as shown in the Figures included herein. These showed the largest separation between the two groups. The highest severity items (committing crimes, risked important opportunity, asked others for help with gambling financial difficulties) showed large differences but only had a moderate probability of endorsement by the third class. Means are reported for ordinal measures using most likely latent class membership in Appendix 2. An examination of the score distributions for each class based on most likely class membership indicated very little overlap in scores, suggesting that problem gambling falls along a dimension of severity. These are reported in tables throughout the chapter. AIC indices indicated a minimum of six latent classes on each LCA, although this appears to be because AIC over fits latent class models with many cases (Nylund et al., 2007). Classification accuracy was generally very high across measures, and did not appear to systematically differ between classes. In addition, information about demographic and game prevalence information for each latent class is reported in Tables 10-15.

Table 9

Summary indices from latent class analyses. Please note for one analysis (DSM-IV >0 scoring, BGPS 1999), one index also showed that a five class model was superior to a four class (LRT $p < .05$).

	BIC	LMR-LRT *p*		BIC	LMR-LRT *p*
DSM-IV – BGPS Scoring			DSM-IV – Polytomous		
BGPS 1999			BGPS 1999		
2-class	3879.849	<.0001	*2-class*	14237.622	<.0001
3-class	**3871.617**	.0104	*3-class*	**14056.334**	**.0038**
4-class	3915.116	**.0327**	*4-class*	14204.715	.7766
BGPS 2007			BGPS 2007		
2-class	5295.76	**<.0001**	*2-class*	16724.245	<.0001
3-class	**5293.249**	0.1013	*3-class*	**16363.372**	**.0278**
4-class	5351.032	0.2883	*4-class*	16434.601	.762
BGPS 2010			BGPS 2010		
2-class	5845.435	**<.0001**	*2-class*	19600.095	<.0001
3-class	**5819.839**	0.1708	*3-class*	**19124.905**	**.0026**
4-class	5863.602	0.5028	*4-class*	19182.884	.7866
SHS/HSE 2012			SHS/HSE 2012		
2-class	4652.381	**<.0001**	*2-class*	17245.979	**<.001**
3-class	**4642.852**	0.2627	*3-class*	**16880.958**	0.7259
4-class	4698.9	0.502	*4-class*	16918.966	0.7699
DSM-IV – >0 Scoring			PGSI		
BGPS 1999			BGPS 2007		
2-class	11592.606	<.0001	*2-class*	9977.427	**.0032**
3-class	**11328.402**	**<.0001**	*3-class*	**9678.144**	.1543
4-class	11344.377	0.1449	*4-class*	9683.177	.828
BGPS 2007			BGPS 2010		
2-class	13287.834	<.0001	*2-class*	11339.296	<.0001
3-class	**12953.825**	**.0004**	*3-class*	10988.334	**.0222**
4-class	12971.168	.087	*4-class*	**10986.805**	.7769
BGPS 2010			SHS/HSE 2012		
2-class	15560.675	<.0001	*2-class*	8998.434	**<.0001**
3-class	**15086.033**	**.0007**	*3-class*	**8837.362**	.0662
4-class	15095.191	.1042	*4-class*	8916.199	.2875
SHS/HSE 2012					
2-class	14217.918	.0109			
3-class	13759.639	**.0296**			
4-class	**13692.114**	.0776			
SOGS			DSM-IV – Y/N		
BGPS 1999			APMS 2007		
2-class	10819.723	<.0001	*2-class*	3412.344	<.0001
3-class	**10728.964**	**.0031**	*3-class*	**3317.343**	**.0013**
4-class	10805.677	.4121	*4-class*	3369.449	.1862

3.4.a Indices of Fit

Results from other indices of fit are reported below. An examination of AICs revealed that these tended to support a four class model for the DSM LCAs where individuals were dichotomised using the BGPS scoring scheme. Although similar to BIC and other indices, a four-class model was rejected as the third class was small (around thirty members) to begin with and the additional class further split this class. For the other LCAs (bar one exception) AIC supported six or more classes. These additional classes tended to split the second and third classes into smaller groups, leaving a class of a few hundred individuals (who overwhelmingly endorsed the preoccupation and loss-chasing items) and small classes with 30-40 members in each. In some cases this was readily interpretable. For example, a number of the >0 DSM LCAs were readily interpretable. However in the majority of LCAs this was not the case; six-class solutions tended to produce a number of very small latent classes (< 10 cases), and it appeared that these were largely spurious.

Classification accuracy was very high across the models, and was similar regardless of the number of classes specified. The entropy of the models changed very little between analyses, with a classification accuracy of approximately 0.9. Classification accuracy for the first class was slightly higher (around 0.95), and very similar for the second and third (around 0.9). This difference is not surprising given that the first class in each LCA contained several thousand individuals that did not endorse any indicator.

3.4.b Consistence over time

It must be noted there are important differences in sampling and elicitation between surveys. However, it is clear that bar one exception, LCAs of the same measure show notable consistency between survey years. Although this cannot be definitively tested, and this should be taken with the caveat that these considerations are ultimately somewhat subjective, the estimated latent class models for assessments used on more than one occasion over the five surveys show notable similarity. Even in the latent classes with smaller sample sizes, these show the same pattern of responding. The one exception to this is the ordinal DSM-IV measure using the BGPS cutting score, which had a very small, inconsistent third class. For other DSM and PGSI LCAs (Figs 6, 7 & 8), these indicate similar latent class models across the different surveys.

3.4.c Demographic and gambling behaviours

In Tables 10 through 15 descriptive statistics concerning demographic information and past-year prevalence on gambling between the latent classes are reported. Comparisons between years are not considered because of market changes and different survey and item elicitation. Overall there are a number of cases (e.g. online gambling/betting, age of first gamble, scratchcard and slot machine play) where considerable differences between the first and second/third classes were observed, but not between the second and third classes. There were also a number of variables (e.g. smoking prevalence, wager amount/monthly spend, FOBT use), which graded alongside the severity of the classes. These paint a picture similar to the LCA indicators; some imply a continuum of severity, others show more marked differences between the second and third classes. There were some differences in gambling behaviour between assessments; in particular the PGSI and SOGS demonstrate higher prevalence of many gambling behaviours. This is likely because fewer individuals endorsed any of the indicators on these measures relative to the ordinal DSM measure. However, a consistent pattern between classes persists.

Table 10

Demographic and gambling behaviour variables for each latent class for the BGPS 1999 DSM >0 LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D*)	Class 3 (*S.D.*)
Age	45.23 (17.49)	36.4 (15.07)	30.7 (12.87)
Number of gambling activities (past year)	2.12 (1.36)	3.72 (1.99)	4.71 (2.75)
Past week spend (£):			
National Lottery	1.77 (2.7)	2.71 (3.99)	3.92 (7.6)
Other lottery	0.114 (0.64)	0.456 (1.82)	1.026 (4.87)
Pools	0.192 (0.972)	0.994 (4.76)	0.682 (1.65)
Bingo	0.287 (1.91)	1.278 (5.09)	1.19 (7.14)
Number of gambling activities (past week)	1.1 (0.97)	2.27 (1.69)	2.8 (1.84)
Attitudes toward gambling score	15.26 (6.85)	21.32 (5.67)	21.45 (5.5)
Sex (REF: Male)	0.503	0.712	0.733
Marital Status:			
Married	0.662	0.459	0.34
Separated/Divorced	0.073	0.108	0.034
Single	0.18	0.376	0.605
Widowed	0.07	0.034	0
Proportion of class members played:			
National Lottery	0.906	0.904	0.835
Other Lottery	0.104	0.212	0.344
Scratchcards	0.291	0.545	0.571
Pools	0.117	0.218	0.222
Bingo	0.099	0.14	0.27
Slots	0.178	0.442	0.659
Private Betting	0.147	0.36	0.429
Horse Racing	0.17	0.4	0.487
Dog Racing	0.045	0.2	0.27
Other Betting	0.03	0.178	0.359
Casino Games	0.03	0.109	0.268
Other Gambling	0.002	0.011	0

Table 11

Demographic and gambling behaviour variables for each latent class for the BGPS 1999 SOGS LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D*)	Class 3 (*S.D.*)
Age	44.84 (17.48)	35.69 (15.05)	32.98 (13.51)
Number of gambling activities (past year)	2.15 (1.4)	4.1 (1.97)	4.84 (2.19)
Past week spend (£):			
National Lottery	1.79 (2.72)	3.13 (6.16)	4.12 (6.72)
Other lottery	0.12 (0.71)	0.73 (3.64)	0.578 (1.75)
Pools	0.19 (0.97)	1.22 (5.68)	1.3 (3.49)
Bingo	0.3 (1.96)	1.57 (6.66)	1.66 (5.73)
Number of gambling activities (past week)	1.13 (1.00)	2.24 (1.81)	3.35 (1.99)
Attitudes toward gambling score	15.48 (6.83)	21.52 (5.07)	21.57 (6)
Sex (REF: Male)	0.506	0.757	0.72
Marital Status:			
Married	0.654	0.457	0.405
Separated/Divorced	0.074	0.066	0.132
Single	0.188	0.42	0.442
Widowed	0.069	0.031	0.021
Proportion of class members played:			
National Lottery	0.906	0.888	0.881
Other Lottery	0.106	0.258	0.221
Scratchcards	0.299	0.569	0.507
Pools	0.118	0.233	0.27
Bingo	0.099	0.166	0.302
Slots	0.184	0.533	0.656
Private Betting	0.15	0.446	0.557
Horse Racing	0.172	0.479	0.537
Dog Racing	0.049	0.211	0.285
Other Betting	0.034	0.161	0.36
Casino Games	0.032	0.15	0.261
Other Gambling	0.002	0.006	0

Table 12

Differences in demographics and gambling engagement between latent class for the BGPS 2007 DSM >0 cutoff LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D*)	Class 3 (*S.D.*)
Age	47.02 (17.33)	36.63 (15.47)	36.63 (12.6)
Number of gambling activities (past year)	2.32 (1.6)	4.63 (2.71)	5.99 (3.69)
Most units drank in one day (past week)	5.84 (6.42)	9.2 (8.25)	16.25 (17.18)
General health	1.91 (0.821)	2.05 (0.839)	2.21 (0.857)
Age of first gamble	21.02 (10.47)	17.45 (5.73)	17.73 (6.72)
Number of gambling activities (past week)	0.88 (0.9)	1.74 (1.8)	2.87 (2.47)
Sex (REF: Male)	0.487	0.702	0.783
Marital Status:			
Married	0.574	0.436	0.278
Separated/Divorced	0.081	0.009	0.115
Single	0.249	0.422	0.542
Widowed	0.067	0.026	0.005
Smoking status (REF: Y)	0.254	0.429	0.526
Drinking status (REF: Y)	0.783	0.84	0.7
Proportion of class members played:			
National Lottery	0.872	0.818	0.916
Scratchcards	0.274	0.538	0.539
Other Lottery	0.169	0.225	0.277
Pools	0.043	0.118	0.089
Bingo	0.101	0.176	0.355
Slot Machines	0.186	0.521	0.634
FOBT in bookmaker	0.023	0.161	0.421
Casino games	0.046	0.19	0.275
Online casino games	0.023	0.213	0.261
Online betting	0.038	0.179	0.227
Betting exchange	0.009	0.072	0.103
Horse racing in person	0.245	0.451	0.54
Dog racing in person	0.063	0.193	0.402
Other betting at bookmaker	0.064	0.26	0.318
Spread betting	0.005	0.055	0.09
Private betting	0.133	0.394	0.425
Other gambling	0.006	0.019	0.032

Table 13

Demographic and gambling behaviour variables for each latent class for the BGPS 2010 DSM > 0 LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D.*)	Class 3 (*S.D.*)
Age	47.6 (18.14)	36.18 (15.1)	34.24 (13.24)
Number of gambling activities (past year)	2.4 (1.7)	4.58 (2.92)	6.21 (3.09)
Most units drank in one day (past week frame)	5.4 (6.79)	7.07 (7.73)	10.04 (14.96)
General Health	1.96 (0.88)	1.94 (0.84)	2.09 (0.98)
Age of first gamble	19.33 (10.88)	16.74 (6.264)	17.71 (6.4)
Estimated monthly gambling spend	15.86 (42.35)	86.77 (215.69)	211.958 (444.66)
Sex (REF: Male)	0.483	0.667	0.81
Marital Status:			
Married	0.641	0.511	0.461
Separated/Divorced	0.085	0.065	0.077
Single	0.209	0.401	0.455
Widowed	0.065	0.022	0.007
Smoker (REF: Yes)	0.255	0.401	0.528
Drinker (REF: Yes)	0.78	0.782	0.778
Proportion played:			
National Lottery	0.805	0.796	0.778
Scratchcard	0.309	0.54	0.616
Other Lottery	0.344	0.32	0.403
Bingo (Online + Land)	0.106	0.244	0.218
Pools	0.046	0.16	0.28
Slot Machines	0.144	0.423	0.487
EGM at bookmaker	0.032	0.251	0.414
Poker	0.016	0.101	0.217
Casino games (Online + Land)	0.049	0.253	0.384
Online fruit/slot machine/ instant win	0.022	0.172	0.205
Horse racing	0.205	0.349	0.431
Dog racing	0.048	0.141	0.281
Spread betting	0.008	0.055	0.115
Private betting	0.136	0.297	0.501
Other sports bets	0.091	0.318	0.508
Other bets	0.004	0.163	0.366
Bingo in person	0.094	0.18	0.21
Bingo online	0.017	0.091	0.041
Slots (inc FOBT prompt)	0.146	0.433	0.5
FOBT	0.028	0.212	0.332
Casino person	0.038	0.159	0.3
Casino online	0.014	0.15	0.128
Online gaming	0.044	0.287	0.321
Horse in person	0.19	0.299	0.409
Horse online	0.022	0.071	0.064
Dogs in person	0.047	0.129	0.249
Dogs online	0.001	0.022	0.041
Sports/other betting land	0.092	0.298	0.569
Other betting in person	0.007	0.052	0.075
Sports online	0.023	0.121	0.093
Sports in person	0.075	0.254	0.486
Online betting exchange	0.008	0.044	0.046
Online bookmaker	0.031	0.129	0.117
Online bookmaker + exchange	0.036	0.151	0.139
Online gaming + lottery	0.154	0.368	0.359
Online gaming	0.048	0.307	0.349

Please see note below

Table 14

Demographic and gambling behaviour variables for each latent class for the BGPS 2010 PGSI LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D.*)	Class 3 (*S.D.*)
Age	47.07 (18.14)	33.8 (14.37)	34.06 (13.00)
Number of gambling activities (past year)	2.49 (1.79)	5.54 (3.19)	6.35 (3.25)
Most units drank in one day (past week frame)	5.41 (6.72)	8.58 (9.42)	12.3 (17.7)
General Health	1.96 (0.88)	1.86 (0.78)	2.27 (0.97)
Age of first gamble	19.21 (10.68)	16.63 (6.18)	16.19 (6.16)
Estimated monthly gambling spend	18.44 (58.3)	109.72 (242.21)	288.28 (518.19)
Sex (REF: Male)	0.489	0.776	0.817
Marital Status:			
Married	0.637	0.444	0.417
Separated/Divorced	0.084	0.06	0.099
Single	0.216	0.479	0.484
Widowed	0.064	0.017	0
Smoker (REF: Yes)	0.262	0.43	0.566
Drinker (REF: Yes)	0.78	0.817	0.712
Proportion played:			
National Lottery	0.804	0.802	0.791
Scratchcard	0.321	0.549	0.636
Other Lottery	0.342	0.36	0.39
Bingo (Online + Land)	0.114	0.22	0.2
Pools	0.05	0.235	0.257
Slot Machines	0.155	0.524	0.564
EGM at bookmaker	0.039	0.362	0.505
Poker	0.018	0.197	0.137
Casino games (Online + Land)	0.058	0.327	0.388
Online fruit/slot machine/ instant win	0.029	0.192	0.27
Horse racing	0.212	0.381	0.477
Dog racing	0.052	0.186	0.307
Spread betting	0.009	0.083	0.14
Private betting	0.14	0.45	0.459
Other sports bets	0.1	0.443	0.495
Other bets	0.046	0.231	0.335
Bingo in person	0.1	0.166	0.176
Bingo online	0.021	0.081	0.064
Slots (inc FOBT prompt)	0.157	0.542	0.564
FOBT	0.033	0.322	0.378
Casino person	0.043	0.216	0.3
Casino online	0.02	0.178	0.176
Online gaming	0.056	0.301	0.399
Horse in person	0.194	0.346	0.453
Horse online	0.025	0.081	0.067
Dogs in person	0.05	0.159	0.283
Dogs online	0.002	0.035	0.036
Sports/other betting land	0.1	0.421	0.534
Other betting in person	0.009	0.007	0.085
Sports online	0.026	0.17	0.083
Sports in person	0.081	0.37	0.478
Online betting exchange	0.01	0.061	0.042
Online bookmaker	0.034	0.177	0.136
Online bookmaker + exchange	0.04	0.197	0.155
Online gaming + lottery	0.164	0.394	0.408
Online gaming	0.06	0.343	0.399

Please see note below

Note for Tables 13 and 14:

'Poker' specifically refers to poker games played for money at a league, pub, tournament or club.

'FOBT' refers to a classification (B2) of gaming machines in the United Kingdom. These are rapid play machines with a maximum stake of £100 (although must individually enter £10 notes into the machine), and a maximum payout of £500. The rate of return to player is approximately 97%. The games on these machines are often presented in the form of casino style games (e.g. roulette, poker), but with a fixed odds of success determined by the machine. These are similar to electronic gaming and poker machines elsewhere in the world.

'Online gaming' in the BGPS 2010 refers to engagement in slot machine/instant win style games, casino games, online bingo and online pools.

References to 'land' forms of gambling capture the distinction between online and 'land-based' gambling (i.e. gambling on the premises of a bookmaker, casino, racecourse etc.) in British gambling legislation.

Table 15

Demographic and gambling behaviour variables for each latent class for the HSE and SHS 2012 DSM > 0 LCA.

	Class 1 (*S.D.*)	Class 2 (*S.D*)	Class 3 (*S.D.*)
Age	46.66 (17.49)	36.02 (16.14)	39.09 (17.1)
Number of gambling activities (past year)	2.11 (1.5)	4.62 (3.38)	5.42 (4.25)
Units drank in previous week	12.86 (21.98)	17.47 (23.64)	15.89 (27.98)
Most units drank in one day (past week)	4.48 (5.86)	7.54 (9.21)	5.86 (8.99)
General health	1.93 (0.895)	1.95 (0.915)	2.12 (1.05)
GHQ Score	1.34 (2.55)	1.88 (2.88)	2.99 (3.63)
Sex (REF: Male)	0.5	0.731	0.786
Marital Status:			
Married	0.662	0.461	0.443
Separated/Divorced	0.087	0.074	0.071
Single	0.203	0.452	0.444
Widowed	0.049	0.012	0.042
Previously smoked (REF: Y)	0.592	0.614	0.629
Current smoker (REF: Y)	0.211	0.319	0.298
Current drinker (REF: Y)	0.846	0.834	0.676
Proportion of class members played:			
National Lottery	0.824	0.776	0.773
Scratchcards	0.295	0.531	0.449
Other Lottery	0.225	0.233	0.398
Pools	0.032	0.203	0.214
Bingo	0.083	0.105	0.238
Slot Machines	0.1	0.34	0.255
FOBT in bookmaker	0.028	0.303	0.32
Casino games	0.041	0.204	0.223
Poker	0.012	0.111	0.202
Online gaming	0.034	0.273	0.242
Online betting	0.067	0.269	0.311
Betting exchange	0.01	0.065	0.13
Horse racing	0.154	0.324	0.371
Dog racing	0.04	0.117	0.15
Sports betting	0.057	0.311	0.461
Other betting	0.01	0.102	0.156
Spread betting	0.004	0.053	0.111
Private betting	0.075	0.241	0.183
Other gambling	0.019	0.063	0.232

3.4.d Adapted DSM-IV Pathological Gambling Criteria (BGPS Series) – BGPS Scoring

All four LCA's indicated a three-class model (Appendix 2). However, fit indices only showed marginal differences between two and three-class models. The LRT's supported a two-class model. Plotting the responses probabilities for two and three latent-class models revealed that two-class models (Figure 4) were more consistent than three-class models (Figure 5). The third class in three-class models varied considerably between samples, on some indicators differing by more than 80%. However, in one instance there was evidence that local independence was violated; examination of the bivariate residuals suggested there was considerable residual covariance between indicators. Three-class models met this assumption. Consequently, although a three-class model was statistically a better fit of the data, the extra class did not show a consistent pattern of responding, likely due to the very low class size (n = 28, 29, 33, 10). Furthermore, none of the response probabilities for class three exceeded 0.75, suggesting these were weak indicators. This was worse for two-class models, where the highest endorsement probability (item 2) was 0.59. In addition it appeared, as discussed below, that the latent class model from this scoring method differed from other DSM based assessments analysed.

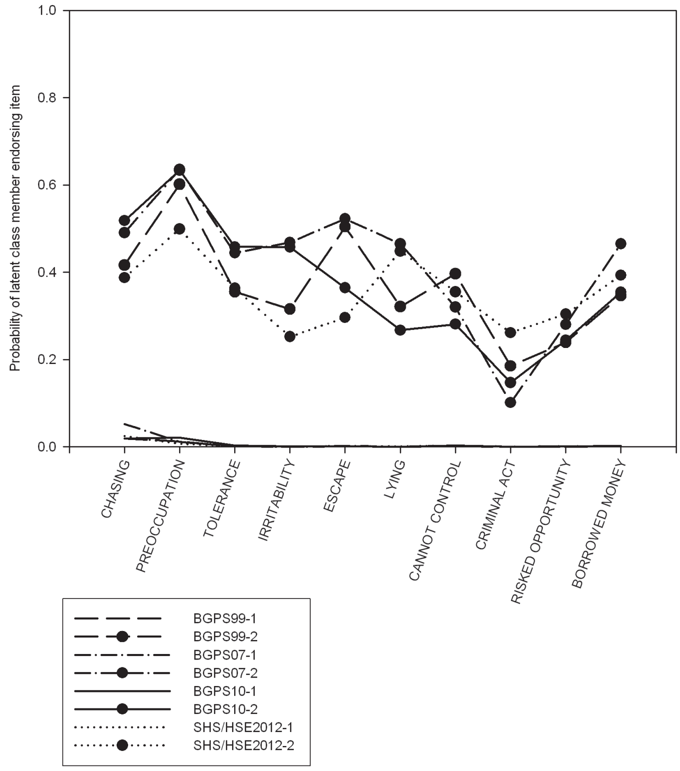

Figure 4

Plot of response probabilities for each item of the DSM-IV Pathological Gambling derived assessment, for two class solutions using the scoring method adopted in the BGPS reports (items rated from 0-3 by respondent, scored as present on items 1 – 7 if > 1, on items 8 – 10 if > 0). Latent classes are sorted by severity/group membership (largest first).

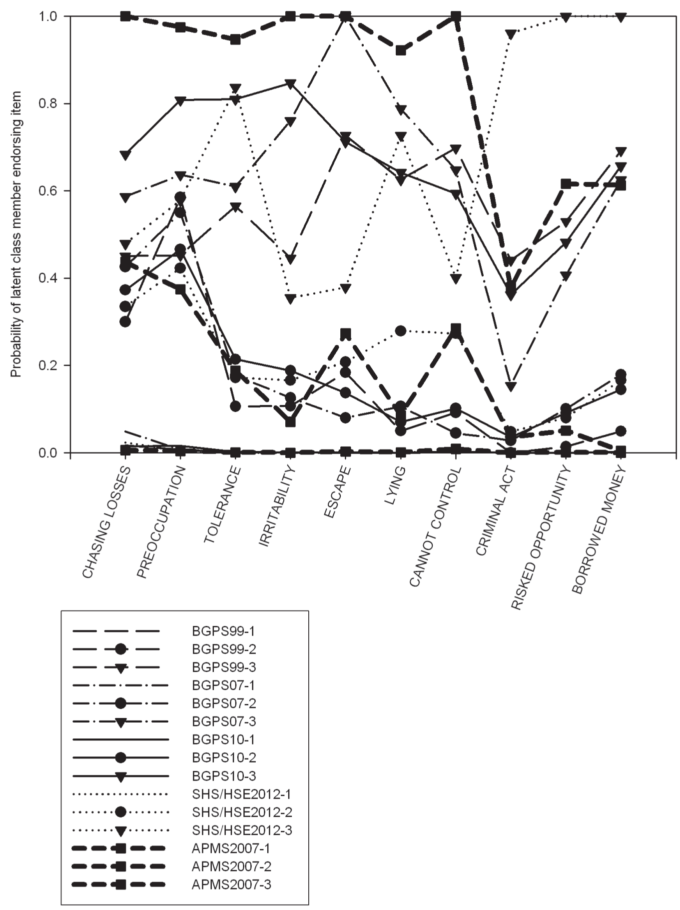

Figure 5

Plot of response probabilities for each item of the DSM-IV Pathological Gambling derived assessment, for three class solutions using the scoring method adopted in the BGPS reports (items rated from 0-3 by respondent, scored as present on items 1 – 7 if > 1, on items 8 – 10 if > 0). Latent classes are sorted by severity/group membership (largest first).

3.4.e Adapted DSM-IV Pathological Gambling Criteria (BGPS Series) – Scores > 0

BIC indices and LRTs supported a three-class solution (Table 9 and Appendix 2) in three analyses. For HSE 2012 data, indices supported a four-class solution, although LRTs supported a three-class model. This fourth class consisted of 10 cases in which respondents endorsed eight or more indicators. Comparisons with other cutoffs indicated this group comprised severe problem gamblers and gamblers likely to endorse many problem behaviours at low frequency.

Plots of the response probabilities (Figure 6) and the distribution of scores between latent classes (Appendix 2) demonstrated a high level of consistency between samples. The recreational gambler subtype comprised almost all of the respondents who endorsed zero or one criteria, the intermediate group between two and four (or two and five in the BGPS 1999 analysis), and the third scores above 5 or 6. Recreational gamblers, where an indicator was likely to be endorsed, this was overwhelmingly the loss-chasing and preoccupation items. Endorsement rates for these criteria were similar for the intermediate and high severity groups. The intermediate groups had a high probability of endorsing the preoccupation and loss-chasing items, and a moderate to low probability of endorsing needing to gamble with more money to get the same feeling of excitement. Items measuring loss of control showed the largest differences between the two latent classes, with 80% or more of the most severe gamblers endorsing these items, versus 15% or so of intermediate gamblers. The final three items, probing consequences of pathological gambling, showed strong differences between the second and third classes, but endorsement probabilities were much lower; these showed fairly low endorsement by the highest severity group, and so while sufficient to discriminate between the two groups, this was not a necessary indicator of group membership in the manner the loss of control items appeared to be.

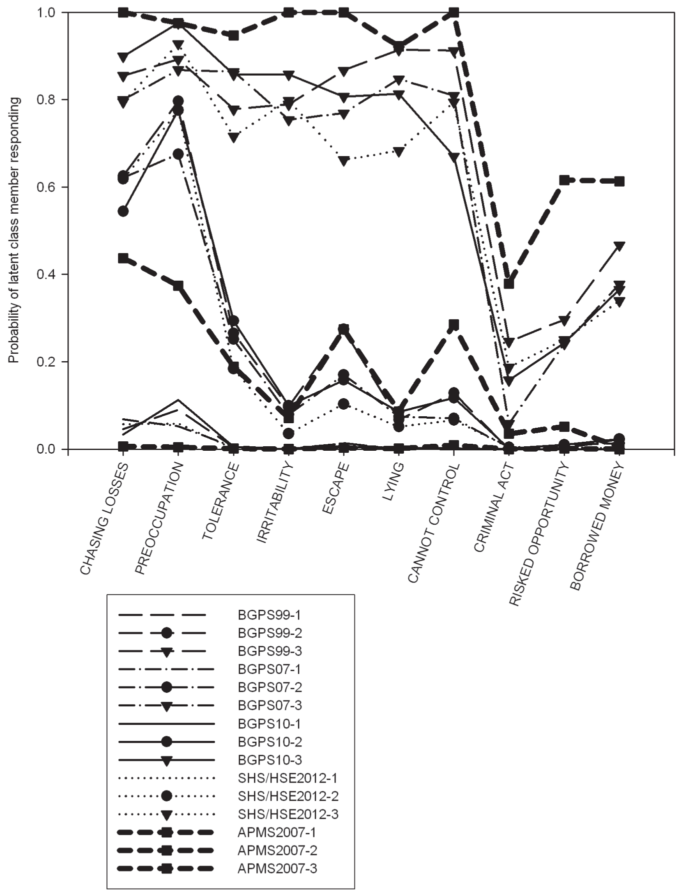

Figure 6

Plot of response probabilities for each item of the DSM-IV Pathological Gambling derived assessment for three class solutions, with symptoms scored as present if a response other than ‘Never’ (or 0) was given. Latent classes are sorted by severity/group membership (largest first).

3.4.f Adapted DSM-IV Pathological Gambling Criteria (BGPS Series) - Polytomous

BIC indices supported a three-class model. Three of four LRT's supported a three-class model as well. The LRT of the HSE 2012 data supported a two-class model. Comparing the response probabilities for each latent class revealed that the latent class models were very similar to those with the >0 cutoff used. Examination of the group means (Figure 7) again revealed a very similar pattern to the response probabilities for the > 0 cutoff (Figure 6).

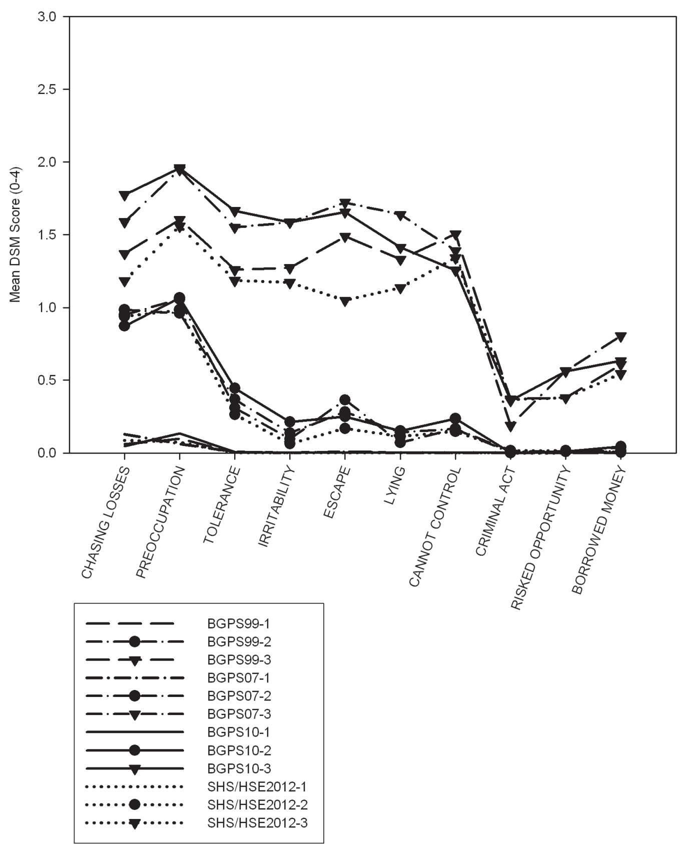

Figure 7

Plot of response probabilities for each item of the DSM-IV Pathological Gambling derived assessment items, three latent class solutions. Latent classes are sorted by severity/group membership (largest first).

3.4.g Adapted DSM-IV Pathological Gambling Criteria (APMS 2007) - Yes/No

LCA supported a three-class model. The proportion the sample assigned to each latent class resembled the BGPS cutoff in class size. This revealed a group of recreational gamblers with minimal probability of endorsing any criterion. The second group showed low endorsement of multiple PG symptoms and higher probability of endorsing preoccupation and loss-chasing indicators. The third group had a high probability of endorsing every indicator with the exception of committing criminal acts to fund gambling. Comparing this LCA with other DSM measures (Figures 5 and 6) revealed that for the first seven criteria the data strongly resembled the three-class model found with the >1 cutoff, but for the remaining items, the pattern of symptom endorsement was more similar to the BGPS cutoffs. The intermediate class was consistent with both the >1 and BGPS cutoffs, as both demonstrated similar response patterns.

3.4.h PGSI Analyses

Two analyses of the PGSI data supported a three-class model and the third marginally supported a four-class model. All of the LRT's supported a three-class model. The first class had minimal probability of endorsing any indicator. The second class had a high probability of endorsing two items (1 – betting more than one could afford to lose, and 3 – loss-chasing), and a moderate probability (between 0.2 and 0.4) of endorsing three of the indicators (2 – needing to gamble with more money to get same feeling of excitement, 7 –

others criticizing gambling, and 9 – felt guilty about gambling). The third had a high probability (>0.7) for all items. However, overall severity remained moderate; item means were between 1.4 and 1.6. In terms of responding to the PGSI, this meant cases within this class gave a response between ‘sometimes’ and ‘most of the time’. Between the second and third classes, high severity items identified by IRT analyses (items 4,6,8) (Miller et al., 2013), and three of the four items measuring loss of control (items 2,3,4,8) (Kincaid et al., 2013) showed considerable separation between classes (> 0.8 for class 3, < 0.2 for class 2). However, as these items overlap, it is difficult to judge between loss of control or severity explanations between latent classes. Item scores were consistent between classes (Figure 8), and the distribution of PGSI scores (see Appendix 2) were similar, indicating that the third class strongly resembled the PGSI category of problem gambler (8+).

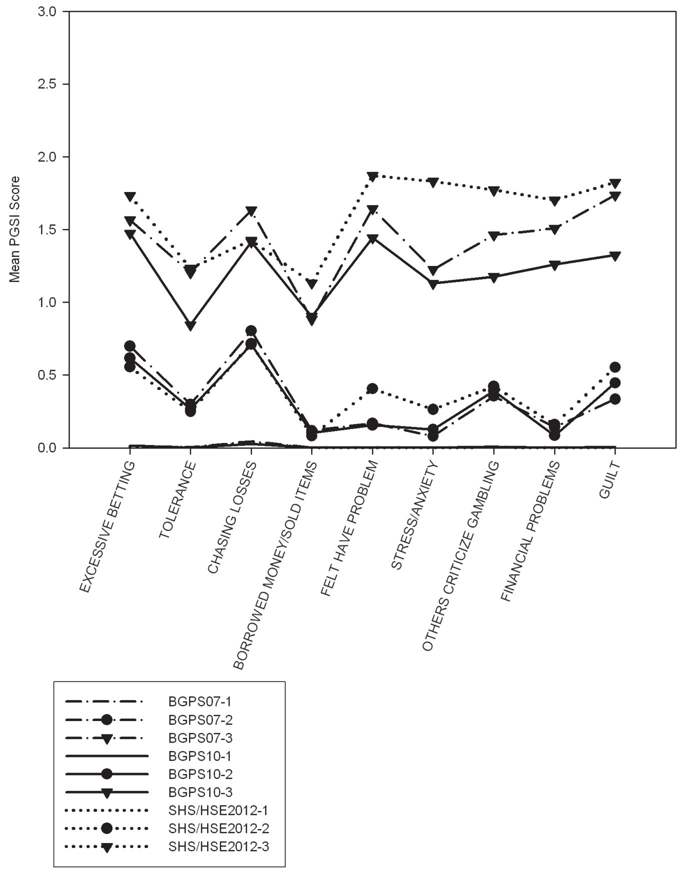

Figure 8

Plot of mean PGSI scores for each item of the PGSI, between latent classes across the three survey years the PGSI was administered.

3.4.i SOGS Analysis

The SOGS LCA supported a three-class model (Appendix 2). The first class had a minimal probability of endorsing any of the indicators. The second class showed moderate (between 0.4 – 0.5) probability of endorsing two items: excessive betting and criticism about gambling not dissimilar to the second class in the PGSI LCA. This group had a lower (<30%) probability of endorsing items querying borrowing household funds to gamble, feeling they might have a problem with gambling, loss-chasing and lying about winning. Comparing most likely class membership against SOGS scores closely resembled the interpretative categories of the SOGS (Appendix 2). However, there were very few strong indicators of latent class membership in the SOGS; item endorsement probability did not exceed 0.8 for any item across the three classes Appendix 2), and the probability of endorsement exceeded 0.7 for only three: excessive gambling, guilt and other criticizing one's gambling.

3.5 Discussion

Analyses of disordered gambling from five nationally representative surveys revealed evidence for a three-class latent structure. The latent structure of these analyses was similar between assessments. The subtypes showed minimal overlap on assessment score. but indicators related to loss of control displayed the greatest differences between the medium and high severity latent classes. Furthermore, with one exception, analyses on the same assessment across time showed notable consistency. These findings are consistent with previous LCAs of DSM data, and extend to two frequent used assessments. Despite these assessments ostensibly measuring different conceptualizations of disordered gambling, they appear to converge on a common structure.

The analysis identified a combination of quantitative and qualitative differences between latent classes. The analyses indicated that the latent classes were ordered along a dimension of severity, as the scores of latent class members showed very little overlap between one another. However, the greatest differences were observed on items relating to loss of control, a central construct in addiction, where there were typically high probabilities of endorsement (c. 80%) for the highest severity class, and low probabilities of endorsement (c. 15%) for the intermediate severity group (Figure 6). This is potentially indicative of a difference in the type of symptoms different groups of gamblers endorsed rather than just the frequency, consistent with a qualitative distinction groups and is convergent with other latent structure analyses of disordered gambling data that identified categorical differences. This was the case with DSM and the SOGS items (where strong indicators were identified), but for PGSI loss of control and 'difficult' (i.e. high severity) items overlapped, meaning it wasn't possible to discriminate between these competing explanations. It remains difficult to characterise disordered gamblers at the extreme end of a continuum, given the overall indicator distribution. Only in one instance did more than a quarter of individuals endorse at least one item. Even then, the indicators were very substantially skewed, as the descriptive statistics in Chapter 2 previously demonstrated. If it can be plausibly claimed that problem gamblers form the extreme of a continuum, then a more sensitive measurement would be highly beneficial.

The third latent class of gamblers closely resembled the taxon previously observed in taxometric analyses of disordered gambling assessments. Taxometric studies, including the analysis reported in Chapter 2, identified a qualitatively distinct category of very high severity gamblers on DSM and PGSI measurements (Kincaid et al., 2013). The present results converge with these findings. It should be noted that response probabilities for these items revealed that the largest differences were on items related to loss of control, not the highest severity items. In some cases it does appear that the boundary where this third class emerges is very slightly lower severity than the one identified by taxometric analysis. The LCA's found that the highest severity category used in the PGSI (8+) was closely calibrated to the lowest score at which cases were assigned to the third latent class. None of the analyses indicated that the original (1-2/3-7) or modified (1-3/4-7) intermediate sub-categories formed distinct latent classes. Previous studies failed to find differences for the original categories (Currie et al., 2013). However, this might be due to the low number of non-zero responses on the PGSI. It might be useful to combine these data to test whether the absence of a severe problem, and the intermediate, categories might be detected with a larger dataset.

Previous taxonomies of disordered gambling have identified the presence of three categories of gamblers across the general population: Shaffer, Hall, and Vander Bilt (1999) for instance outline a standardisation of terminology for, identifying three levels of disordered gambling. Level one gamblers consist of recreational or non-gamblers, level two gamblers display subclinical difficulties with gambling, and level three gamblers meet clinical criteria for Gambling Disorder or Pathological Gambling. The findings of these analyses appear to strongly support such a demarcation, both in the number of groupings identified and the types of behaviours members of the identified latent classes are likely to endorse.

These results inform a wider debate concerning the reclassification of Gambling Disorder in the DSM-5. The manual makes three major alterations from the conceptualisation of Pathological Gambling in the DSM-IV; one criterion was removed (engaging in criminal acts to fund gambling), the clinical cutoff was reduced from five criteria to four, and it implemented a more graded approach to classifying disordered gamblers, distinguishing between low, moderate and high severity disordered gamblers. These findings suggest that moderate and severely disordered gamblers form a distinct latent class from other disordered and (non-clinical) problem gamblers. In addition, the results demonstrate that the removal of the illegal acts criterion ought to make very little difference of the ability of the criteria to distinguish between different levels of gambling problems, in line with the rationale for removing this criterion. However, concerns have been raised that although removing this item is beneficial for prevalence research as the item shows minimal incremental validity, this might shape clinical practices in a manner that might be counterproductive (Bowden-Jones, 2013). There are two other criteria that behave in a similar manner across studies, but more importantly between the moderate and high severity gamblers there are other items that discriminate these groups more comprehensively.

Analysis of the SOGS data indicated that this assessment measures a similar latent structure to the other screens in this report. It appears that gamblers in the second/intermediate latent class endorse relatively similar items across measurements as well. The scores for latent class members closely resembled the three subtypes for the SOGS. Although of declining importance in population assessment (Williams et al., 2012a), this finding remains of interest as the SOGS is widely used in experimental research.

The cutoff's used in the BGPS DSM measure did not produce consistent results for the highest severity latent class. Endorsement probabilities of PG behaviours varied between samples in contrast to the other measures. BIC indices for two and three-class models were consistently close to one another; LRT's conducted on the latent class model supported a two-class model. This cutoff was used in an analysis that found that UK PG prevalence increased between 2007 and 2010. The report itself (Wardle et al., 2011b) and the present analysis highlight that this should be taken with caution. Although comparisons between gambling and health surveys should be made with caution as survey framing affects responding (Williams et al., 2012a), the DSM cutoff used in the BGPS/HSE surveys produced similar levels of endorsement to the APMS measure but did not demonstrate similar levels of disordered gambling prevalence (Table 8). It might be of benefit to pool these data to compare class membership between samples in a similar manner to the BGPS analysis (Wardle et al., 2011b).

An important caveat is that while these findings identify a common latent structure in measurements of problem gambling, it is not possible to claim this generalises to other jurisdictions. As the analysis was restricted to British gamblers, these results may not translate to other countries where different restrictions on gambling or other circumstances prevail. However, there is some cause for optimism in this regard. Studies in the USA and South Africa have found commensurate results under different conditions; in the USA, LCA of NESARC data based off a structured interview revealed a similar pattern of results, and taxometric analysis of South African data identified a distinct latent class (albeit with much higher prevalence than UK/USA) in PGSI data.

The findings from this chapter provide a strong basis to further understand the profiles of different types of gambler that emerge from gambling assessment screens. In particular an analysis by Wardle et al. (2011) as part of the BGPS 2010 report modelled changes in problem gambling prevalence over time in a logistic regression model including a range of demographic variables. The work in the following chapter extends this to newer data as well as reporting changes in demographic profiles between groups (as this was unreported in the BGPS report).

To conclude, seventeen LCAs of disordered gambling assessment data revealed a consistent three-class structure in which gamblers differed in severity, and that clusters of disordered gambling indicators (loss-chasing/preoccupation, loss of control) characterised class membership. This final group appeared to show qualitative differences from the other latent classes on the basis that items measuring a loss of control showed the greatest differences between the latent classes. These analyses of these large-scale surveys suggest that research on the transition from recreational to disordered gambling should focus on the factors that make individuals susceptible to loss of control. These may be internal to the individual, such as impulsivity; external to the individual, such as the schedules of reinforcement of the gambling games, or an interaction between the two.

CHAPTER 4 -

SOCIODEMOGRAPHIC CORRELATES OF GAMBLING LATENT CLASSES[1]

4.1 Overview

In the previous chapter a common structure of gambling subtypes emerged across numerous gambling datasets and assessments. This chapter extends this modelling to look at the sociodemographic predictors of different subtypes of problem gambling. Utilising the same modelling approach reported in the British Gambling Prevalence Survey 2010, data was pooled from responses to the DSM-IV screen in three gambling prevalence surveys, and a three-class latent class model was estimated. The most likely latent class was then used as the outcome variable in a multinomial logistic regression model including a number of demographic covariates. These revealed a number of predictors of problem gambling severity; being male, a smoker and British Asian. A number of indicators (ethnic minority membership, age, sociodemographic background) also predicted membership of the intermediate/severe gambling subtypes. In addition widowers were more likely to be in the most severe

[1] Data and analyses from this chapter have been published as James, O'Malley & Tunney (2016) "Sociodemographic predictors of latent class membership of problematic and disordered gamblers" in *Addictive Behaviors Reports*.

group. These provide further insights about gambling behaviours that are likely to form the indicators used in the experimental chapters.

4.2 Introduction

The aims of population-wide measurements of disordered gambling are to examine or uncover trends in gambling involvement and assess whether problem gambling prevalence is changing. Identifying these trends is crucial to directing appropriate resources towards reducing or mitigating harm and informing interventions, particularly as disordered gambling appears to show considerable heterogeneity and may require distinct treatment goals (Blaszczynski & Nower, 2002). There is also a close degree of correspondence between the assessments used in UK gambling prevalence research and screens administered by healthcare practitioners to gamblers seeking treatment (Bowden-Jones & George, 2015). Recent commentaries have suggested that rather than comparing disordered gambling prevalence across timeframes or jurisdictions, the greatest benefit from prevalence research has emerged from comparing across sub-samples of gambler (Markham & Young, 2016). This chapter pools data from multiple British surveys using similar survey designs to uncover the predictors of latent class membership from socio-demographic correlates and other addictive behaviours, building on latent class analyses (LCAs) of problem gambling assessments that have consistently observed three subtypes of gambler, particularly those reported in Chapter 3 and a number of other analyses of problem gambling data (Carragher & McWilliams, 2011; McBride et al., 2010). Pooling data has the potential to be beneficial in uncovering the demographic correlates of those showing the greatest difficulties with gambling, where individual gambling surveys have tended to be unable to sample enough of these gamblers to draw strong inferences about this group.

The LCAs of disordered gambling data reported in Chapter 3 strongly indicated that the measures of pathological gambling included in representative samples of the British population have a similar latent structure that appears to be similar across time. LCAs have been conducted on two adaptations of the DSM-IV Pathological Gambling criteria (American Psychiatric Association, 2000), the South Oaks Gambling Screen (Lesieur & Blume, 1987) and the Problem Gambling Severity Index (Ferris & Wynne, 2001), suggesting that a broadly similar profile emerges. These tended to produce consistent results which suggest the presence of three interpretative categories of gambler across the measurements analysed. These identify an initial category of gamblers who have minimal likelihood of endorsing a problem gambling indicator, making up 85–95% of the sample, a second category of gamblers who showed some problems with gambling but mostly at a sub-clinical level (with endorsement primarily limited to loss-chasing and preoccupation indicators) and a third category of gamblers all of whom exceeded the most severe category of the instrument being used. These categories appeared to be quantitatively and qualitatively distinguishable. Subtypes differed in problem severity and showed relatively little overlap, strongly indicative of a dimension of severity. However, the indicators that showed maximal differences between the second and third highest severity categories were the loss of control items, similar to the taxometric analysis reported in Chapter 2.

The British Gambling Prevalence Survey (BGPS) was a series of nationally representative surveys that assessed gambling attitudes and behaviours, and problem gambling prevalence, between 1999 and 2010 in the United Kingdom (Sproston et al., 2000; Wardle et al., 2011b; Wardle et al., 2007). The first survey was conducted in light of major changes to the gambling market over the 1990s, and the second and third were conducted to provide baseline and follow-up measurements in light of major gambling legislation (the Gambling Act 2005, enacted in July 2007). Further data was also collected in a module of the Health Survey for England 2012 and the Scottish Health Survey 2012. The survey in 2010 (Wardle et al., 2011b) found a significant increase in the prevalence of 'problem' gambling between 2007 and 2010, using an assessment that was adapted from the DSM-IV Pathological Gambling criteria (p = .046). Although the DSM criteria doesn't have a subtype of problem gambling, a cutoff of three has often been used to identify individuals who exhibit significant subclinical difficulties with gambling (Chou & Afifi, 2011; Nower et al., 2013; Sproston et al., 2000). This increase was identified using a logistic regression model in which problem gambling status was predicted for each survey year, age, sex, marital status, ethnicity, socio-economic status, general health status and incidence of cigarette smoking. Many caveats were applied to this finding at the time, as the authors of the BGPS report noted that other, unobserved factors may explain this difference (Wardle et al., 2011b). Recent commentaries (Sharman, Aitken, & Clark, 2014) have pointed out that the absolute number of individuals driving this difference was very small; for example, the 2010 dataset contained around twenty additional problem gamblers, with both surveys having fewer than one hundred problem gamblers each. This highlights one of the limitations of using gambling prevalence survey data to compare between subgroups of gambler (Doughney, 2007; Lorains, Cowlishaw, & Thomas, 2011). Although it is desirable to make comparisons across data that can generalised to the wider population it has proven to be highly problematic because of the difficulties in sampling a sufficient number of the gamblers reporting the greatest number of problems to uncover consistent associations. Pooling data across surveys can potentially make this problem more tractable. The British prevalence data lends itself better than many other datasets to pooling because the different studies had similar approaches to sampling and weighting, recruited similar sample sizes and used the same problem gambling assessments that have a similar latent class structure. The response rates across the surveys are similar (52%, 47%, 56%), and are much higher than some other gambling prevalence surveys (Markham & Young, 2016), where responses have fallen as low as 20%. The British prevalence surveys also appear to concord with many of the best practices identified by Williams and Volberg (2010).

Nevertheless, there are a number of caveats that result from pooling data from the datasets covered in this analysis, in addition to the limitations associated with gambling prevalence surveys. To start, the amount of missing data for problem gambling assessments is different between the surveys conducted. The completion rates across the three datasets amongst the respondents who were administered them were 89.97% (BGPS 2007), 99.75% (BGPS 2010) and 88.94% (SHS & HSE 2012). The higher completion rate on the BGPS 2010 data is likely due in part to the utilisation of a computer aided procedure to administer the questionnaire, whereas the other surveys were paper based. In addition, only around three in four respondents (77.39%) to the HSE/SHS surveys were asked any questions from the gambling module. It is unclear whether the difference between the respondents who were given the gambling module or not was random or systematic. The BGPS and HSE/SHS surveys were framed very differently to one another; the British Gambling Prevalence Survey was presented as a leisure survey, but the problem gambling questions were situated towards the end of an extensive questionnaire probing gambling behaviour. The Health Survey for England was explicitly framed as a health questionnaire, and asked a range of questions about health and wellbeing related behaviours. The way in which a gambling questionnaire is framed has an important impact on estimates of gambling involvement (Williams et al., 2012a), with health surveys eliciting lower rates of responding to questions about gambling behaviour.

Although there are important limitations with comparing across the different sets of data, the potential benefits outweigh the costs. As mentioned previously the greater sample of problem gamblers allows identification of commonalities, if any exist, where it has been difficult to do so previously. The health survey data contains more granular data on a number of areas pertinent to gambling, particularly on other licit addictive behaviours such as drinking and smoking. Given that models of problem gambling identify the role of impulsive personality traits and hypothesize that the causal mechanism behind the most severe problem gamblers is a common risk factor for addictive behaviours, comparing across sub-samples using this data can provide broader information on the interaction between gambling and addictive behaviours across a wider spectrum. Some of this data has been utilised previously. Wardle et al. (2014) used alcohol and smoking frequency data from two health surveys in studying the predictors of at risk gambling (defined as a score between 3 and 7 on the PGSI), and problem gamblers (identified using either the PGSI or DSM screen), using a logistic regression procedure to compare between these groups and respondents who did not fall into the target group (or a higher severity group). This was based on a simulated stepwise procedure to determine which predictors were significant from a set of socio-economic and health indicators. These other addictive behaviours, along with being more likely to be younger, male and Muslim, were associated with 'at risk' gambling, but not problem gambling. The health survey data includes a wider range of data about these behaviours that may provide valuable insights into the engagement gamblers have with other addictive behaviours, including several variables not considered in previous analyses. There is also the issue that coding the DSM data using the underlying logic of the DSM (i.e. a behaviour is classified as present or absent) identifies a much greater rate of endorsement than the PGSI, with around twice as many gamblers typically endorsing a problem gambling behaviour than using the PGSI, as data from Chapter 3 (Table 8) shows. This also applies to the proportions of at-risk and problematic gamblers.

In this chapter the correlates of subtypes of problem gambling derived from latent class modelling are observed. A three latent class model was estimated as previous research that has found this consistently captures the different subtypes of gambler that emerge from gambling assessment data. From this, a multinomial logistic regression was estimated using the most likely latent class each case belonged to as the outcome variable. The relationship between gambling and smoking and alcohol use in the health survey data was subsequently examined.

4.3 Method

4.3a Sample

This study pooled data from past-year gamblers that completed the problem gambling assessment derived from the DSM-IV Pathological Gambling criteria in the BGPS 2007 ($n = 5503$), BGPS 2010 ($n = 5699$), and combined data from the SHS 2012 and HSE 2012 ($n = 6909$), resulting in a total sample of 18,111 respondents. Latent class analysis was conducted using MPlus version 6.1.1 (Muthén & Muthén, 1998-2011). The other analyses were conducted in STATA v. 14 SE (StataCorp, 2015). The data was collected by the National Centre for Social Research in 2007, 2010 and 2012, and is publicly available from the UK Data Archive (National Centre for Social Research, 2008, 2011; National Centre for Social Research & University College London. Department of Epidemiology and Public Health, 2014; Scottish Centre for Social Research, University College London. Department of Epidemiology and Public Health, & University of Glasgow. MRC/CSO Social and Public Health Sciences Unit, 2014; Scottish Centre for Social Research and NatCen Social Research & Survey Research Centre, 2015).

The statistical analyses were adjusted for survey design. The datasets include probability weights that can be used to adjust the samples to the ONS mid-point population estimates for the year the data was collected in. Further variables are included in the dataset to adjust for the primary sampling unit respondents were drawn from and stratification. For the multinomial logistic regression analysis two strata had to be merged into the subsequent stratum because there would have only been one primary sampling unit in the strata with non-missing data on at least one of the variables. Weighted demographic data are reported in Table 16.

Table 16

Weighted count data for the sociodemographic indicators

Variable	Class 1 (*n* = 16,716)	Class 2 (*n* = 1,281)	Class 3 (*n* = 267)
Sex:			
Male	7994 (7780, 8209)	887 (809, 965)	215 (180, 251)
Female	8274 (8068, 8481)	394 (349, 438)	52 (37, 67)
Age:			
18-24	1853 (1718, 1987)	349 (297, 400)	67 (46, 88)
25-34	2681 (2540, 2822)	339 (291, 387)	71 (51, 90)
35-44	3166 (3014, 3318)	238 (204, 273)	56 (39, 73)
45-54	2946 (2809, 3083)	173 (144, 202)	44 (29, 58)
55-64	2633 (2508, 2758)	99 (78, 121)	18 (10, 26)
65-74	1752 (1662, 1841)	58 (43, 72)	10 (4, 16)
75+	1232 (1149, 1314)	25 (15, 36)	2 (-1. 4)
Smoking Status:			
Yes	3866 (4305, 4662)	490 (438, 543)	127 (101, 154)
No	13232 (12905, 13559)	784 (715, 853)	140 (112, 167)
Marital Status:			
Married/Civil Partnership	10220 (9932, 10508)	607 (551, 663)	106 (84, 129)
Separated or Divorced	1376 (1296, 1455)	95 (74, 117)	25 (14, 36)
Single	3564 (3387, 3741)	544 (479, 609)	126 (98, 153)
Widowed	964 (899, 1029)	25 (16, 35)	8 (3, 14)
Ethnicity:			
White British	15338 (14982, 15694)	1126 (1040, 1211)	206 (173, 238)
Mixed	166 (132, 200)	24 (13, 35)	8 (2, 15)
Asian British	354 (294, 414)	58 (36, 79)	27 (15, 40)
Black British	270 (225, 316)	46 (29, 63)	17 (6, 28)
Chinese British/Other	87 (63, 111)	22 (11, 32)	8 (0, 15)
Socio-economic status:			
Professional/managerial	6535 (6293, 6778)	410 (357, 462)	70 (49, 91)
Intermediate occupation	1597 (1486, 1709)	150 (120, 180)	16 (8, 25)
Small employer/self-	1765 (1634, 1896)	128 (102, 154)	27 (14, 39)

employed			
Lower supervisory/technical	1745 (1624, 1866)	122 (96, 147)	29 (13, 44)
Semi-routine occupation	4112 (3930, 4295)	393 (345, 441)	105 (83, 127)

Note: There are missing data in a number of these instances.

4.3.b Analytic Procedure

4.3.b.i. Latent class analysis

A weighted LCA was conducted on individual items from the DSM-IV Pathological Gambling criteria, coded as present/absent in the manner as other LCAs of British Pathological Gambling data (McBride et al., 2010) and in Chapter 3. Only a three class model was estimated as it appears that this is consistent across multiple surveys. LCA is a method of identifying distinct subtypes within a latent categorical variable. It assumes that both the manifest and latent variables in the analysis are categorical, and that the indicators entered into the analysis are independent from one another at the level of the latent class. This assumption of local independence was tested by examining the Chi-square test of overall model fit in the output, which indicated that the assumption was met ($p > 0.05$).

4.3.b.ii Regression analysis

Sociodemographic indicators were entered into a logistic regression model with most likely latent class as the outcome variable, adopting an identical approach where possible to the analysis conducted by (Wardle et al., 2011b). Covariates were selected on the analysis conducted by (Wardle et al., 2011b). The variables included were as follows:

– Survey year (2007, 2010 and 2012).

– Ethnicity (categorised as White British/non-British, mixed ethnic background, Asian British, Black British and Chinese British or other ethnicity).

– Socio-economic status (NS-SEC 5 category classification used — managerial/professional occupation, intermediate occupation, small employers and own-account workers/self-employed, lower supervisory and technical occupations, and semi-routine occupations).

– Marital status (married/living as married/civil partnership, separated/divorced, single (never married), and widowed).

– Self-reported health status (measured on a five point scale from 'very good' to 'very bad', with 'fair' as the middle option).

– Present smoking status (yes/no).

– Age (categorised into seven bands, < 24, 25–34, 35–44, 45–54, 55–64, 65–74, 75 +).

– Sex (male/female).

- Average number of alcohol units drank per week. Alongside other smoking variables: number of cigarettes smoked per week, level of engagement with smoking by ex-smoker and whether advised by a doctor to quit smoking, further regression analyses were conducted on these data based on the outcome of the covariate analysis reported in section 4.4.b.

All variables apart from self-reported health were dummy coded. The reference categories for each variable are reported in Table 17. The ethnicity variables for the BGPS 2007 and SHS/HSE datasets were recoded to cover the same categories as the BGPS 2010 data, because the number of categories differed between surveys. For the HSE & SHS 2012 data, this meant referring back to the original SHS & HSE data files downloaded from the UK Data

Agency (National Centre for Social Research & University College London. Department of Epidemiology and Public Health, 2014; Scottish Centre for Social Research et al., 2014). The ID variable (an eight digit number) and age data were used to match respondents, and the 'origin' variable, which asks about ethnicity in greater detail, was used to generate commensurate groups. Some categories of the marital status variable were merged for the same reason.

Table 17 (part 1 of 2)

Multinomial logistic regression of demographic variables on latent class membership. The intermediate severity class (Class 2) is the reference class.

Variable - Class 1 v Class 2	RRR	S.E.	*t*	*p*	95% C. I.
Year (REF: 2007)					
2010 **	0.775	0.066	-3.000	0.003	0.655, 0.916
2012	1.191	0.118	1.770	0.076	0.982, 1.446
Ethnicity (REF: White British/Non-British)					
Mixed	0.742	0.218	-1.010	0.312	0.417, 1.322
British Asian **	0.542	0.131	-2.530	0.011	0.337, 0.871
Black British ***	0.439	0.091	-3.950	0.000	0.292, 0.661
British Chinese/Other Ethnicity ***	0.300	0.088	-4.090	0.000	0.169, 0.535
Socio-economic Status (REF: Professional/Managerial)					
Intermediate occupation **	0.662	0.082	-3.310	0.001	0.519, 0.846
Small employer or self-employed	0.894	0.114	-0.880	0.379	0.696, 1.148
Lower supervisory or technical occupation	0.958	0.119	-0.340	0.731	0.75, 1.224
Semi-routine occupation **	0.738	0.072	-3.100	0.002	0.609, 0.895
Marital Status (REF: Married)					
Separated/Divorced	0.797	0.105	-1.720	0.086	0.614, 1.033
Single **	0.760	0.074	-2.800	0.005	0.628, 0.921
Widowed	1.123	0.286	0.460	0.648	0.682, 1.852
Age (REF: <= 24)					
25-34	1.194	0.151	1.400	0.162	0.931, 1.531
35-44 ***	2.005	0.266	5.240	0.000	1.545, 2.602
45-54 ***	2.655	0.368	7.040	0.000	2.022, 3.485
55-64 ***	4.198	0.739	8.150	0.000	2.971, 5.93
65-74 ***	4.640	0.823	8.650	0.000	3.276, 6.573
>= 75 ***	6.938	1.954	6.880	0.000	3.992, 12.058
Smoker (REF: Yes) ***	1.466	0.114	4.940	0.000	1.259, 1.707
General Health ***	0.783	0.035	-5.410	0.000	0.717, 0.856
Sex (REF: Female) ***	2.409	0.184	11.530	0.000	2.074, 2.798

Table 17 (part 2 of 2)

Multinomial logistic regression of demographic variables on latent class membership. The intermediate severity class (Class 2) is the reference class.

Variable - Class 3 v Class 2	RRR	Std. Error	*t*	*p*	95% C. I.
Year (REF: 2007)					
2010	1.092	0.206	0.470	0.638	0.755, 1.58
2012	0.918	0.204	-0.380	0.701	0.594, 1.419
Ethnicity (REF: White British/Non-British)					
Mixed	1.331	0.679	0.560	0.576	0.489, 3.621
British Asian *	2.286	0.815	2.320	0.021	1.136, 4.601
Black British	1.673	0.636	1.350	0.176	0.793, 3.526
British Chinese/Other Ethnicity	1.948	1.348	0.960	0.335	0.501, 7.575
Socio-economic Status (REF: Professional/Managerial)					
Intermediate occupation	0.622	0.208	-1.420	0.156	0.323, 1.199
Small employer or self-employed	1.070	0.351	0.200	0.838	0.562, 2.037
Lower supervisory or technical occupation	1.247	0.429	0.640	0.520	0.635, 2.449
Semi-routine occupation	1.395	0.305	1.520	0.129	0.908, 2.143
Marital Status (REF: Married)					
Separated/Divorced	1.353	0.382	1.070	0.284	0.778, 2.353
Single	1.352	0.297	1.370	0.170	0.879, 2.081
Widowed **	3.788	1.701	2.970	0.003	1.57, 9.14
Age (REF: <= 24)					
25-34	1.101	0.303	0.350	0.726	0.642, 1.89
35-44	1.394	0.417	1.110	0.268	0.775, 2.509
45-54	1.369	0.484	0.890	0.374	0.684, 2.741
55-64	0.944	0.390	-0.140	0.889	0.42, 2.123
65-74	0.704	0.316	-0.780	0.434	0.291, 1.699
>= 75	0.246	0.209	-1.650	0.098	0.047, 1.298
Smoker (REF: Yes) *	0.701	0.115	-2.160	0.031	0.507, 0.968
General Health	1.204	0.115	1.950	0.052	0.999, 1.451
Sex (REF: Female) **	0.541	0.107	-3.120	0.002	0.368, 0.797

There are multiple approaches that have been used to explore the effect of covariates on latent class membership. Feingold, Tiberio, and Capaldi (2014) outline one, three and revised three step approaches. The three step approach, in which most likely latent class membership is included as a predictor in a logistic regression with covariates as the indicator variables, was used in this case. In some cases it has been demonstrated that this approach is inappropriate because it underestimates the effect size and standard errors for the potential covariates. In contrast, with a one-step approach the covariates and latent regression are included in the latent class model. However, this is equally troublesome; Vermunt (2010) critiques this approach because it requires re-estimation of the latent class model every time a covariate is added or removed, and adds additional computing time to conducting an analysis, as well as going against the intuitive logic of building a statistical model. Instead, a modified three-step approach was proposed in which the third step (regressing most likely class membership on covariates) is modified using a maximum likelihood correction that was subsequently found in simulations to produce more accurate estimates when the classes are well separated. However, studies of real world and simulated data have indicated when the entropy (a measure of classification accuracy) of a latent class model is greater than 0.8, then a traditional three-step logistic regression procedure including most likely latent class membership as the predictor variable produces accurate estimates that do not excessively inflate or deflate standard errors (Clark & Muthén, 2009). The entropy of the latent class model was 0.895, meaning that a three step approach was appropriate for this data. The intermediate severity group was chosen as the reference class to examine differences between intermediate and high severity gamblers.

4.4 Results

4.4.a Latent class analysis

The estimated three class model identified one class that showed only a small probability of endorsing any of the pathological gambling indicators, a second class that had a high probability of endorsing the preoccupation and between-session loss-chasing indicators and a low probability of the remaining indicators and a third class that had a high to moderate probability of endorsing most indicators, but showed the largest differences on loss of control related items (pathological gambling indicators 3–7). The indicators strongly differed quantitatively, with relatively little overlap on overall symptom count; the first class endorsed either zero or one of the DSM criteria, the second class between one and five indicators (the majority between one and four) and the third class more than five. The third class typically endorsed five or more criteria, on average endorsing between six or seven. Indicators three through seven showed similar probabilities of responding (between 0.755 and 0.84). These show relatively large differences in relative rates of endorsement but quite small in absolute terms (all are endorsed by between 2 and 4% of the sample), and item response theory analyses of these data suggest that these span the dimension of severity that has been observed using the DSM data (Strong & Kahler, 2007).

4.4.b Covariate analysis

Table 17 reports the full results of the logistic regression model (Table 16 reports count data for each variable in the regression and Table 18 reports data for additional covariate not included in the regression). A number of differences were observed between the group showing minimal or no problems, and the group endorsing some problem gambling indicators. Gamblers in the intermediate group were around twice as likely to report coming from a Black or Asian British background, and three times more likely to come from another ethnic minority, relative to a White British background. They were one and a half times more likely to be a smoker, and two and a half times more likely to be male.

Between the low and intermediate severity groups, there were also a number of significant differences amongst the sociodemographic correlates that subsequently did not differ between the intermediate and higher severity groups. These included socioeconomic grouping, marital status, self-reported general health and membership of an ethnic minority. General health did not differ between the intermediate and higher severity groups ($p = 0.052$, 95% CI = 0.999–1.45). Relative to the moderate severity latent class, on four indicators there were greater log odds of being found in the third or most severe latent class: whether the respondent was a current smoker, male, British Asian or widowed. Three of these were also significant between the lowest severity class and the reference group, suggesting that these track alongside problem gambling severity. Although the three classes differed in overall severity (i.e. problem gambling score), many differences one might expect between the latent classes, such as perceived general health and age (disordered gambling is more prevalent in younger individuals) failed to emerge.

Table 18

Smoking and alcohol indicators across the different latent classes in the combined Health Survey for England and Scottish Health Survey 2012 datasets.

Variable	Class 1 (n = 6,241)	Class 2 (n = 396)	Class 3 (n = 93)	Linear regression/Chi-square Test
Current smoking status:				χ (6) = 2.95, p = 0.009
Never	2,939	166	47	
Ex-occasional smoker	343	22	3	
Ex-regular smoker	1,635	81	15	
Regular smoker	1,323	127	28	
Number of cigarettes smoked:				
Weekday	11.897	12.961	13.613	N.S.
Weekend	13.158	13.482	15.716	N.S.
Smoking frequency (ex-smokers):				χ (4) = 19.706, p = 0.07
Regularly	1,635	343	155	
Occasionally	81	22	7	
Only tried once or twice	15	3	7	
Advised by doctor to quit smoking				χ (2) =2.377, p = 0.09
Yes	842	62	19	
No	2404	158	24	
Number of units:				
Drank per week	12.545	16.396	16.694	2>1
Unit risk status:				χ (4) = 5.19, p = 0.0001
Low	4369	235	67	
Increasing	1650	131	18	
Higher	244	32	8	

4.4.c Smoking

One finding of particular interest was that smoking prevalence tracked alongside problem gambling severity. Theoretical models of problem gambling claim that the most severe problem gamblers are characterised by antisocial and impulsive personality traits, and that these gamblers should show a common risk of addictive behaviours. From the Health Survey data it is possible to get more detailed information about prevalence of smoking, amount of cigarettes smoked per day and previous engagement with smoking, whereas the gambling data only includes current smoking status. In the HSE 2012 dataset there were 1560 current smokers (22.57% of the sample). Table 18 reports the descriptive statistics concerning smoking. Of particular interest was that it appeared that fewer individuals in the most severe gambling group had never smoked relative to the other two classes, as well as are more likely to be current smokers; the two more severe gambling groups trended towards having a lower prevalence of social/occasional smokers than the least severe gamblers. Across all groups present smokers tended to smoke one to two additional cigarettes on a typical weekend day relative to a weekday. This has previously been identified in studies of university students (Colder et al., 2006). However, there was no evidence that the number of cigarettes smoked was associated with class membership. Among ex-smokers, the pattern of smoking behaviour was relatively constant across groups; around 3 in 4 ex-smokers reported being regular smokers, with the remainder of occasional and rare (i.e. 1 or 2 cigarettes) being evenly distributed. There were a couple of potential areas where trends were observed that could not be conclusively established due to the low number of respondents (only around half of the most problematic gamblers, already a very small group, smoked). The survey data also queried whether respondents had been advised by their medical practitioner to quit smoking. As with smoking frequency, there was a trend with class membership, but this was not significant. This might be of interest for further research.

4.4.d Alcohol use

To look at alcohol consumption, the number of average units drank per week was regressed on latent class membership, with the recreational gambler group used at the reference category. This revealed that the second group (showing preoccupation and loss-chasing behaviours) consumed a significantly greater number of units than the recreational group ($b = 4.60$, SE = 1.61, $p = .004$, 95% CI = 1.443–7.766) but that the most severe gamblers did not ($b = 3.031$, SE = 3.81, $p = .43$, 95% CI = − 4.453, 10.514). In addition, there was a significant association between alcohol risk group and gambling latent class. Using the Chief Medical Officer's Guidelines of < 14 units (both genders), as 'low risk', 14–49 units as 'increasing risk', and 50 + units as 'higher risk', there was a significant association between latent class and risk group (Table 18).

4.5 Discussion

The results of these analyses identify a number of sociodemographic characteristics that predict membership of latent classes derived from indicators of disordered gambling. Compared to the reference class (who tended to endorse the loss-chasing and preoccupation indicators), the subgroup endorsing minimal to zero gambling problems were less likely to come from semi-routine and intermediate occupational groups, less likely to come from a number of ethnic minority groups (Black British and Chinese British/other ethnicity), reported better general health, less incidence of smoking and was more likely to be female. The most severe problem gamblers were more likely to be male, a current smoker, come from a British Asian background and divorced. Latent class membership also appeared to be associated with multiple different types of engagement with drinking and smoking.

The analysis compared differences between latent classes on a number of demographic attributes. In some instances, the proportion of members belonging to a certain group or engaging in a specific behaviour tracked alongside latent class membership and thus severity. The odds of being male or a smoker increased with membership of a higher problem gambling severity latent class. The likelihood of a class member being British Asian also increased with latent class severity, with 1.7%, 3.9% and 8.75% of the low, moderate and high severity classes coming from this group. The other ethnic minority groups (mixed ethnicity individuals aside) were more likely to be in the intermediate class relative to the low gambling severity class, but there were no differences in membership between the second and third severity classes (although all had greater odds of being in the problem group too). It has been frequently observed that men have higher prevalence of numerous addictive disorders (Keyes, Martins, Blanco, & Hasin, 2010; Khan et al., 2013), although women show a ‘telescoping’ effect in which initiation of drug, drinking or gambling begins later but the transition to disordered behaviour is shortened (Grant, Odlaug, & Mooney, 2012; Keyes et al., 2010). Studies of younger cohorts suggest that these differences might be diminishing (Keyes et al., 2010), but caution should be applied in comparing between timeframes, as critiques of prevalence studies have pointed out that structural changes in responding mean that this might be at least partially artefactual (Markham & Young, 2016). The demographic differences between the second and third latent classes were relatively minor. As noted above, the odds of the second and third classes differing on most demographic variables were small. Combined with the findings from previous LCAs of this data, this should be taken as stronger evidence that the primary difference between these groups lies in a loss of control over gambling but with the caveat that more intensive research with a subgroup of these gamblers would be highly informative.

The prevalence of problem gambling is higher in more disadvantaged socioeconomic groups, although with some assessments this relationship has been confounded by a preponderance to assess disordered gambling using items related to excessive monetary spending or borrowing. Research that has looked at the density of gaming machines, which are typically associated with harmful play, has found that these are more common in more deprived areas (Wardle et al., 2012b). This study found that respondents from this group were less likely to show very few gambling problems, in line with most of the literature on this topic (Welte, Barnes, Wieczorek, Tidwell, & Parker, 2002). In addition, respondents from 'intermediate occupations', a more affluent group, were also less likely to be in the group with the least gambling problems. This is potentially a group that requires further study. Similar findings have been found in alcohol harms, where pockets of greater consumption have been identified amongst comparatively better off drinkers

(Jones, Bates, McCoy, & Bellis, 2015) Further scoping research would be beneficial to study gambling behaviours amongst this group.

Previous research has found an elevated risk of problem gambling amongst British Asian adolescents (Forrest & McHale, 2012). Using pooled adult and adolescent data (including the BGPS 2007/2010 data), a similar finding was observed, with a significantly higher level of problem gambling amongst British Asian women (Forrest & Wardle, 2011). While this analysis broadly replicates this finding, as the ratio of British Asian to White British problem gamblers was 8.34 (versus 1.99 for males), this should be taken with extreme caution as only six female British Asian problem gamblers were identified across the three weighted samples. As noted by Forrest and Wardle (2011), the BGPS 2007 identified that British Asians held some of the most negative attitudes towards gambling, although this may be a consequence of the increased prevalence of problem gambling amongst this community. A similar finding was observed in widowed people, another group where attitudes towards gambling were similarly negative (Wardle et al., 2007). There is a broader evidence base here, as a literature has developed looking at gambling in older people. The Pathways Model predicts that traumatic life events are associated with certain pathways to problem gambling, and previous analyses based on directly testing this model included recent family death as an indicator in a LCA of US data, finding that more severe pathological gamblers tended to have a higher probability of reporting a recent bereavement (Nower et al., 2013).

A number of socio-demographic variables appear to map onto constructs related to risk-taking and impulsivity, which are known to be associated with increased endorsement of disordered gambling indicators. The issue of the relationship between gambling and smoking has been investigated (Petry & Oncken, 2002), but is somewhat less well explored than associations between gambling and other drug addictions (McGrath & Barrett, 2009). This research indicates that many of these gamblers smoke, but potentially are more likely to be advised by a clinician to quit. It should be noted that the age distribution of the two classes endorsing problem gambling items is similar to that of smokers in the UK (Health and Social Care Information Centre, 2015). This also has a wider impact as there is a preponderance towards focusing on the individual nature of disordered gambling behaviour, in contrast to the addiction literature, which has recognised the influence of acute exposure on state impulsive behaviour (de Wit, 2009), including acute nicotine exposure (Hogarth, Stillwell, & Tunney, 2013b). The high levels of cigarette use observed in the most problematic gamblers highlight that many gamblers will be involved with numerous behaviours that appear to increase the likelihood of engaging in further risk taking behaviours such as gambling, or certain types of gambling behaviour. The problem gambling literature has extensively studied the trait or determinant aspects of impulsivity, repeatedly finding that problem and pathological gamblers show higher self-reported and behavioural levels of trait impulsivity, particularly when the questionnaire content probes retrospective behaviour (Fortune & Goodie, 2010). However, the issue of state impulsivity has been relatively sparsely addressed in this context. There are two potential benefits in doing so. The first is that it is well established, and further found here, that the most severe levels of problem gambling are comorbid with other addictive behaviours. Studying these acute effects has the potential to further our understanding of the relationship between gambling, addictive behaviours and impulsivity, as it may be the case that these state effects are associated with certain features or sequences of risky gambling activity. It may also be the case that gambling exhibits a similar effect on other addictive behaviours. The second is that in the wider addiction literature, gambling has the potential to be the most interesting probe of this problem as the acute effects of gambling can be (ethically) manipulated by altering the schedule of reinforcement, whereas the opportunity for doing so in with substance use is more constrained. The gambling literature has noted the presence of dissociative experiences, stereotypically in machine gambling play. Further research on this matter has the potential to contribute to an important issue in the addiction literature, where it has been argued that the study of gambling has had less of an impact than might be expected (Cassidy, 2014).

These findings have a potential impact in the context of public health and campaigns designed to raise awareness of problem gambling. Similar demographic profiles were identified in the two groups that systematically endorsed problem gambling indicators. It is common to target specific populations in the information materials and interventions aimed at public health priorities. The data brought together in this study allows clearer identification of which groups problem gambling is more likely to be found. This approach is already being taken in some instances, with recent campaigns by industry self-regulatory bodies that have been specifically aimed at younger men. These analyses identify groups where a targeted focus might be beneficial with a view towards designing messaging that is relevant to them —

one of the issues with problem gambling (and addictive behaviours in general) is the low levels or treatment seeking amongst those experiencing the greatest harm or with a use disorder. In understanding the demographic correlates of different gambling groups it is possible to direct further research towards identifying the products or behaviours that may be the target of intervention in the future. Concerns have been raised that the choice of location of gambling products has been the source of consistent criticism from gambling pressure groups. It has often been claimed that gambling locations are set up in communities where problematic gambling is more common, and gambling pressure groups have recently accused some operators of targeting the placement of shops in areas with majority ethnic minority populations (Ramesh, 2016), who in this study were consistently associated with endorsing problem gambling behaviours.

There are some limitations with this analysis relating to the datasets used. The first is that the sampling or administration method changed between surveys, even if the questionnaire content was identical. For instance, the BGPS 2010 introduced a computer aided self-interview schedule. More substantially, a considerable minority of respondents to the HSE & SHS datasets were not administered the gambling module. It is unclear whether the respondents who were and were not administered the questionnaire significantly differed in any sense. In addition the use of a past-year gambling criterion for administering problem gambling assessments has been identified as potentially problematic due to the risk of false positives, primarily when very low problem gambling thresholds are used (Williams et al., 2012a). While it is frequently noted that one of the advantages of using a nationally representative survey is to draw conclusions about the wider population, research on the correspondence between prevalence surveys and clinical assessment has been modest at best. However, this again tends to occur when lower thresholds are used. Moreover, because many of the demographic variables (ethnicity in particular, but also SES and marital status to an extent) have the vast majority of respondents affirming one or two categories, the confidence intervals are quite broad, particularly for comparisons against the most severe gamblers. This is also the case for the smoking and drinking data, where the subsamples of the three classes were analysed. While a number of effects are not significant, the truncated sample means that it would be premature to claim that there is no effect in a number of these cases. However, these are indicative of where more intensive research may be beneficial on specific subsamples of gambler.

Although the latent classes identified have been consistently found using different samples and across different jurisdictions, the use of gambling prevalence survey data is ultimately limited in this regard. LCA does not provide a conclusive answer concerning the qualitative differences between gambling subtypes, particularly as the subtypes are accompanied by a notable difference in symptom count. Analyses that tend to be more sensitive in identifying qualitative differences (McGrath & Walters, 2012) have suggested that some of the most severe problem gamblers form a taxon, such as the one identified in Chapter 2 or other studies (Kincaid et al., 2013). However while these analyses show greater sensitivity, these only inform the presence of a qualitative difference and not the number of distinct subtypes. Self-reported gambling assessments are also likely to under and over represent responding in certain contexts (Doughney, 2007). The LCA findings, taken with other latent variable analyses are indicative of a mixed latent structure. However, given the restricted set of indicators and small samples of problem gambler, more in-depth research perhaps with a sample of highly engaged gamblers might begin to tease out some of the differences that emerge in these groups in further detail. These analyses provide broad indications concerning where these differences may lie, but research going beyond gambling prevalence would need to be conducted to directly test this.

To conclude, sociodemographic predictors of latent classes derived from gambling assessment data were studied on pooled data from four surveys. Overall there appeared to be more similarities than differences between moderate and severe problem gamblers. Gamblers showing some problems but not meeting the clinical threshold for Pathological Gambling tended to be male, single, younger, come from a number of ethnic minority backgrounds, smoke, report poorer general health and emerge from two specific socioeconomic strata (intermediate and semi-routine occupations). The most severe gamblers, relative to the group showing problems, were more likely still to be male, smoke and come from a British Asian background. There was also an association between membership of the most severe gambling group and being widowed. These predictors appeared to be stable across the different datasets.

CHAPTER 5 -

FURTHER TAXOMETRIC ANALYSES OF PROBLEM GAMBLING DATA[1]

5.1 Overview

Although the analyses in the first two chapters support the presence of a problem gambling taxon, it is noted that these were conducted on ordinal data. While highly recommended for taxometric analysis, the DSM criteria for Pathological Gambling (and every other disorder) are dichotomous, measuring the presence or absence of a specific behaviour over a certain time point. Many taxometric analyses however test the latent structure of DSM disorders by conducting analyses on dichotomous DSM data, creating a continuous variable to form the input by summing all but one or two variables. Previous studies have suggested that this does not improve the detectability of a taxon, and with a range of ordinal and continuous variables, is less effective than the traditional approach of iterating through each possible combination of variables. Systematic investigation of this issue is necessary both in understanding the statistical relationship between gambling and other addictions, which has been previously explored in Chapters 2 and 4, and the enterprise of using this kind

[1] The analyses and content contained in this chapter are currently being written up towards publication.

of approach on addiction and other areas of mental health. An alternative to this is to designate a quantitative input variable and then conduct taxometric analyses using the remaining dichotomous variables. This chapter compares multiple approaches to binary data, using both simulated data and some of nationally representative gambling survey data utilised in Chapters 2-4. The first two studies involved a Monte Carlo analysis of two sets of simulated data using different taxometric approaches. Although taxometrics performed poorly in some instances, it was found that the L-Mode Factor Analysis and summed input MAMBAC and MAXCOV approaches accurately identified a pre-specified latent structure. Two subsequent analyses were then reported on gambling data. The first aimed to replicate the analysis reported in Chapter 2, using the same dataset but the binary indicators used in Chapter 3. The second analysis then extended this to the South Oaks Gambling Screen, using data from the British Gambling Prevalence Survey 1999. In both cases, the analyses support the presence of a distinct latent class of high severity gamblers.

5.2 Introduction

Taxometric analysis is a form of latent structure analysis designed to test whether a latent variable, measured by a number of observable variables (or indicators), best fits a taxonic model. Although the meaning of taxonic latent structure has been the source of some controversy, this has typically been understood to mean the presence of a distinct latent class. Non-taxonic findings have generally been used to judge a construct as dimensional but it is unclear whether non-taxonic findings should be treated as a null finding or positive evidence in support of a latent factor or factors (Beauchaine, Lenzenweger, & Waller, 2008). Taxometric analysis was originally designed to test Meehl's hypothesis that schizotypal individuals formed a distinct latent category or *taxon* (Meehl, 1973) with a distinct causal (genetic) mechanism. Since then, it has almost exclusively been used to test whether indicators of specific psychiatric disorders are best represented as categories or continua, an approach stimulated as of late by controversy over the almost exclusive use of categories in prominent manuals of mental disorders, such as the DSM (American Psychiatric Association, 2013) in psychiatry. Much of this criticism has been driven by the use of categorical approaches to personality disorders; this manner of classification strongly contrasts with psychological traditions in the study of personality (Widiger & Trull, 2007). Furthermore unlike cases such as Schizotypy, which Meehl hypothesized to emerge from a restricted number of genetic mutations, most psychopathologies appear to have numerous causal factors that make small contributions to the risk of developing a disorder, more typical of a dimensional model. This remains the case for disorders that have some evidence for a taxonic structure such as autism or pathological gambling (Leeman & Potenza, 2013; Robinson et al., 2016a).

Research on this question has overwhelmingly indicated that most disorders are dimensional in nature (Haslam et al., 2012), with few types of disorder showing evidence for a taxon. However, in many cases it is noted these analyses use dichotomous data (Haslam, 2003), such as individual DSM criteria. Such approaches have been the source of criticism because it appears that taxometric analyses perform significantly better with polytomous ordinal or continuous data (Walters & Ruscio, 2009). It has been suggested that taxometric analysis could be adapted for use in other behavioural contexts, but such research is highly sparse (Ruscio et al., 2006).

Systematic evidence of the ability of taxometric analysis to identify the appropriate latent structure in dichotomous data is relatively sparse. This chapter outlines previous approaches to binary data and the significance of understanding the issues concerning the use of taxometric analysis on these data, before conducting two Monte Carlo analyses on simulated data to test the efficacy of traditional taxometric analysis, a summed input approach and a variant of the traditional method using a continuous input variable to identify latent structure, advanced by (Meehl, 1995). The most efficacious of these methods is then applied to real British gambling data in three further analyses. The first aims to replicate the taxometric analysis of the latent structure of problem gambling reported in Chapter 1 using binary DSM indicators. The second extends this to a formerly prevalent assessment of pathological gambling, the South Oaks Gambling Screen (Lesieur & Blume, 1987).

5.2.a An recap of the taxometric method and procedures

In taxometric analysis, variables are selected on a theoretical (i.e. diagnostic indicators of a psychiatric disorder) or data driven (i.e. composite variables derived from summing items that load onto a factor, or factor scores) basis. Cases are the sorted along one of these variables, referred to as the *input* variable. Then, a statistical procedure is computed along another variable, couplets of variables or the remaining variables, which is/are referred to as the *output* variable/s. Different taxometric methods involve the computation of different metrics to determine the latent structure of the construct under examination. Mean Above Minus Below A Cut, or MAMBAC (Meehl & Yonce, 1994), involves a series of cuts being made into the input variable and the mean difference above/below the cut is plotted to determine whether an optimal cutting point in the data exists. MAXCOV (Meehl, 1973) and MAXEIG (Waller & Meehl, 1998) use multiple output indicators, computing correlations (MAXCOV) or eigenvalues (MAXEIG) to observe where there are asynchronies when the sample is divided into a series of independent or overlapping windows. Normally, these analyses are repeated through each possible combination of input and output variable. The average taxometric curve is plotted, and frequently the visual appearance of the plot is compared against prototypical plots from Monte Carlo analyses under varying conditions of effect size between hypothesized taxon and non-taxon members, correlations between variables, skew and kurtosis. Additionally, it has become common (Haslam et al., 2012) to use bootstrapped data with categorical and dimension structures to calculate deviation from observed data (in the form of the root mean square difference) and use the residuals from this comparison to compute quantitative indices to compare the two competing models. This is referred to as the Comparison Curve Fit Index (Ruscio & Marcus, 2007), and while subject to some scrutiny, particularly in its infancy (Beauchaine et al., 2008), it has been widely adopted across the literature (Haslam et al., 2012). The other type of taxometric analysis, L-Mode Factor Analysis (Waller & Meehl, 1998), behaves quite differently. Cases are sorted and then a unidimensional least squares factor analyses is estimated, looking for evidence of a bimodal distribution along this factor.

Taxometric analysis assumes a number of conditions are met by the data that is being analysed. First is that there are a sufficient number of cases. It is widely recommended that the dataset being analysed should consist of a minimum 300 cases. Ruscio et al. (2006) identified an increasing trend towards using data from nationally representative large-scale surveys, which is further indicative that the number of cases analysed is increasing. The second is that there are sufficient members of the hypothesized taxon. Meehl (1995) recommended that at least 10% of the sample should be members of the putative taxon, but that ideally it should be equal numbers of taxon and complement (non-taxon) members. Subsequent analyses (Walters & Ruscio, 2009) have suggested that valid taxa can be identified where only 5% of the sample are members of the taxon. This remains the case even when data are not especially amenable to taxometrics, for instance when the data is highly non-normal. Others have noted the relative importance of the overall number of taxon members, not dissimilar to observations in latent class analysis (Yang, 2006). In addition, taxometric analysis assumes there are substantial inter-group differences between taxon and complement (or non-taxon members) on the indicators in question. For the indicators entered into the analysis, it is assumed that the between groups effect size, standardised as Cohen's d, should be greater than 1.25. Previous taxometric analyses of simulated data (Lubke & Tueller, 2010) failed to find valid taxometric findings relative to mixture modelling when simulating data with smaller effect sizes. Finally, it is assumed that the 'nuisance covariance' or correlation coefficient r between indicators entered into taxometric analysis is small. Ideally, at the level of taxon and complement, the overall level of correlations indicators should have an $r < 0.3$. This is analogous to the assumption of local independence that is generally required for latent class modelling. It is also assumed that the shared covariance in the total sample is greater than the covariance within the taxon or the complement. Although not explicitly an assumption of taxometric analysis, one should be aware of the overall distribution of scores along an indicator. Highly skewed data can produce misleading findings, particularly in suggesting the presence of a low base rate latent taxon (Ruscio et al., 2004).

5.2.b Previous studies of dichotomous taxometric analyses

A small literature exists concerning the use of dichotomous indicators. Maraun, Slaney, and Goddyn (2003) analysed the mathematical proofs behind certain taxometric assumptions when applied to dichotomous data. They strongly suggested that the use of one taxometric procedure (MAXCOV) had no basis for demonstrating meaningful findings in dichotomous variables for a latent unidimensional taxonic structure, as the statistical assumptions Meehl and colleagues have made about taxonic latent structure do not hold with binary data. It is also held that similar problems emerge for continuous data (Maraun & Slaney, 2005), and a lack of specificity concerning the definition of a taxonic latent structure (Maraun & Hart, 2016). In a similar vein to the issues raised by Maraun et al. (2003), Ruscio (2000) suggested that dichotomous variables could be used for taxometric analysis provided that a modified MAXCOV procedure was applied. However, these studies, the former in particular, primarily focus on the visual analysis of taxometric plots. Since then, the introduction of quantitative indices of fit to interpret these plots has altered the manner in which decisions about whether to accept or reject a taxon are made.

Previous use of dichotomous variables in taxometrics has frequently involved a method referred to as the 'summed-input' approach, in which the input variable for the analysis is formed by summing all of the indicators not specified as the output/s (Gangestad & Snyder, 1985). This has been frequently used with dichotomous indicators to produce a composite quantitative input indicator. However, studies have shown that in instances where this is applied, the results tend to be less clear than traditional taxometric approaches. Walters and Ruscio (2009) investigated the use of the summed-input approach, but also systematically varied the number of levels each taxometric indicator had. They found that analyses with dichotomous or trichtomous indicator variables, using traditional or summed approaches there was little difference. For items with more ordered categories, the summed-input approach *reduced* the interpretability of taxometric findings. From this, they concluded that indicators entered into a taxometric analysis should consist of four or more ordered categories, which in the case of dichotomous variables requires composite indicators to be generated.

An alternative, highlighted by Meehl (1995), was the potential that taxometric procedures could be conducted on a continuous input variable using dichotomous output variables. This could be a conceptually related but distinct measurement of the same phenomenon, such as alternative psychometric scale or another variable of some kind. The use of multiple psychometric scales in taxometric analysis is not uncommon (e.g. Lenzenweger, 1999). Conceptually this has a number of similarities to the summed input approach; it computes single analyses for the different combinations of output variables, the only difference being that there is only a single input variable rather than a composite of the various inputs included in the analysis.

5.2.c The importance of understanding taxometrics on dichotomous variables

Although it has been recommended that polytomous or continuous indicators should be used (Walters & Ruscio, 2009), in practice many taxometric analyses use dichotomous variables with a summed input. Because many analyses related to the taxonic or dimensional nature of a psychiatric disorder outlined in one of the DSM manuals, it is frequently the case that indicators are based on presence/absence of behaviour or patterns of behaviours. One important area is the latent structure of addictive behaviour. This represents a potentially promising ground for the presence of a taxon, as a number of studies have found evidence for categorical latent structure in different dependence disorders (Haslam et al., 2012), such as smoking, alcohol and gambling (Kincaid et al., 2013). A simple examination of studies in the area reveals that it is one of the few areas where there are more findings in favour of a taxon than of not. However, in many cases, taxometric analyses of substance use data have used dichotomous data to draw conclusions about the latent structure of addictions. Importantly, there appears to be something of a divergence in the literature based on the indicators entered into a taxometric analysis, although this may be coincidental. Many studies failing to find evidence for a taxon have use summed dichotomous indicators (Denson &

Earleywine, 2006; Slade et al., 2009). Whether coincidental or not, the majority of analyses using dichotomous indicators have found evidence for a latent dimension, and analyses using polytomous or continuous indicators have found evidence for a taxon. Understanding the ability of taxometric analysis to reliably detect whether a latent class or common factor model is the most appropriate statistical model to adopt therefore has the potential to have a real impact on the understanding and conceptualisation of addiction.

5.2.d An overview of the studies reported in the present chapter

In studying the performance of dichotomous indicators in taxometric analysis the same approach was taken that has been used in a number of other studies looking at the performance of taxometric analysis (McGrath & Walters, 2012; Walters & Ruscio, 2009). This involves a Monte Carlo analysis of thousands of simulated taxonic and dimensional datasets. The taxometrics program developed by Ruscio (2013/4) has a number of functions for the generation of taxonic data. This allows for parameters such as nuisance covariance, effect size, sample size, number of indicators and number of ordered categories to be manipulated. For the dimensional data the same approach as Ruscio and Kaczetow (2009) was followed. First, a target correlation matrix is generated for each dataset. Then, for each dataset a *g* and *h* distribution is generated with different parameters for skew and kurtosis, from which the dataset is populated according to the number of indicators and the sample size. The resulting values are then trimmed into binary data, and the program Ruscio & Kaczetow use to generate their dimensional data is used to fit the simulated binary data to the pre-specified correlation matrix.

The real data used in this analysis has previously been studied using taxometric and latent class analyses in Chapter 2 and 3, and so the latent structure is relatively well understood. Latent class analyses of this data to follow up the taxometrics confirmed the presence of this taxon, as well as an additional intermediate group that could not have been located using the aforementioned taxometric analysis as zero scoring respondents were excluded. This identifies quantitative and qualitative differences between the subtypes. Moreover, the latent class analyses suggested a similar class structure between questionnaires; BIC indices revealed that in this sample (and across others), that these assessments measured a three-class structure, showing little overlap in overall scoring between latent classes, strongly suggesting the presence of a dimension of severity. In addition, there was evidence, particularly with DSM-based indicators, that the largest divergence was located in items probing loss of control, a central feature of dependence and addiction models, which the DSM-IV Pathological Gambling criteria were structured around (Gerstein et al., 1999). This means it is potentially a useful dataset; a latent category within this dataset has been located using convergent taxometric analyses and confirmed with latent class analyses. Moreover, with multiple measures of problem gambling that show quantitative and qualitative divergences, it is feasible to use the problem gambling score on one screen as an indicator variable against dichotomous indicators from another. In addition, these indicators fall broadly under three bands; the first two indicators (loss-chasing and preoccupation) show comparatively minor effect size differences and are heavily endorsed by both intermediate and high severity latent classes, the following five indicators diverge between classes on indicator quality and between-group effect size, and the final three show large effect sizes but low overall endorsement by both latent classes.

5.3 Study 1 – Standard Taxometric Analyses on Dichotomous Data

The existing literature suggests taxometrics performs poorly using dichotomous data, but requires further investigation. The present study aims to fill a fundamental gap in the literature by studying this problem. It is unclear the extent to which there is differentiation in performance based on many parameters that have been differentially studied before, and whether these shown the same variation that have been found with ordinal and continuous variables. To this end, the first study reports a Monte Carlo analysis conducting taxometric analyses on dichotomous data under various parameters to examine if taxometrics and comparison data can identify the latent structure of a dataset as designed.

5.3.a Method

The same approach as Walters and Ruscio (2009) was adopted in order to produce sets of simulated data. 4500 sets of taxonic and dimensional data were respectively generated using the same approach outlined by Ruscio and Kaczetow (2009). The number of indicators (*k* – 1:9) was randomly sampled with replacement. The remaining parameters, taxon base rate (*br* – 0.05:0.5), sample size (*n* – 300:1000), standardised between groups effect size (*d* – 1.25:2), skew (*g* - 0:0.3), kurtosis (*h* – 0:0.15), taxon and complement nuisance covariance (r – 0 : 0.3) and correlation between indicators (r – 0 : 0.6) were randomly sampled with replacement from a uniform distribution. Taxonic and dimensional data were created slightly differently, as some parameters (between-groups effect size, base rate, taxon/complement nuisance covariance) do not translate to dimensional data, following previous Monte Carlo analysis (Walters & Ruscio, 2009). Instead the overall correlation between indicators was modelled in these type of data.

The function to produce simulated data included in the *R* program developed by (Ruscio, 2013) (CreateData) was edited and subsequently used to generate dichotomous datasets that differed in sample size, effect size, number of indicators, levels of nuisance covariance, skew and kurtosis. Apart from number of indicators, all of these variables were sampled randomly with replacement from a uniform distribution with the ranges reported by Walters & Ruscio (2009). The number of indicators was sampled randomly with replacement, such that there were 500 datasets with each number of indicators. The CreateData function was edited to sample data points randomly from a *g* and *h* distribution when assigning cases to taxon and complement members. Like Walters & Ruscio (2009), this analysis only looked at positive skew and kurtosis.

To generate the indicators, scores are sampled from a uniform distribution and subsequently assigned to categorical or ordinal values, based on the number of 'cuts' the user specifies. Dichotomising the variables had an effect on the between-subjects effect size; 29.84% of the taxonic datasets had a Cohen's $d < 1.25$. However, in the majority of cases the deviation from the necessary d was small ($d < 0.15$), and the vast majority of datasets with a $d <$

1.25 (86%) had a $d > 1$. Deviations from the required between-groups differences did not appear to be related to the number of indicators. The observed d was very highly linearly correlated to the pre-specified effect size ($r = 0.80$) (Figure 9). It is also worth bearing in mind that although there is deviation from the inputted d, this is likely to be in part due to the dichotomization of the indicators, and in part due to drawing from non-normal distributions with vary skew and kurtosis, which will affect the separation of the variables. In the Supplementary Materials sensitivity analyses are reported, focusing on the datasets with a $d > 1.25$. In terms of overall accuracy, analyses on datasets with an average $d > 1.25$ tended to be 3-5% more accurate.

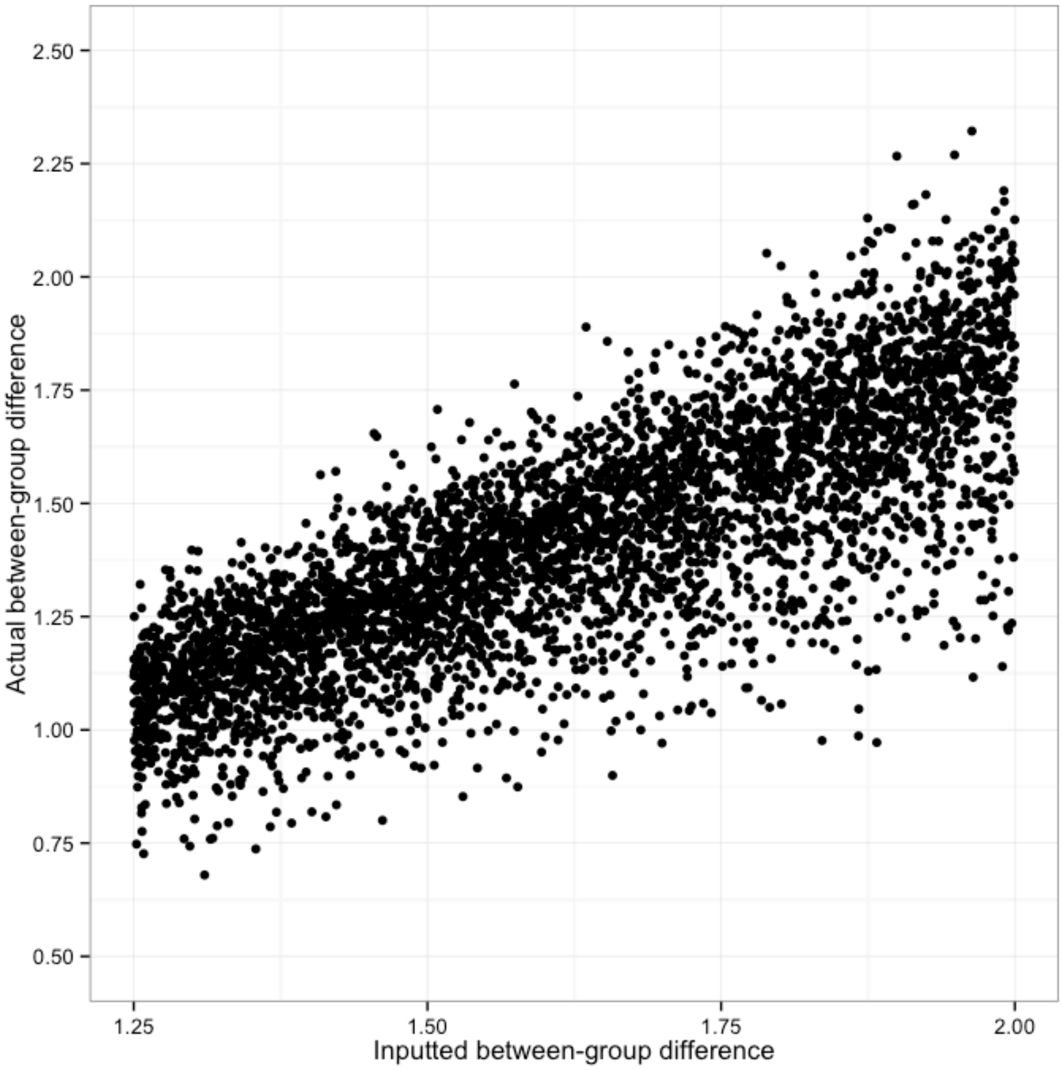

Figure 9

Scatterplot of relationship between inputted and actual between groups differences (measured in terms of Cohen's *d*).

5.3.a.ii Analytic Procedure

Performance was primarily examined using the CCFI. Ten sets of taxonic and dimensional comparison data were generated for each dataset. Cases were assigned to taxon and complement, for the purpose of generating the comparison dataset, using the base rate method advised by (Ruscio, 2009). Ten internal replications were carried out on each taxometric analysis. Previous studies have noted the importance in selecting an appropriate comparison sample for the CCFI (Ruscio, Ruscio, & Meron, 2007).

In a number of cases for the dimensional data, almost entirely where 2 indicators were used, the taxometric procedure identified all cases as belonging to the taxon or complement. In these instances, the base rate was manually set at 0.5. Because the base rate was set at 0.5, this almost invariable meant the CCFI identified a dimensional latent structure. The taxometric program code was also edited to output the estimated mean base rate from the taxometric indicators. For taxonic datasets the output of the base rate was compared against the cases assigned to the taxon based on the output of the data generation script.

5.3.a.ii Analyses of results

The primary dependent variable from the taxometric analysis was the CCFI. To compare the results against previous analyses of the efficacy of the CCFI, accuracy was compared using a dichotomous (0 = miss or false alarm, 1 = hit or correct rejection), or trichotomous (0 = hit or miss, 0.5 = ambiguous, 1 = hit or correct rejection) classification. For further comparison the predictors of the CCFI were subject to a linear regression to understand the effects of different levels of separation, indicators, distributional factors on the ability to interpret taxometric findings. Linear and logistic regression models were estimated to study the factors predictive of the CCFI and taxon base rates, and overall accuracy/taxonicity.

5.3.b Results

5.3.b.i Overall accuracy

The overall results (Figure 10, Tables 19-21), particularly for MAXCOV and MAXEIG, show a broad similarity with the summary statistics reported by Walters & Ruscio (2009). There is a clear drop off with a small number of indicators, and a clear difference between MAMBAC and MAXCOV/MAXEIG analyses (L-Mode analyses were not conducted). In the present analysis however, there appears to be substantial differences between data types; while MAXCOV and MAXEIG perform at similar rates, this belies a high false positive rate in the dimensional but not in the categorical data. Only one method, the L-Mode Factor Analysis, appeared to perform well using a 'traditional' approach. Overall it appeared performance improved with a greater number of indicators, which were the main findings from Walters & Ruscio's (2009) Monte Carlo analysis. For dichotomous variables a greater number of indicators seem to be required relative to ordinal or continuous data; like Walters & Ruscio (2009) this analysis finds a sharp increase in accuracy using > 4 indicators, but for L-Mode analysis a larger number (>8) were required to generate accurate results across both data types.

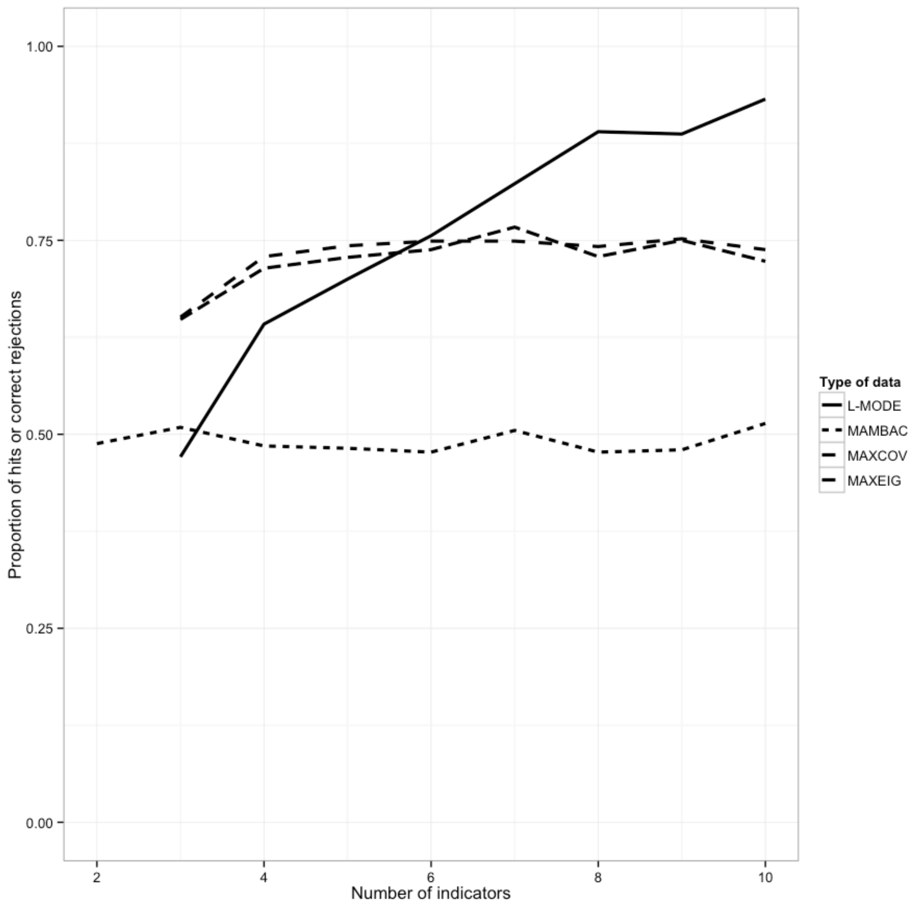

Figure 10

The proportion of instances where taxometric analysis correctly identified the predetermined latent structure of a dataset, across different types of analysis and number of indicators.

One reason for this was that the base rates for the simulated taxonic data appeared to substantially diverge from the estimates parameters entered into the model. Essentially, the analyses are more accurate when the base rate was manually entered, particularly where the base rate analyses performed poorly (MAMBAC, small number of indicators etc.). However in the case of MAMBAC, they still perform extravagantly badly; even when the class membership is known, MAMBAC performs at chance. For base rates exceeding 0.5, base rates were transformed by subtracting the estimated base rate from 1 to produce a scale ranging from 0 to 0.5. In most cases the base rate generated from the taxometric curve was substantially greater than the inputted base rate, producing an erroneous comparison sample. For some analytic approaches, the correlation between the inputted base rate and the one emerging from the taxometric curve/indicators was (given the very large sample size) barely significant, and in some instances was negatively correlated.

Table 19

Hit rates for taxometric analysis of dichotomous data based on the CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI supports the presence of a taxon or dimension (> or < than 0.5)

Categorical (> 0.5)	2	3	4	5	6	7	8	9	10
MAMBAC	0.12	0.18	0.29	0.29	0.29	0.35	0.36	0.39	0.43
MAXCOV	N/A	0.71	0.74	0.87	0.9	0.95	0.95	0.96	0.97
MAXEIG	N/A	0.71	0.78	0.87	0.9	0.94	0.94	0.94	0.96
L-MODE	N/A	0.31	0.48	0.49	0.64	0.73	0.86	0.85	0.91
Dimensional (< 0.5)									
MAMBAC	0.85	0.84	0.68	0.67	0.66	0.66	0.60	0.57	0.60
MAXCOV	N/A	0.59	0.69	0.59	0.58	0.59	0.51	0.54	0.48
MAXEIG	N/A	0.59	0.68	0.62	0.6	0.56	0.55	0.56	0.52
L-MODE	N/A	0.63	0.81	0.91	0.87	0.92	0.92	0.92	0.95
Both									
MAMBAC	0.49	0.51	0.49	0.48	0.48	0.51	0.48	0.48	0.51
MAXCOV	N/A	0.65	0.71	0.73	0.74	0.77	0.73	0.75	0.72
MAXEIG	N/A	0.65	0.73	0.74	0.75	0.75	0.74	0.75	0.74
L-MODE	N/A	0.47	0.64	0.7	0.76	0.82	0.89	0.89	0.93

Table 20

Hit rates for taxometric analysis of dichotomous data based on the CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI *substantially* supports the presence of a taxon or dimension (> 0.6 for a taxon, < 0.4 for a dimension)

Categorical (> 0.6)	2	3	4	5	6	7	8	9	10
MAMBAC	0.01	0.03	0.05	0.06	0.07	0.09	0.1	0.09	0.15
MAXCOV	N/A	0.58	0.59	0.77	0.83	0.91	0.90	0.91	0.93
MAXEIG	N/A	0.57	0.60	0.76	0.82	0.88	0.90	0.90	0.93
L-MODE	N/A	0.12	0.22	0.24	0.28	0.32	0.38	0.34	0.40
Dimensional (< 0.6)									
MAMBAC	0.68	0.61	0.42	0.36	0.34	0.32	0.30	0.33	0.33
MAXCOV	N/A	0.41	0.49	0.44	0.43	0.44	0.33	0.37	0.33
MAXEIG	N/A	0.41	0.49	0.45	0.41	0.41	0.34	0.34	0.36
L-MODE	N/A	0.32	0.52	0.58	0.61	0.67	0.74	0.76	0.73
Both									
MAMBAC	0.35	0.32	0.23	0.21	0.20	0.21	0.20	0.21	0.24
MAXCOV	N/A	0.49	0.54	0.60	0.63	0.67	0.62	0.64	0.63
MAXEIG	N/A	0.49	0.54	0.60	0.61	0.65	0.62	0.62	0.64
L-MODE	N/A	0.22	0.37	0.41	0.45	0.50	0.56	0.55	0.57

Table 21

Mean accuracy of classification based on the CCFI, using the trichotomous classification used by Walters & Ruscio (2009) (0 <- miss/false alarm, 0.5 <- ambiguous, CCFI between 0.4 and 0.6, 1 <- hit/correct rejection).

Categorical (> 0.6)	2	3	4	5	6	7	8	9	10
MAMBAC	0.17	0.24	0.32	0.36	0.36	0.38	0.41	0.41	0.44
MAXCOV	N/A	0.70	0.73	0.86	0.89	0.94	0.93	0.94	0.95
MAXEIG	N/A	0.70	0.74	0.85	0.89	0.93	0.94	0.94	0.95
L-MODE	N/A	0.41	0.54	0.58	0.62	0.65	0.68	0.67	0.70
Dimensional (< 0.6)									
MAMBAC	0.84	0.80	0.71	0.68	0.67	0.66	0.65	0.67	0.67
MAXCOV	N/A	0.57	0.66	0.60	0.57	0.58	0.52	0.54	0.48
MAXEIG	N/A	0.58	0.66	0.61	0.58	0.57	0.52	0.53	0.53
L-MODE	N/A	0.59	0.74	0.78	0.80	0.82	0.86	0.87	0.87
Both									
MAMBAC	0.51	0.52	0.52	0.52	0.51	0.52	0.53	0.54	0.55
MAXCOV	N/A	0.53	0.52	0.58	0.61	0.63	0.65	0.65	0.67
MAXEIG	N/A	0.53	0.52	0.57	0.60	0.63	0.64	0.65	0.65
L-MODE	N/A	0.50	0.64	0.68	0.71	0.74	0.77	0.77	0.78

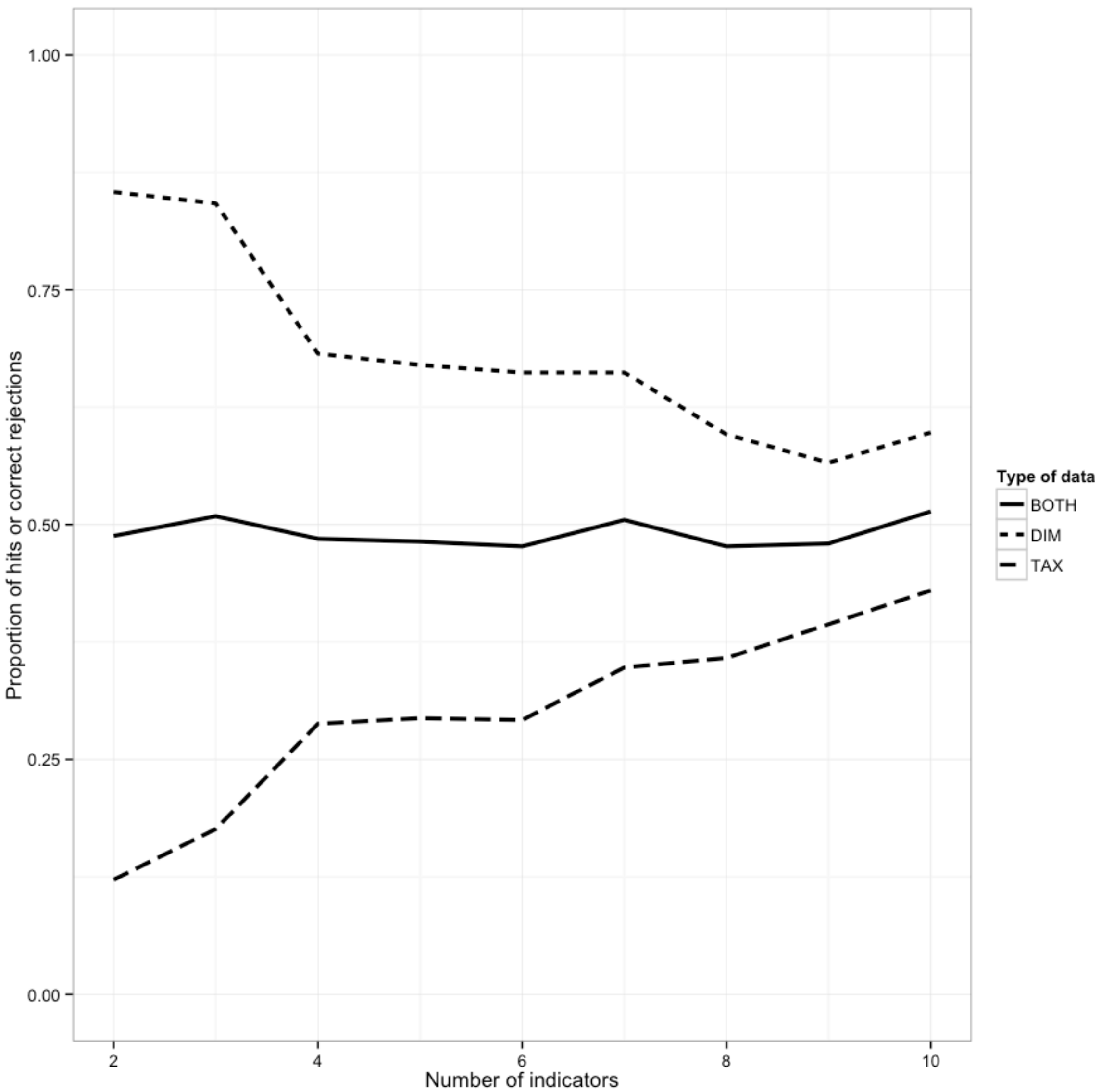

Figure 11

The proportion of instances in which the MAMBAC taxometric analyses identified the correct predetermined latent structure of a dataset, sorted by type of dataset and the number of indicators

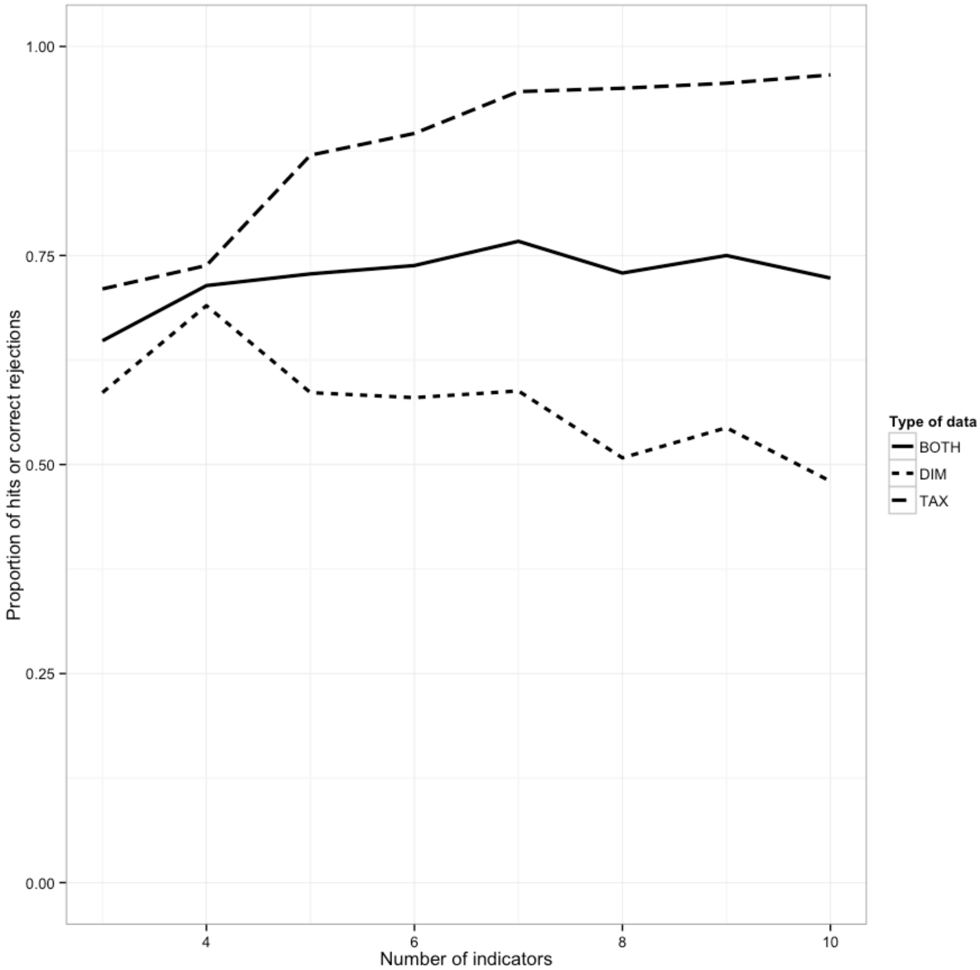

Figure 12

The proportion of instances in which the MAXCOV taxometric analyses identified the correct predetermined latent structure of a dataset, sorted by type of dataset and the number of indicators

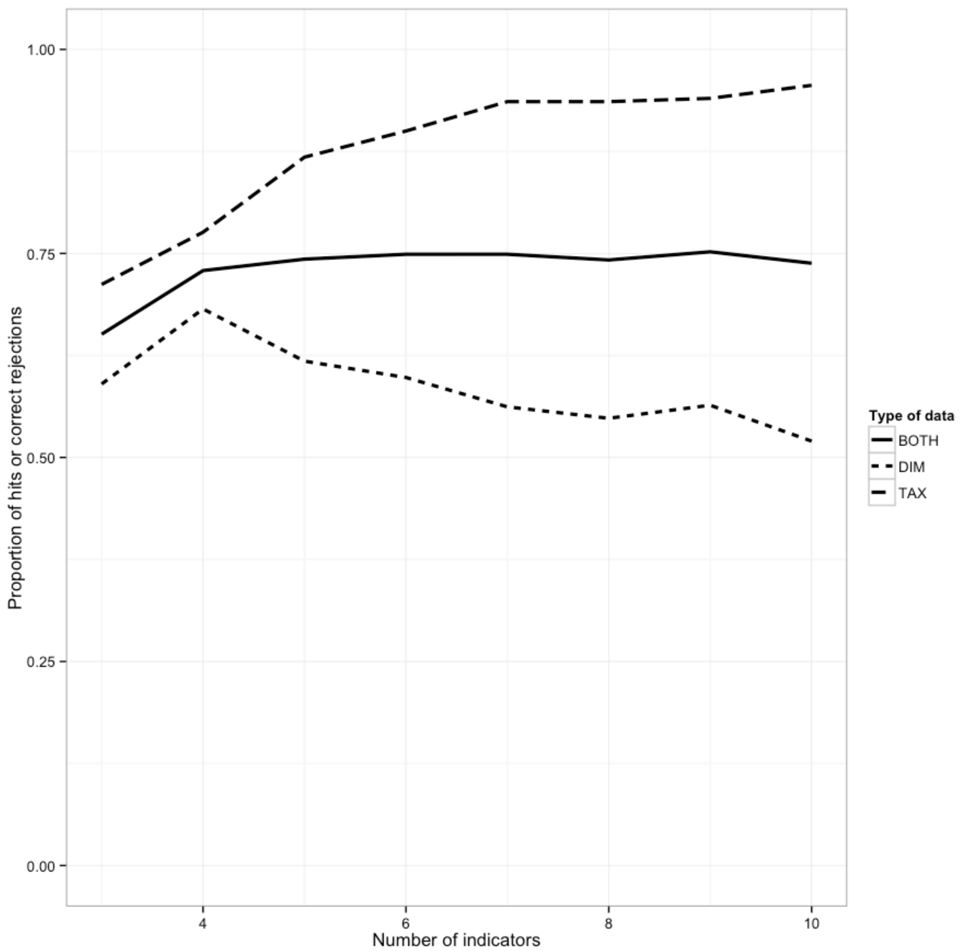

Figure 13

The proportion of instances in which the MAXEIG taxometric analyses identified the correct predetermined latent structure of a dataset, sorted by type of dataset and the number of indicators

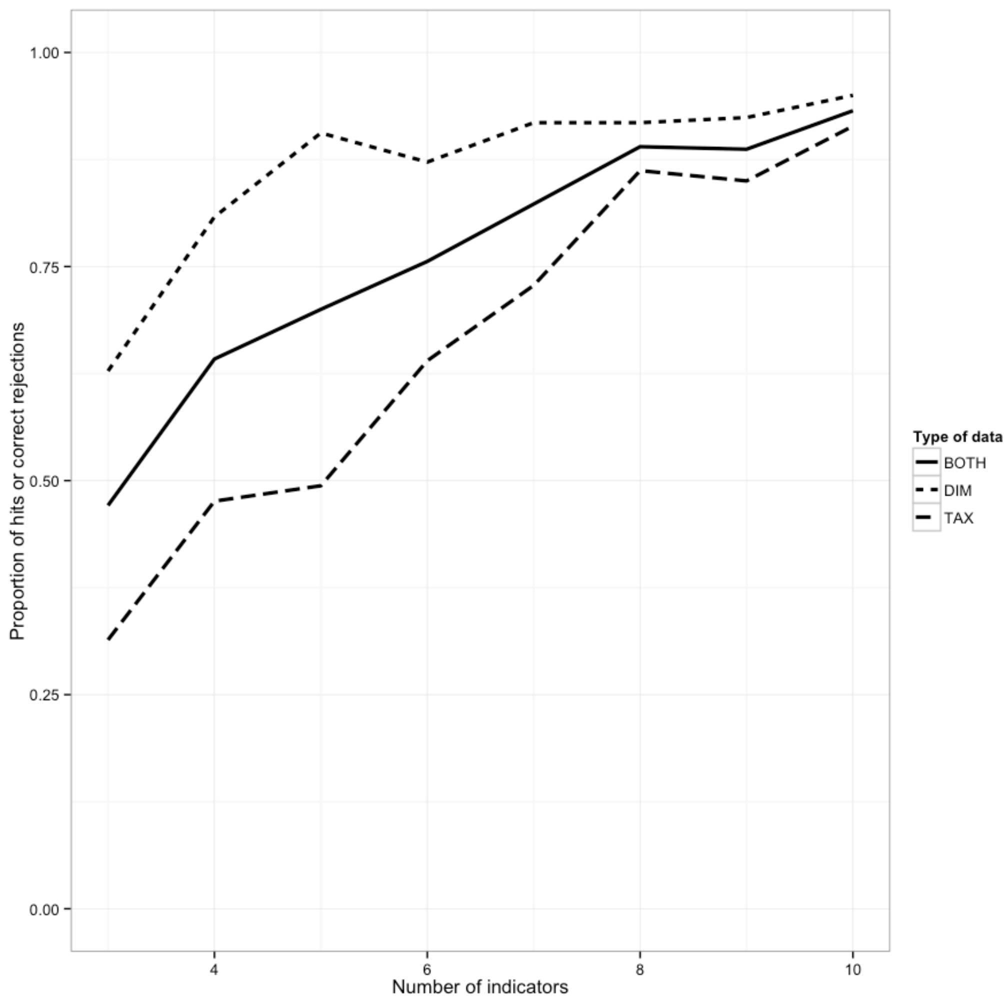

Figure 14

The proportion of instances in which the L-Mode factor taxometric analyses identified the correct predetermined latent structure of a dataset, sorted by type of dataset and the number of indicators

The overall ability of MAMBAC, MAXCOV and MAXEIG (Figure 10-14) analyses was very similar to the figures reported in Figure 2 in Ruscio & Walters (2009) (L-Mode analyses were not reported in these cases). However, comparing whether the dataset was generated as taxonic or dimension revealed substantial differential performance between structure and procedure. MAMBAC correctly identified latent structure around 55-60% of the time. However, it was also found that MAMBAC performed below chance for taxonic datasets, although it did successfully identify latent continua around two-thirds of the time. Similarly MAXEIG and MAXCOV analyses performed very well at identifying discontinuities typical of a latent class in the taxonic datasets, but performed very poorly in the dimensional datasets. The only technique that performed well across both datasets was the L-Mode Factor analysis.

5.3.b.ii Predictors of accuracy

Three analyses were modelled to study the effects of the various parameters on the overall accuracy of the CCFI and the generated CCFI, as the proximity/distance from 0.5 is interpreted as a measure of the confidence one has in interpreting the data in one manner or another. Linear and logistic regression models were estimated, using CCFI as a continuous dependent variable, and hit/correct rejection as a binary outcome. For the logistic and linear regression modelling, models were first estimated for taxonic data (hits) and dimensional (correct rejections), and then across both.

For the taxonic data, the logistic regression revealed a number of commonalities across different taxometric procedures. First was that the effect of the number of indicators appeared relatively constant across the different techniques. MAMBAC apart (and possibly because of its poor performance), the effect of the number of indicators on accuracy was relatively constant. The second was the between-groups effect size; the level of separation between taxon and complement positively predicted hit rate. Across all analyses, larger levels of skew or kurtosis increased the probability of a false negative. Sample size had a negligible effect on hit rates.

There were some differences that are worth noting. The L-Mode Factor Analysis appeared to be far more sensitive to levels of nuisance covariance than other taxometric procedures. Increased levels of correlation within taxon and within complement increased the likelihood of a hit and a miss respectively. The second difference pertained to the inputted base rates; higher base rates positively predicted hits in MAMBAC and L-Mode analyses, but negatively in MAXCOV and MAXEIG. For MAMBAC analyses, this appeared to be because datasets with small base rate taxa tended to assigned substantially deviant comparison samples (i.e. clustered around 0.4, 0.5). In contrast, MAXCOV and MAXEIG analyses on small samples tended to produce CCFI's that clustered more closely to 1 than larger base rates (Appendix 3). L-Mode appeared to behave quite differently, displaying a relationship similar to a step function: CCFI's for small base rates tended to cluster in the 0.5-0.55 region, whereas taxonic datasets with a larger base were more dispersed, but included notably clustering around 0.9-1 (see Appendix 3).

Unsurprisingly, across both kinds of dataset and all methods, the strongest effect on the base rate that emerged from the taxometric analysis was the inputted indicator skew. Although true for all analyses, there was particularly striking evidence of a linear negative correlation between increasing positive indicator skew and the generation of small base rate comparison samples. For taxonic data, greater levels of nuisance covariance intra-taxon were associated with larger base rate estimates, and the opposite for intra-complement correlations. Larger levels of between-groups separation were associated with smaller base rates; this is likely another manifestation of the relationship between larger between groups effect sizes and CCFI's. With smaller effect sizes, the base rates emerging from the taxometric curves are greater, which tends to assign a larger number of complement members to the taxon than specified in dataset generation, thus creating comparison data that tends to produce inconclusive or (more often) dimensional CCFI's.

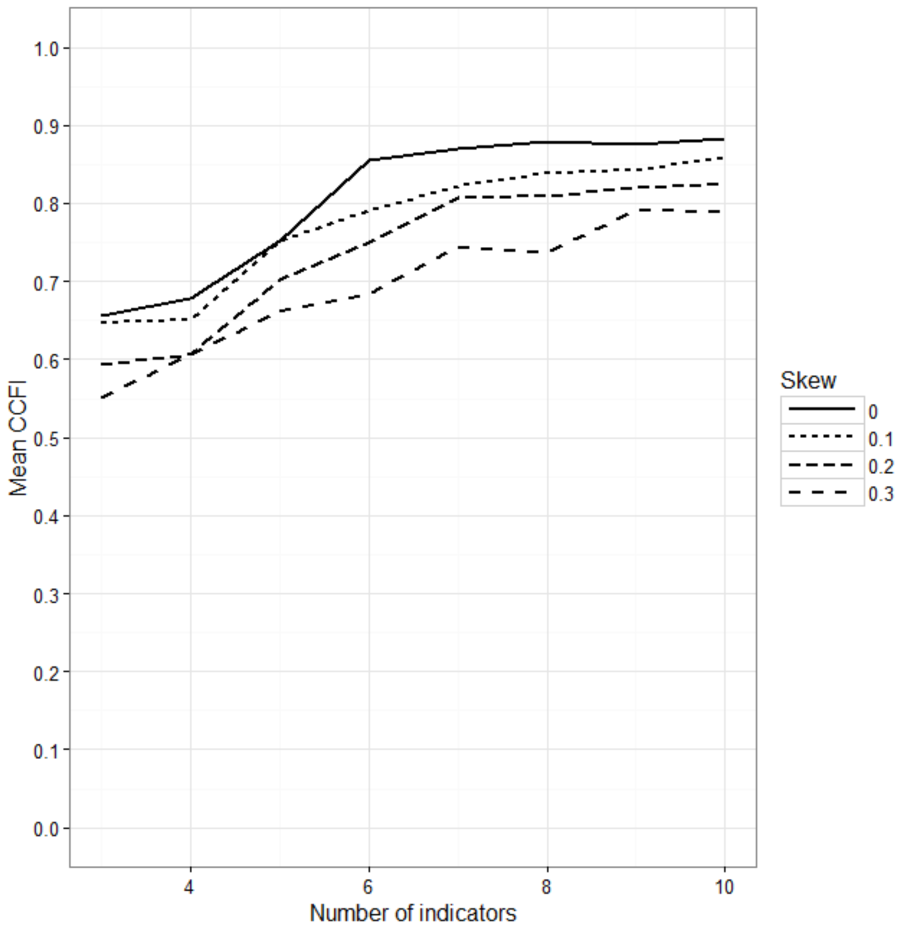

Figure 15

Plot of average CCFI values across different indicators and different levels of skew (rounded to one digit), for taxonic MAXCOV analyses.

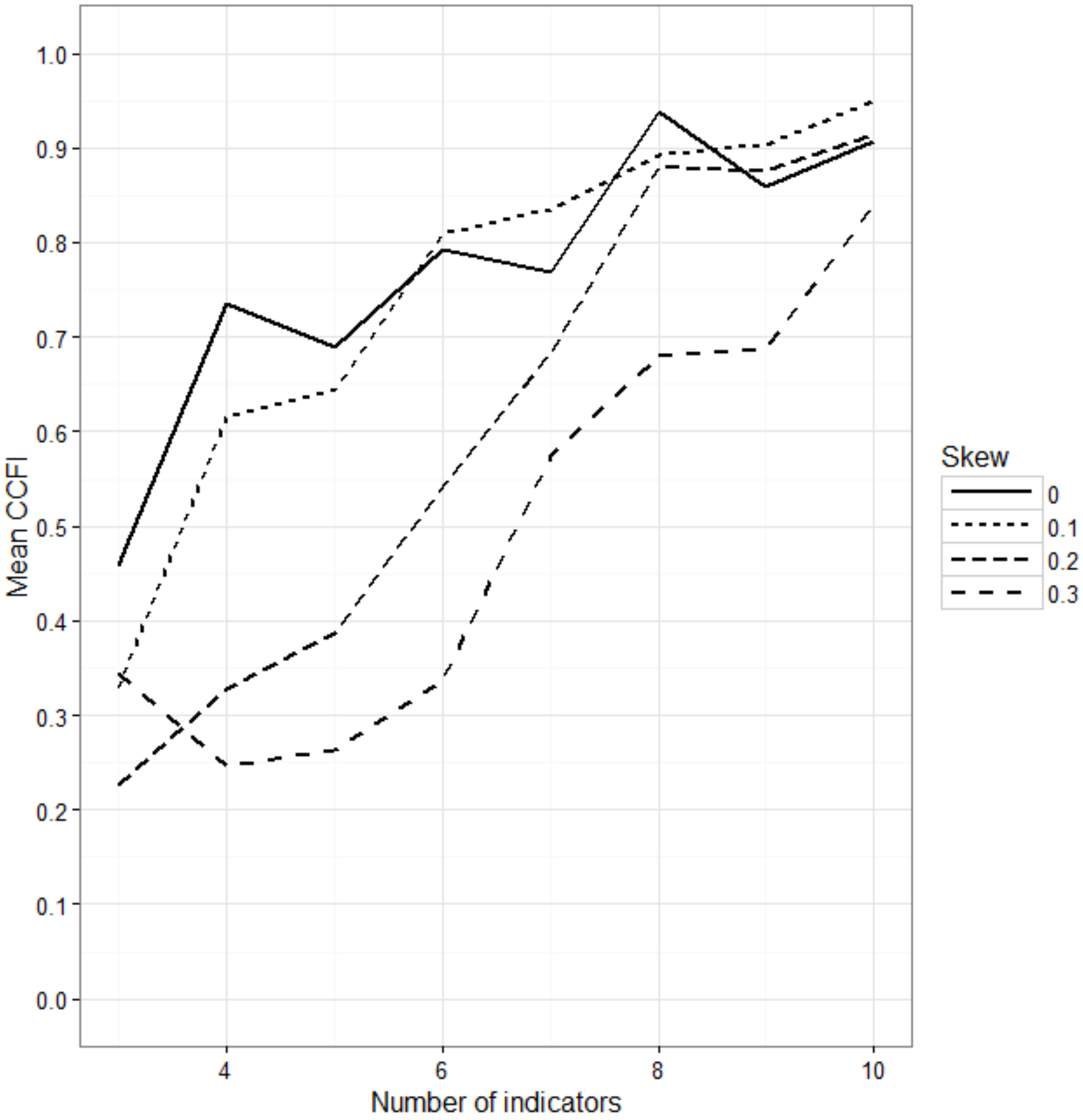

Figure 16

Plot of average CCFI values across different indicators and different levels of skew (rounded to one digit), for taxonic L-Mode factor analyses.

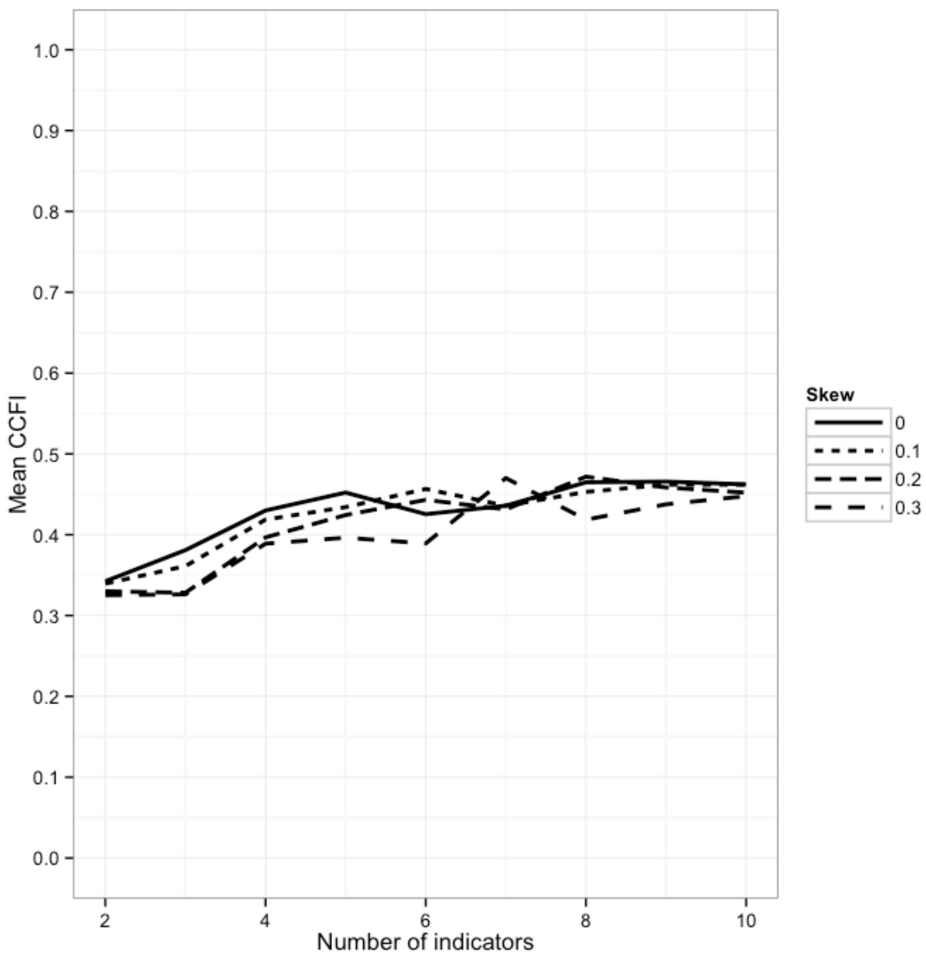

Figure 17

Plot of average CCFI values across different indicators and different levels of skew (rounded to one digit), for dimensional MAMBAC analyses.

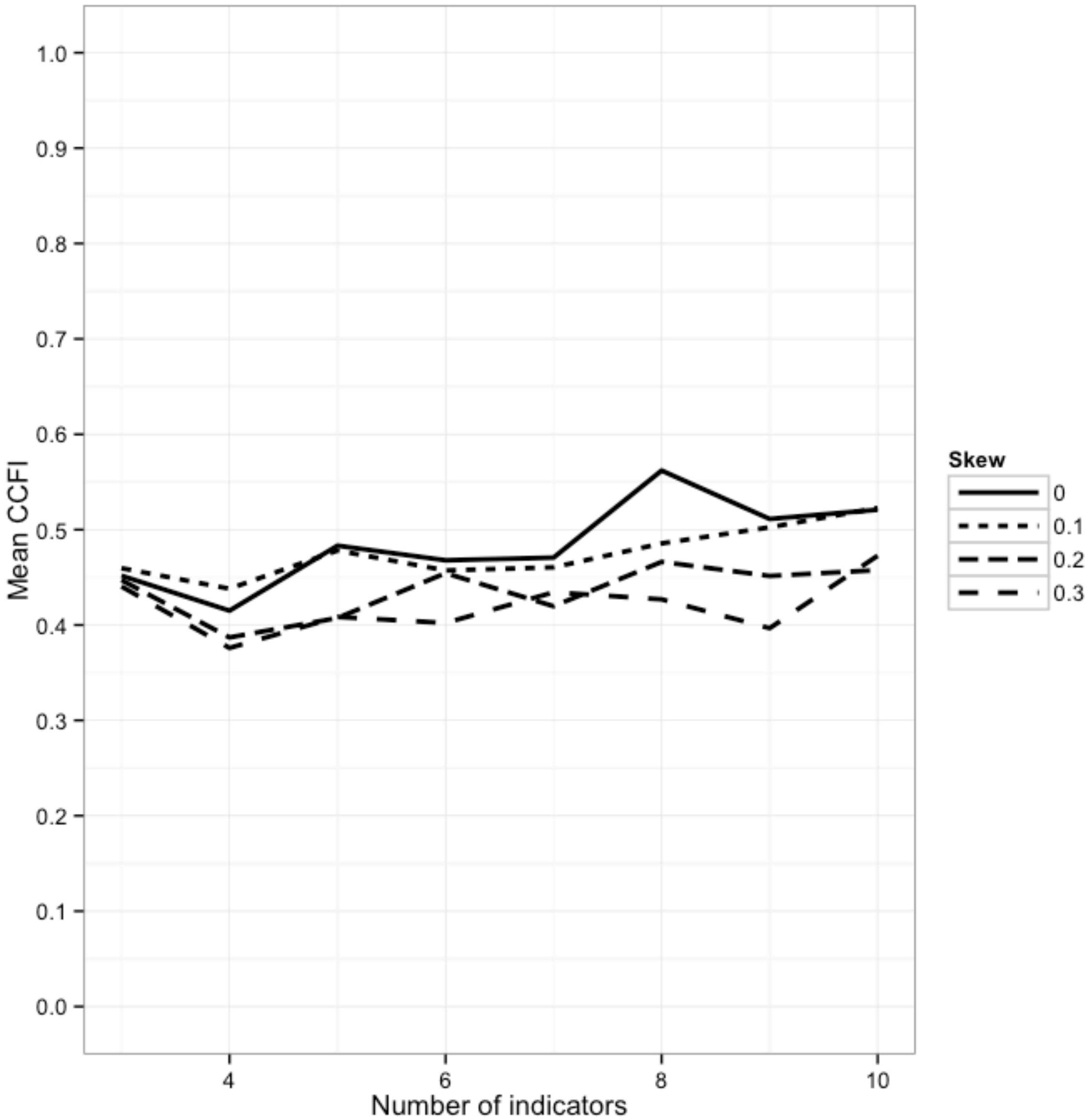

Figure 18

Plot of average CCFI values across different indicators and different levels of skew (rounded to one digit), for dimensional MAXCOV analyses.

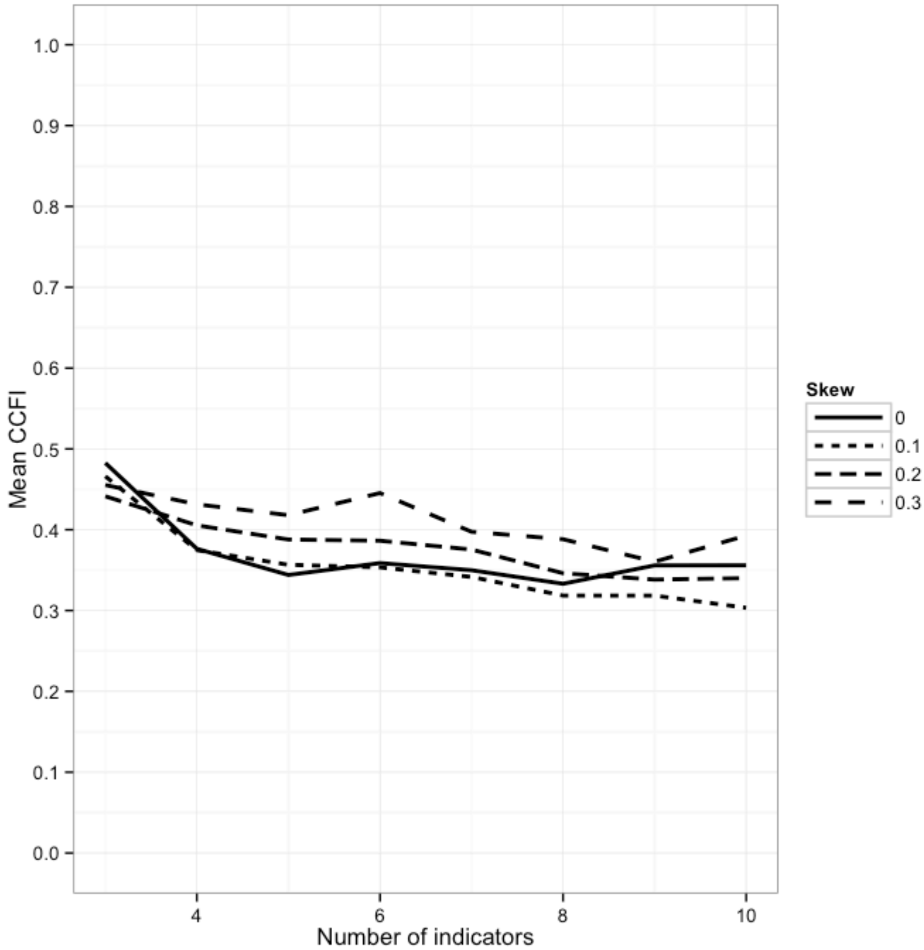

Figure 19

Plot of average CCFI values across different indicators and different levels of skew (rounded to one digit), for dimensional L-Mode factor analyses.

Table 22

Output of logistic regression estimations of the predictors of a hit (CCFI > 0.5) in taxonic data.

	MAMBAC			MAXCOV			MAXEIG			L-Mode		
Indicator	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
Intercept	-2.334	0.36	-6.55	0.492	0.50	0.99	-0.479	0.48	-1.00	-5.385	0.38	-14.1
n	-0.001	0.00	-5.77	0.000	0.00	-0.80	0.000	0.00	-0.36	0.000	0.00	0.75
k	0.181	0.01	13.07	0.513	0.03	16.75	0.407	0.03	14.7	0.430	0.02	21.61
d	1.150	0.14	8.35	1.870	0.24	7.94	2.462	0.24	10.36	1.238	0.16	7.62
br	-1.118	0.51	-2.21	-8.123	0.54	-15.2	-7.040	0.52	-13.5	6.960	0.56	12.45
g	-0.523	0.44	-1.19	-6.655	0.69	-9.71	-5.082	0.65	-7.87	-5.938	0.48	-12.3
h	-1.385	0.80	-1.73	-3.140	1.34	-2.34	-3.064	1.31	-2.34	-1.373	0.95	-1.44
Tax.*r*	-0.322	0.40	-0.81	0.488	0.66	0.74	1.066	0.64	1.66	1.839	0.47	3.92
Comp.*r*	-0.087	0.40	-0.22	-0.550	0.66	-0.83	-1.094	0.65	-1.69	-2.025	0.48	-4.26

Note: t statistics exceeding 1.96 are equivalent to $p < .05$. Dependent variable = CCFI > 0.5

Table 23

Output of linear regression modelling of the predictors of the Comparison Curve Fit Index for taxonic data

	MAMBAC			MAXCOV			MAXEIG			L-Mode		
Indicator	*b*	SE	*t*	*b*	SE	*t*	*b*	SE	*t*	*b*	SE	*t*
Intercept	0.313	0.02	17.79	0.537	0.02	27.98	0.487	0.02	25.99	-0.035	0.02	-1.64
n	0.000	0.00	-8.56	0.000	0.00	1.34	0.000	0.00	3.38	0.000	0.00	1.18
k	0.017	0.00	24.47	0.035	0.00	36.06	0.032	0.00	33.55	0.025	0.00	24.45
d	0.088	0.01	12.55	0.162	0.01	17.91	0.189	0.01	21.40	0.163	0.01	17.75
br	-0.116	0.02	-4.73	-0.627	0.02	-30.6	-0.590	0.02	-28.9	0.671	0.03	20.35
g	-0.063	0.02	-2.87	-0.499	0.03	-19.2	-0.500	0.03	-19.6	-0.262	0.03	-9.70
h	-0.055	0.04	-1.33	-0.111	0.05	-2.08	-0.100	0.05	-1.91	0.061	0.06	1.11
Tax.*r*	-0.006	0.02	-0.30	0.088	0.03	3.37	0.100	0.03	3.91	0.079	0.03	2.95
Comp.*r*	-0.041	0.02	-1.99	-0.058	0.03	-2.20	-0.085	0.03	-3.27	-0.096	0.03	-3.57

Note: t statistics exceeding 1.96 are equivalent to $p < .05$. Dependent variable = CCFI > 0.5.

Table 24

Output of logistic regression estimations of the predictors of a correct rejection (CCFI < 0.5) in dimensional data.

	MAMBAC			MAXCOV			MAXEIG			L-Mode		
Indicator	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
Intercept	2.389	0.18	13.56	0.840	0.18	4.69	1.242	0.18	6.87	-0.874	0.26	-3.43
n	0.000	0.00	0.47	0.001	0.00	3.87	0.000	0.00	2.39	0.002	0.00	7.99
k	-0.165	0.01	-12.5	-0.084	0.02	-5.75	-0.066	0.02	-4.52	0.333	0.02	14.13
g	0.245	0.39	0.64	2.830	0.39	7.26	1.334	0.39	3.44	-1.496	0.56	-2.66
h	1.289	0.77	1.67	1.628	0.78	2.09	1.360	0.78	1.75	-2.609	1.12	-2.34
r	-2.535	0.20	-12.9	-3.144	0.20	-15.8	-3.321	0.20	-16.6	-0.040	0.28	-0.15

Note: t statistics exceeding 1.96 are equivalent to $p < .05$. Dependent variable = CCFI < 0.5

Table 25

Output of linear regression modelling of the predictors of the Comparison Curve Fit Index for dimensional data

	MAMBAC			MAXCOV			MAXEIG			L-Mode		
Indicator	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*z*	*B*	*SE*	*t*
Intercept	0.323	0.01	23.18	0.668	0.03	23.03	0.572	0.03	21.15	0.438	0.01	33.09
n	0.000	0.00	-1.94	0.000	0.00	-6.40	0.000	0.00	-5.75	0.000	0.00	-13.6
k	0.016	0.00	20.91	0.011	0.00	8.46	0.008	0.00	7.19	-0.015	0.00	-20.8
g	-0.143	0.02	-5.88	-0.782	0.05	-14.8	-0.510	0.05	-10.5	0.244	0.02	11.44
h	-0.222	0.05	-4.99	-0.311	0.07	-4.57	-0.225	0.06	-3.59	0.187	0.04	4.93
r	0.286	0.01	25.14	0.331	0.02	17.52	0.362	0.02	21.13	-0.012	0.01	-1.21
br	-0.095	0.02	-4.30	-0.538	0.05	-11.7	-0.411	0.04	-9.64	0.155	0.02	7.09

Note: *t* statistics exceeding 1.96 are equivalent to $p < .05$.

5.3.c Discussion

A Monte Carlo analysis of the use of taxometric analysis on dichotomous indicators revealed substantial differences in performance between taxometric methods across different latent structures. In some cases the evidence of differential performance between taxonic and dimensional data may raise important issues for the interpretation of taxonic findings. Three of the four main taxometric procedures seemed to fail to identify the appropriate latent structure either in taxonic or dimensional data.

Only one taxometric procedure (L-Mode Factor Analysis) can be recommended on binary datasets without any caveats. Looking at the relationship between accuracy and the number of indicators, the L-Mode Factor Analysis showed a similar pattern of behaviour to the data reported by Ruscio & Walters (2009) under more optimal conditions (i.e. continuous indicators): an r-shaped pattern after which accuracy reached asymptote in the low to mid ninety per cent range. Again, a similar number of indicators was required, a minimum of eight, to reach asymptote.

The predictors of hits, correct rejections, base rates and the CCFI reinforce some of the previous findings that have emerged from the literature. The first is the effect of skew. Increasing the level of skew in the data increased the probability of the base rate approach identifying a small base rate category for bootstrap comparison. This increased the likelihood of identifying a false positive in dimensional data. Moreover, increasing indicator skew notable effects on the CCFI for both dimensional and categorical data. Increasing the level of skew appeared to have an effect on the CCFI similar to criterion bias, as it shifted the CCFI downward (i.e. closer to 0).

The second is that overall, increasing the number of indicators increases overall accuracy. However, a serious qualification to this was that when the pre-specified latent structure was dimensional, increasing the number of indicators increased the probability of observing a false positive result. This seriously questions the rationale of performing a taxometric analysis on binary data, although previous Monte Carlo analyses have reached a similar conclusion (Walters & Ruscio, 2009).

Interestingly, while sample size was associated with increased accuracy and CCFI's further away from 0.5, the effect tended to be rather small. While this may differ for ordinal or continuous variable, this poses an interesting qualification. The increasing use of general population data for taxometrics has generally been regarded as a positive. However, many measurements of psychiatric disorder using these samples use the sort of dichotomous variables discussed here (e.g. DSM criteria). In such data, the effect of larger samples is positive, but it is unclear how it attenuates with larger samples. In the Appendix 3 LOWESS (locally weighted smoothed regression) curves plotting the relationship between *n* and CCFIs are reported. While in the dimensional data the effect is clearly linear, in the non-MAMBAC analyses (simply because MAMBAC failed to validly identify taxa), the relationship appeared to attenuate in larger samples, going into reverse for L-Mode Factor Analyses. Further modelling ought to test the manner in which this might continue to attenuate with larger *n*'s. The importance of considering this is that, given that general population data studying the structure of psychiatric disorders is almost a given to be highly positively skewed, it might be the case that any benefits from an increased sample size and the inferences that can be drawn from such a sample might at times be offset by it's other distributional statistics.

Even under the most conductive circumstances (when class membership was known and used to generate the comparison sample), the comparison approach failed to reliably identify taxa using a MAMBAC analysis on dichotomous data. In addition, there was a substantial false positive rate using MAXCOV and MAXEIG analyses. Regardless of the number of variables, neither type of analyses performed substantially above chance with a specific form of prespecified data. All of the analyses using less than four variables had substantial false negative rates in identifying taxa, and this remained the case for the L-Mode Factor Analysis for an even greater number of indicators. This reiterates the need, as enunciated by Walters & Ruscio (2009), to use a sufficient number of valid indicators. Valid taxometric results have been identified using only two indicators (Walters & Ruscio, 2010), but these require continuous indicators (or a very large number of ordered categories) and highly valid indicators. These conditions do not apply to the sort of dichotomous data reported in this analysis however.

Given that there appears to be little evidence to support the use of the 'traditional' (iterative) approach to taxometrics on dichotomous data, in the following study the focus instead moves toward looking at two alternatives that might perform better, primarily to study whether the performance of taxometrics reported in this study is a function of the type of data used i.e. that taxometrics cannot be recommended on dichotomous data at all, or whether there are certain caveats that are idiosyncratic to binary data.

5.4 Study 2 – The efficiacy of summed or continuous input approaches

The findings from Study 1, indicated that a number types of taxometric analysis, even under the most optimal situations, failed to identify a pre-specified latent structure. Before rejecting the idea that taxometrics can be conducted on binary data, it is worth exploring alternative methods of conducting taxometric analysis. The first is the summed input introduced by Gangestad and Snyder (1985). This involves the summing of non-input variables into a quantitative indicator. This has been used. Moreover, while Walters & Ruscio (2009) advise against the use of the summed input in their Monte Carlo, the analysis looks at its efficacy over both dichotomous and continuous data, whereas it appears to have been designed primarily for use on the former. In contrast, most studies utilising the summed input (and the summed input alone) do so in dichotomous data. Their analysis does not indicate an interaction between method and number of indicators. However, given the intended use of the summed input, it is unclear whether this is the appropriate contrast. It would be equally plausible to simply contrast 2 ordered categories versus > 2 categories. Given the lack of specificity in this analysis related to dichotomous variables, further exploration of the summed input ought not to be precluded.

The second consideration is the approach described by (Meehl, 1995). While this is similar to the summed input, there are a number of situations where this sort of approach may be more appropriate. For instance, research on gambling prevalence assessments has frequently shown that these screens are moderately correlated, contain latent classes (and taxa) and are strongly unidimensional. The standard approach of using a principal components analysis or exploratory factor analysis therefore contains the risk of creating composite variables that are less straightforward to interpret. In addition while meaningful factors or components may be derived, this might be restricted to a subsample. Again, similar findings in gambling have been observed, where multidimensional structures have been observed in one assessment of problem gambling (PGSI) in samples restricted to those endorsing more than one of the PGSI items (Holtgraves, 2008). Moreover it is useful to compare against the summed input if, as has been suggested before, the summed input approach to taxometric analysis is shown to perform poorly.

5.4.a. Method

Ruscio's taxometric was edicted code to create 6,075 dichotomous datasets without dichtomising the first variable (but instead specifying an additional variable to determine the number of ordered categories), and secondly to iterate through sets of indicators with the initial indicator being used as the input, and iterating through the remaining variables.

For the summed input analyses, the datasets were the same as Study 1. For the continuous input analyses, a total of 6075 datasets were generated. The number of indicators was again systematically manipulated alongside the number of ordinal categories in the input variable. As in Study 1 these were randomly sampled with replacement. The same parameters for the taxonic and dimensional data were sampled from a uniform distribution with the bounds reported in Study 1. In addition, the number of cuts made in the input variable was systematically manipulated, with between 4 and 12 cuts made into the input. Alongside the number of indicators, each cell was populated by 75 simulated datasets.

5.4.b Results

In contrast to the traditional taxometric analyses, both analyses performed well (Tables 26-30). The summed input performed better than the continuous input, and both outperformed the traditional taxometric analysis. For the continuous input, it was observed in both cases that the hit rate for dimensional data began to drop off as the number of indicators increased. Both performed consistently in the 80-90% range. In contrast, the summed input method, given a sufficiently large number of variables, correctly identified structure in excess of 90% of the time. For certain types of analysis, the summed MAMBAC in particular, a larger number of variables were required to positively identify the presence of a taxon.

Table 26

Hit rates for summed input taxometric analysis of dichotomous data based on the CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI supports the presence of a taxon or dimension (> or < than 0.5)

Categorical (> 0.5)	2	3	4	5	6	7	8	9	10
MAMBAC	0.12	0.24	0.40	0.48	0.65	0.82	0.88	0.94	0.96
MAXCOV	N/A	0.71	0.67	0.75	0.87	0.93	0.97	0.98	0.98
Dimensional (< 0.5)									
MAMBAC	0.85	0.88	0.93	0.99	0.99	0.98	0.99	0.99	0.99
MAXCOV	N/A	0.59	0.92	0.94	0.95	0.91	0.94	0.96	0.96
Both									
MAMBAC	0.49	0.56	0.66	0.74	0.82	0.90	0.94	0.97	0.98
MAXCOV	N/A	0.65	0.79	0.84	0.91	0.92	0.96	0.97	0.97

Table 27

Hit rates for continuous input taxometric analysis of dichotomous data based on the CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI supports the presence of a taxon or dimension (> or < than 0.5)

Categorical (> 0.5)	2	3	4	5	6	7	8	9	10
MAMBAC	0.47	0.80	0.86	0.91	0.95	0.95	0.96	0.98	0.96
MAXCOV	N/A	0.60	0.84	0.91	0.95	0.97	0.98	0.99	0.99
Dimensional (< 0.5)									
MAMBAC	0.81	0.80	0.73	0.65	0.65	0.62	0.61	0.53	0.51
MAXCOV	N/A	0.81	0.82	0.80	0.76	0.75	0.76	0.32	0.72
Both									
MAMBAC	0.64	0.80	0.80	0.78	0.80	0.79	0.79	0.76	0.74
MAXCOV	N/A	0.70	0.83	0.85	0.86	0.86	0.87	0.86	0.85

Table 28

Hit rates for the summed input taxometric analysis of dichotomous data based on the summed CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI *substantially* supports the presence of a taxon or dimension (> 0.6 for taxonic data < 0.4 for dimensional)

Categorical (> 0.6)	2	3	4	5	6	7	8	9	10
MAMBAC	0.01	0.14	0.23	0.29	0.44	0.61	0.71	0.83	0.84
MAXCOV	N/A	0.58	0.47	0.58	0.75	0.82	0.84	0.81	0.81
Dimensional (< 0.4)									
MAMBAC	0.68	0.79	0.82	0.91	0.92	0.91	0.93	0.93	0.91
MAXCOV	N/A	0.41	0.82	0.84	0.84	0.81	0.85	0.85	0.84
Both									
MAMBAC	0.34	0.46	0.53	0.60	0.68	0.76	0.82	0.88	0.88
MAXCOV	N/A	0.49	0.64	0.71	0.80	0.82	0.84	0.83	0.82

Table 29

Hit rates for the continuous input taxometric analysis of dichotomous data based on the summed CCFI, varying by method and number of indicators. Hit rate is computed based on whether the CCFI *substantially* supports the presence of a taxon or dimension (> 0.6 for taxonic data < 0.4 for dimensional)

Categorical (> 0.6)	2	3	4	5	6	7	8	9	10
MAMBAC	0.18	0.51	0.63	0.72	0.79	0.80	0.81	0.82	0.82
MAXCOV	N/A	0.39	0.67	0.82	0.89	0.92	0.95	0.96	0.96
Dimensional (< 0.4)									
MAMBAC	0.52	0.46	0.33	0.28	0.27	0.27	0.22	0.19	0.18
MAXCOV	N/A	0.58	0.65	0.56	0.55	0.50	0.51	0.49	0.45
Both									
MAMBAC	0.35	0.48	0.48	0.50	0.53	0.53	0.52	0.51	0.50
MAXCOV	N/A	0.49	0.66	0.69	0.72	0.71	0.73	0.72	0.71

Table 30

Logistic regression model predicting correct rejections of dimensional summed input data.

	MAMBAC			MAXCOV		
Indicator	*b*	*SE*	*t*	*b*	*SE*	*t*
Intercept	0.118	0.38	0.31	-1.273	0.29	-4.47
N	0.001	0.00	3.61	0.002	0.00	6.95
K	0.554	0.04	12.53	0.413	0.03	14.64
G	1.461	0.88	1.65	-0.047	0.63	-0.08
H	0.970	1.73	0.56	-0.762	1.25	-0.61
R	-2.217	0.45	-4.89	-0.148	0.31	-0.48

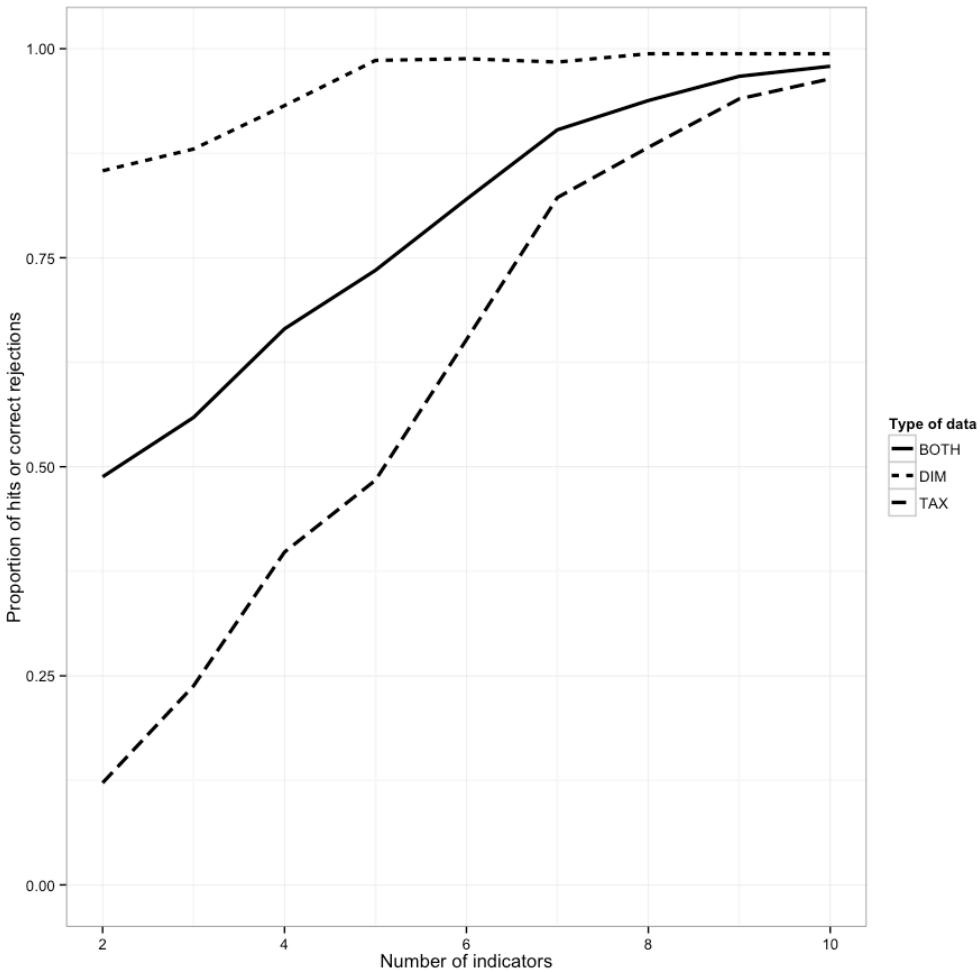

Figure 20

Plot of the hit and correct rejection rates for categorical and dimensional (and both) dimensional data respectively when subjected to a summed input MAMBAC procedure

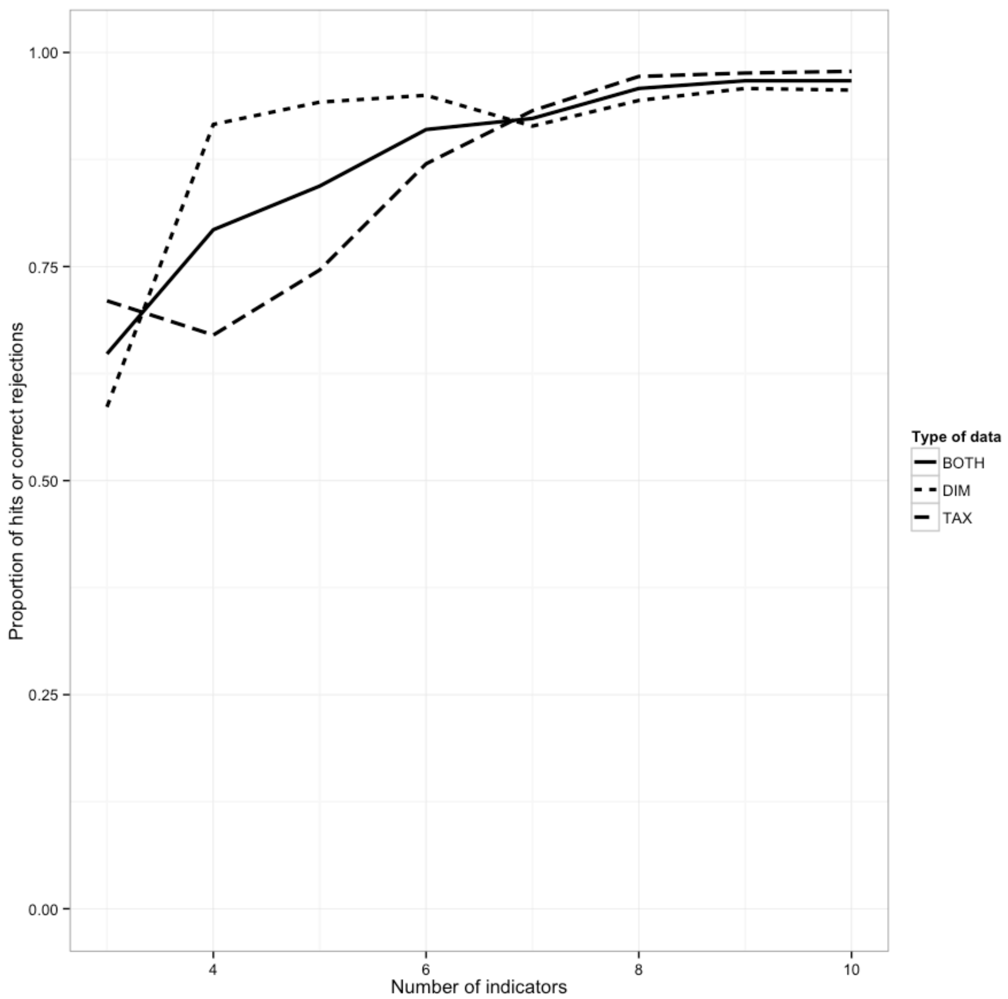

Figure 21

Plot of the hit and correct rejection rates for categorical and dimensional (and both) dimensional data respectively when subjected to a summed input MAXCOV procedure

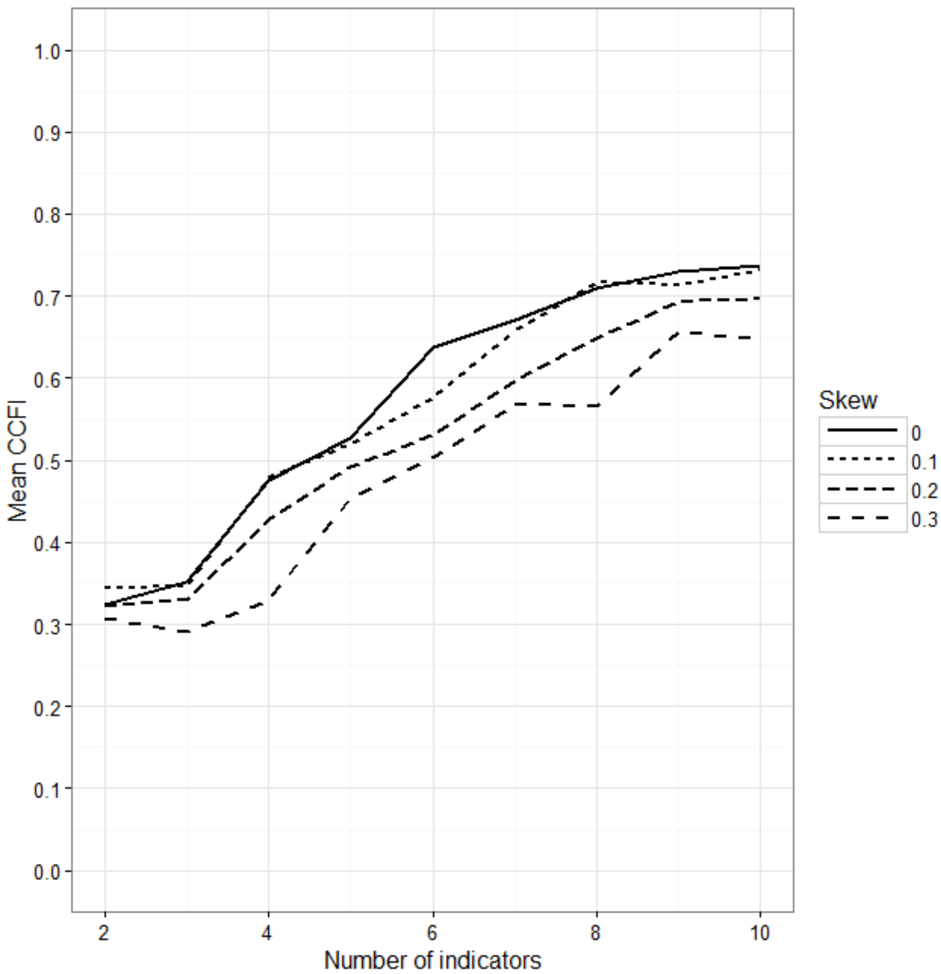

Figure 22

Plot of mean CCFI values across different number of indicators, separated by different levels of indicator skew (rounded to the nearest single decimal place), for categorical data subjected to a summed input MAMBAC procedure.

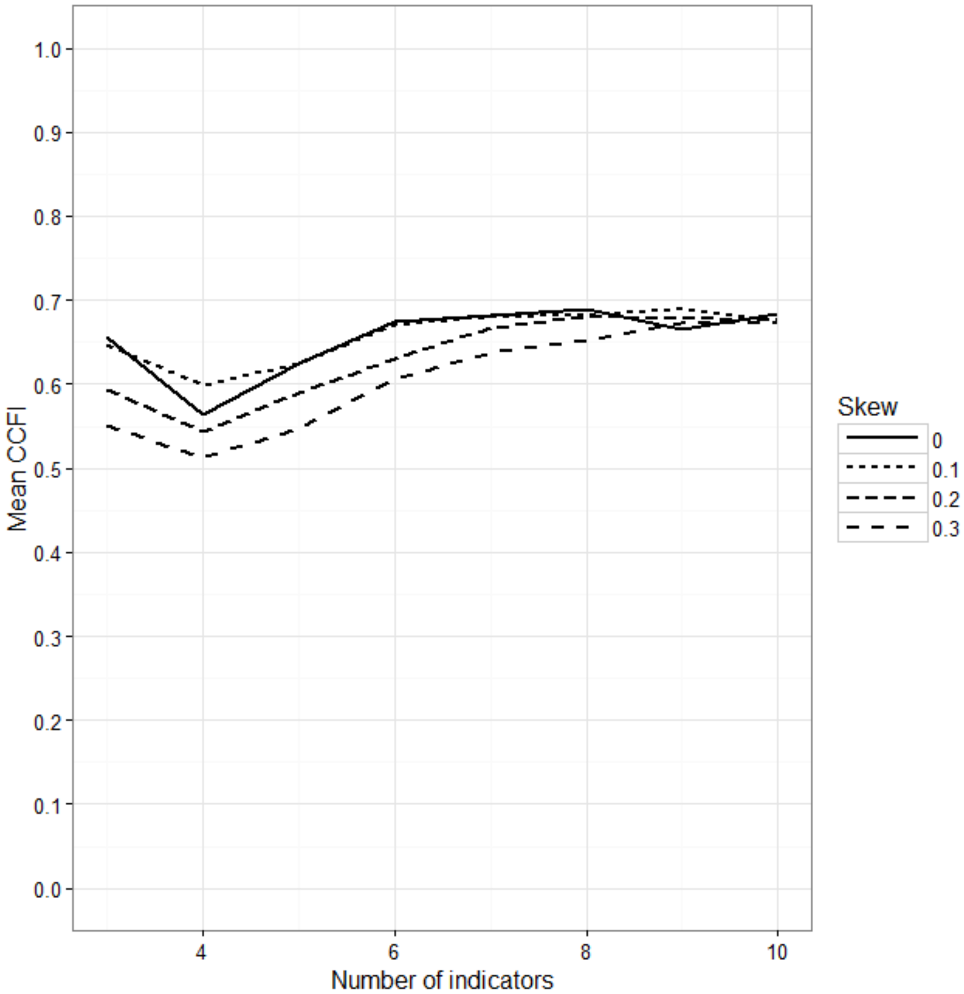

Figure 23

Plot of mean CCFI values across different number of indicators, separated by different levels of indicator skew (rounded to the nearest single decimal place), for categorical data subjected to a summed input MAXCOV procedure.

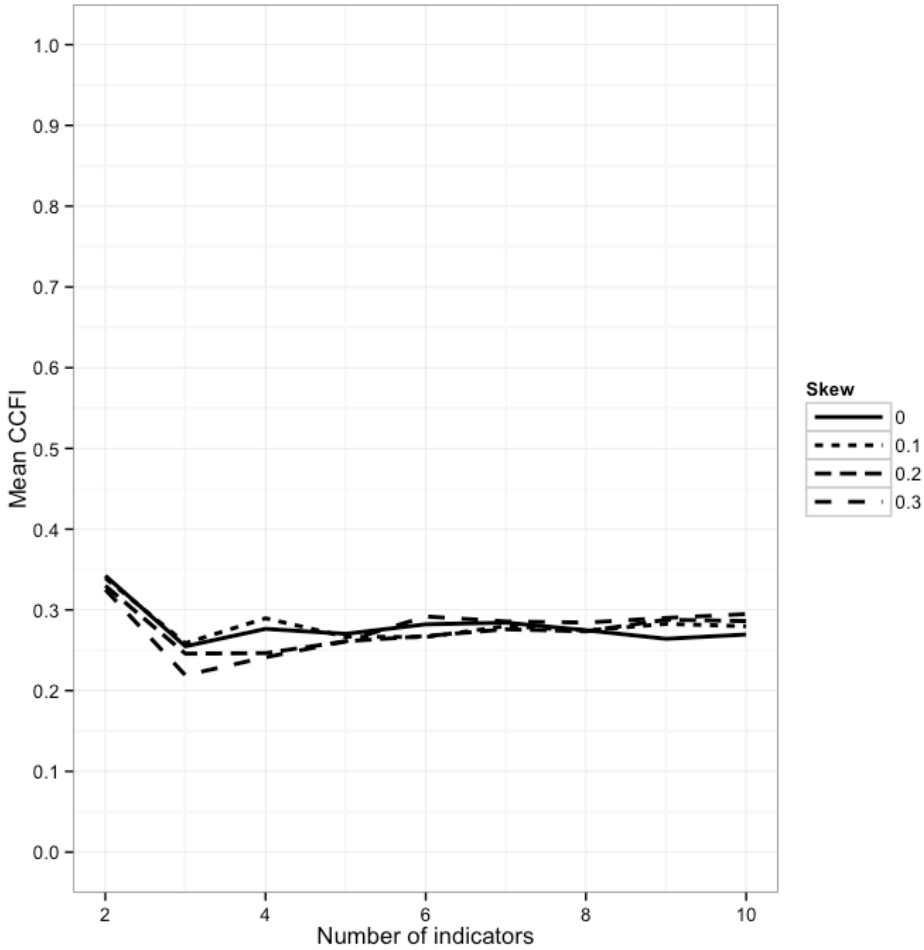

Figure 24

Plot of mean CCFI values across different number of indicators, separated by different levels of indicator skew (rounded to the nearest single decimal place), for dimensional data subjected to a summed input MAMBAC procedure.

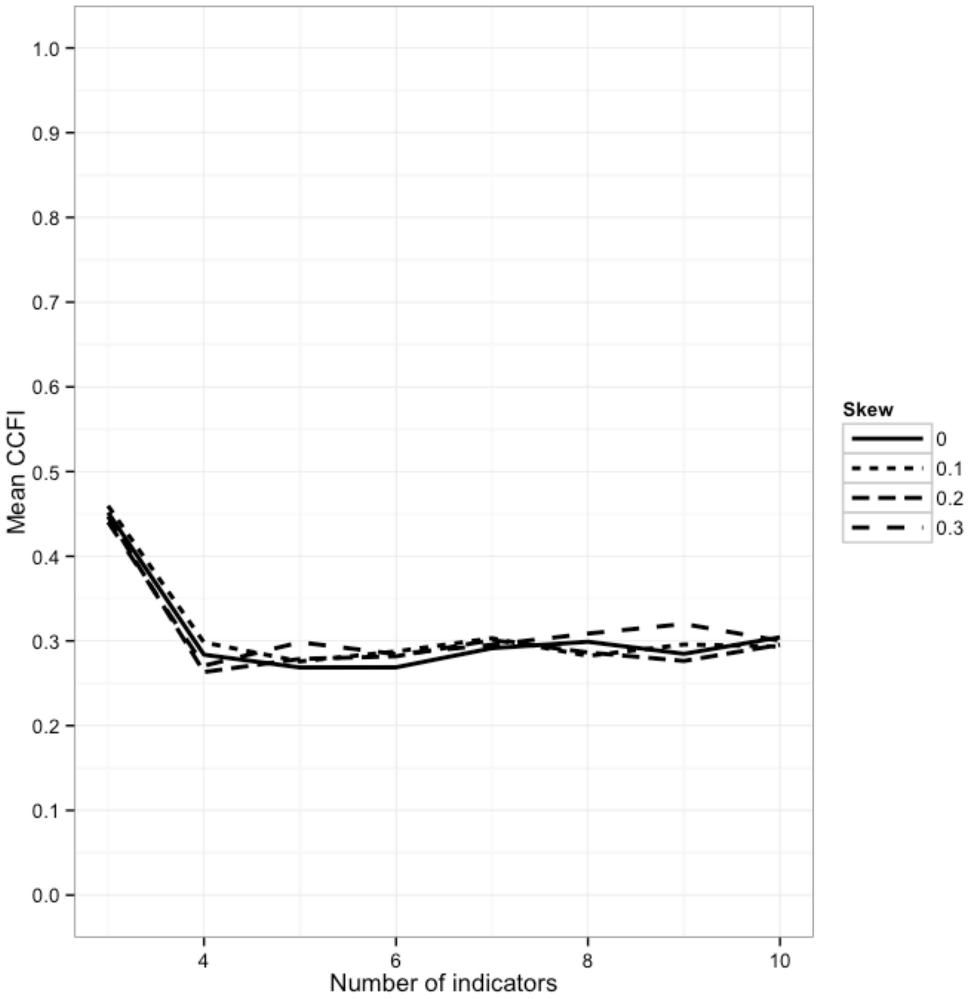

Figure 25

Plot of mean CCFI values across different number of indicators, separated by different levels of indicator skew (rounded to the nearest single decimal place), for dimensional data subjected to a summed input MAXCOV procedure.

Table 31

Logistic regression model of the predictors of a hit (CCFI > 0.5) for taxonic data using a summed input approach

	MAMBAC			MAXCOV		
Indicator	*b*	SE	*t*	*b*	SE	*t*
Intercept	-4.531	0.34	-13.3	-7.732	0.52	-15.0
N	-0.001	0.00	-6.31	0.000	0.00	0.25
k	0.722	0.02	33.41	0.598	0.03	19.33
D	2.307	0.17	13.55	5.587	0.29	19.03
br	-2.027	0.33	-6.23	-1.075	0.43	-2.49
G	-5.484	0.49	-11.2	-3.667	0.63	-5.81
H	-1.442	0.97	-1.48	-1.946	1.31	-1.48
Tax.*r*	1.383	0.48	2.89	0.621	0.64	0.97
Comp.*r*	-0.781	0.49	-1.61	-2.320	0.66	-3.54

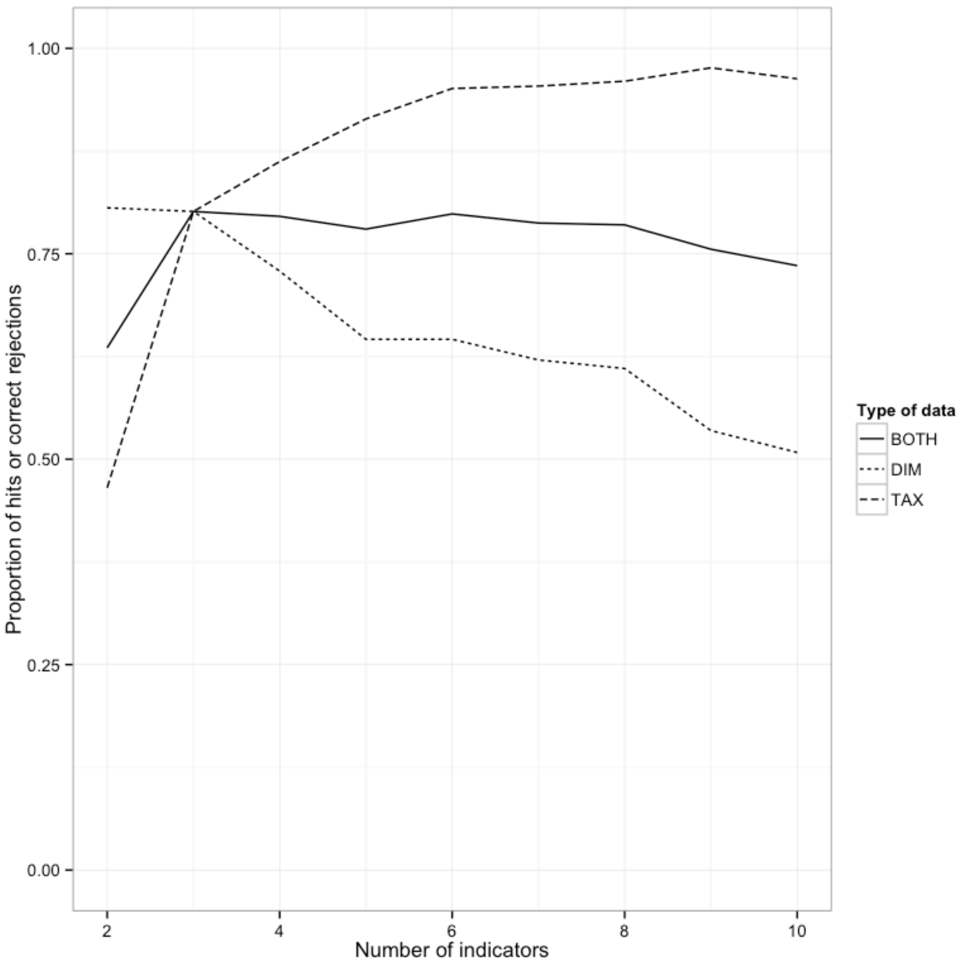

Figure 26

Plot of the hit and correct rejection rates for categorical and dimensional (and both) dimensional data respectively when subjected to a continuous input MAMBAC procedure.

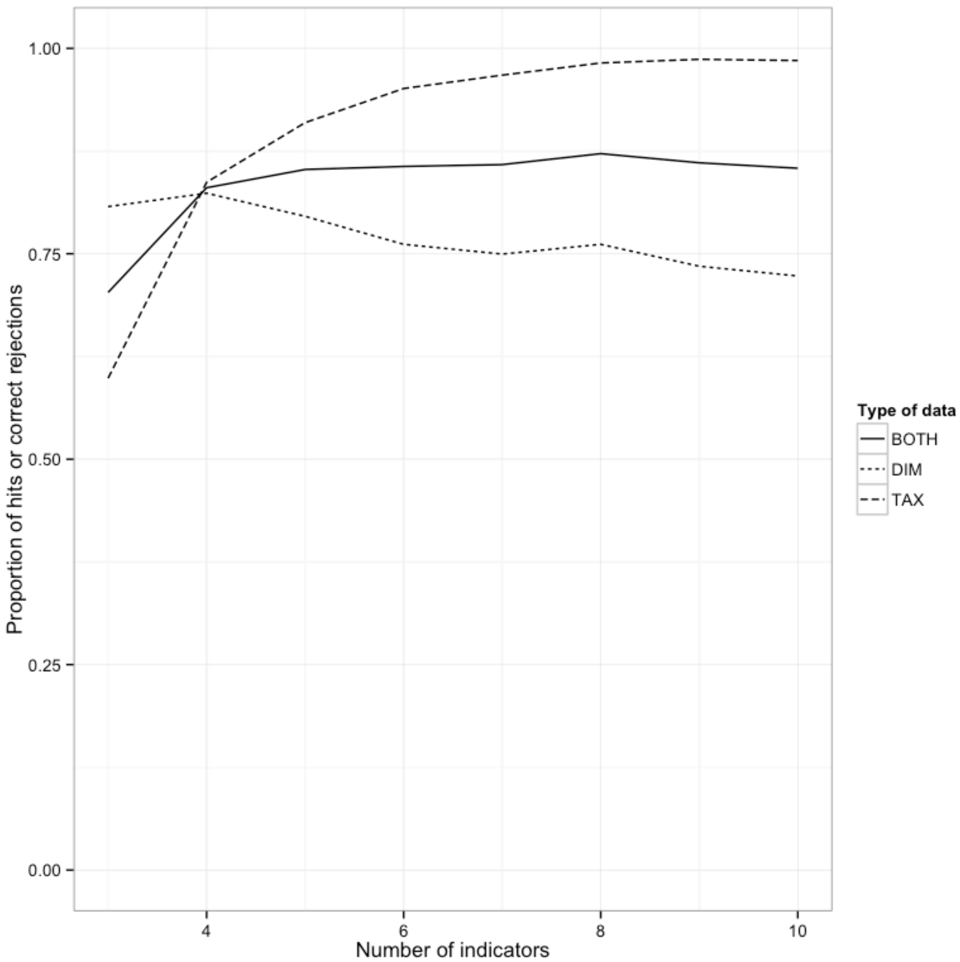

Figure 27

Plot of the hit and correct rejection rates for categorical and dimensional (and both) dimensional data respectively when subjected to a continuous input MAXCOV procedure.

Table 32

Logistic regression model of the predictors of a correct rejection for dimensional data using a continuous input approach

	MAMBAC			MAXCOV		
Indicator	*b*	*SE*	*t*	*b*	*SE*	*t*
Intercept	0.592	0.035	16.9			
Cut num	0.005	0.002	2.36			
N	0.000	0.000	14.7			
K	-0.038	0.002	-16.7			
G	-0.088	0.067	-1.31			
H	0.163	0.136	1.20			
R	-0.087	0.034	-2.57			

Note: Coefficient on *N* effect is $4.257 * 10^{-4}$, SE $2.892 * 10^{-5}$.

Table 33

Logistic regression model of the predictors of a hit (CCFI > 0.5) for taxonic data using a continuous input approach

	MAMBAC		
Indicator	*b*	SE	*t*
Intercept	0.111	0.040	2.74
Cut num	0.004	0.002	2.89
N	0.000	0.000	3.37
k	0.045	0.002	30.1
D	0.295	0.018	16.1
br	-0.174	0.026	-6.80
G	-0.177	0.046	-3.88
H	-0.170	0.091	-1.87
Tax.*r*	0.163	0.045	3.64
Comp.*r*	0.114	0.045	2.54

Note: coefficient on the effect for *N* is $6.432 * 10^{-5}$, *SE* is $1.910 * 10^{-5}$

PREDICTORS OF ACCURACY

Like the traditional taxometric analyses, logistic and linear regression models were estimated to study the predictors of the CCFI and accurate identification of a pre-declared latent structure. In the taxonic data, it was again found that the number of indicators was a strong predictor of both CCFI and overall correct identification. The largest effect, perhaps unsurprisingly, was the degree of separation between putative taxon and complement. Smaller base rates (i.e. further away from 0.5) were associated with a taxonic findings, as were lower levels of indicator skew. MAMBAC was sensitive to the level of nuisance covariance in the taxon whereas MAXCOV was sensitive to nuisance covariance in the complement. Fewer meaningful effects were observed in the dimensional data; greater accuracy was associated with larger sample sizes and a greater number of indicators, but no other consistent differences among the analyses emerged. The summed input analyses appeared to be more resistant to deviations from normality than the traditional taxometric analysis.

Table 34

Linear regression modelling of the predictors of the comparison curve fit index for taxonic data using a summed input approach.

	MAMBAC			MAXCOV		
Indicator	*B*	SE	*t*	*b*	SE	*t*
Intercept	0.162	0.018	9.24	0.277	0.017	16.59
N	0.000	0.000	-7.32	0.000	0.000	1.36
k	0.052	0.001	61.54	0.016	0.001	17.74
D	0.152	0.009	17.52	0.188	0.009	23.07
br	-0.169	0.017	-9.74	0.105	0.015	6.83
G	-0.384	0.025	-15.2	-0.207	0.023	-8.83
H	-0.061	0.052	-1.18	-0.025	0.048	-0.51
Tax.*r*	0.113	0.025	4.45	0.022	0.024	0.93
Comp.*r*	-0.057	0.026	-2.21	-0.067	0.024	-2.79

Note: The coefficient for *N* for the MAMBAC CCFI analysis was -7.836 * 10^{-5}, with a standard error of 1.07 * 10^{-5}. For the MAXCOV analysis, the coefficient for *N* was 1.35 * 10^{-5}, standard error 9.92 * 10^{-6}.

5.4.c. Discussion

Overall it does appear most taxometric studies use approaches that have a higher hit rate; the summed input was the most accurate of the three methods tested. Simply using a criterion of greater or less than 0.5, these procedures (base rate estimation, summed input), are accurate in excess of four out of five times. However, this analysis highlights considerable evidence for criterion bias; taxon detection in a taxonic dataset is notably lower than overall accuracy. In previous critiques of the comparison method, Beauchaine et al. (2008) outline issues concerning the disconfirmation of the presence of latent taxa. The present analysis suggests that this is particularly important for the use of binary data, as it appears that for some analyses that there is a tendency towards taxometric procedures that are used in an exploratory fashion finding disconfirming evidence for taxa, even when applied to taxonic data. This largely seems to be the case regardless of the manner in which cases are assigned to taxon and complement, and the manner in which input variables are prepared, although there are substantial degrees of difference among these.

Where the summed input differs most from traditional taxometric procedures is in the number of taxometric curves that are produces. In the traditional approach (note that L-Mode does not use this style of approach), where the analysis iterates through all combinations of input and output, increasing the number of indicators increased the hit rate on taxonic data, but at a cost of also increasing the false positive rate. This was not found in the summed data. Taxometric procedures were able to identify a prespecified latent dimension with even a small number of indicators. However, with few indicators there was a substantial false negative rate, which the rest of the discussion focuses upon.

It further appears that that the effect of the summed input on the CCFI is not symmetrical, and this may have serious implications for interpreting taxometric findings. Overall, the summed input appears to have a downward criterion shift, reducing the CCFI on both taxonic and dimensional data relative to traditional taxometric analyses of the same datasets (traditional MAMBAC analyses aside, due to poor performance in Study 1). Whilst for dimensional data this puts the average CCFI away from 0.5 and increasing the probability of successfully identifying a dimension, it also has the same effect on taxonic data, reducing the relative confidence of determining the presence of a latent taxon. This problem is exacerbated under circumstances, such as with high indicator skew, which also has a similar shift on the CCFI. In particular, Figures 22 through 25 show how this effect is asymmetrical; whereas the level of skew increases the rate of false negatives for taxonic data, it has limited impact on dimensional data. In many studies the use of the CCFI and bootstrapped data has been sparked by concerns about deviations from normality (skew, kurtosis) on the presence of false positive taxa. However, the findings from this study highlight how with the CCFI, summed input analyses under certain conditions have substantial false negative rates that must be taken into account. Moreover the effect of the number of indicators on the less ambiguous criterion for the presence of a taxon (CCFI > 0.6) is reduced with the summed input. Whereas the hit rate here starts the same for both kinds (0.58), it increases to 0.9 with traditional taxometric methods, but only to 0.81 with the summed input. Thus, using the CCFI, a summed input will give indices that are more likely to identify the most appropriate latent structure, but in a number of cases may produce a result that is difficult to interpret.

In both cases the concerns that arise relate back to those enunciated by Beauchaine et al (2008) concerning the interpretation of non-taxonic findings. For certain circumstances (the use of the summed input, high indicator skew), the use of the CCFI in interpreting dichotomous taxometric findings is likely to have a false negative rate associated with it; these increase the probability of detecting an ambiguous or dimensional result. Of greater concern is that these circumstances appear to be more common in the use of DSM data for taxometric analysis, which has been one of the more common applications over recent years, particularly in the field of addiction. As such, for dichotomous data specifically, greater caution must be exercised in emphatically rejecting the presence of a taxon in scenarios such as the analysis of DSM criteria. This is especially true if the number of indicators analysed is small; at 5 indicators, the probability of a false negative (using a > 0.5 CCFI criterion) in taxonic data is approximately 50% for MAMBAC and 25% for MAXCOV using the summed input.

These issues are particularly important when selecting how to generate comparison data. Across taxometric procedures as a whole there is evidence that a base rate approach is most effective (Ruscio, 2009). It appears that a greater level of justification is required for binary data. The base rate approach appeared to frequently over-estimate the base rate of a taxon in dichotomous data. It might be the case that taxometric analysis (minus MAMBAC) can be conducted if the base rate of a putative taxon is well known, in a sample where the structural features are similarly well understood. For example if nationally representative data is used where a putative taxon, such as a disease or disorder, comprises a certain proportion of the population, this approach. It may also be useful to consider. It is unclear whether converging evidence from multiple sources (population base rate, estimated base rate, psychometric cutoff), similar to non-redundant taxometric methods, will alleviate the issues concerning the use of taxometric on such data however.

The summed input appeared to perform well in comparison to the standard approach to taxometrics iterating through each potential combination of input and output variable. This is in contrast to the findings from Walters & Ruscio (2009), who found that using the summed input produced less interpretable findings, and failed to find an interaction between the number of indicators and taxometric method (standard vs summed). However, across both MAMBAC and MAXEIG the summed input tended to shift the CCFI downwards across both datasets (less consistently for dimensional data), meaning in taxonic datasets that the summed input may reduce the interpretability of findings, as Walters & Ruscio (2009) concluded. When taxometrics perform well, the summed input makes findings more difficult to interpret. When taxometrics perform badly, the summed input improves accuracy but with relatively little benefit to the analyst's confidence in conclusively interpreting the results. This might explain some of the inconsistency between the findings from this present exercise and from Walters & Ruscio's (2009) Monte Carlo study.

5.5 – Application to gambling data – a replication of the findings in Chapter 2

Having identified the most appropriate taxometric procedure to apply to dichotomous data, this technique is now applied to three different sets of gambling data. This in part because the gambling data is available to hand, and also because it has been extensively analysed using a number of latent variable approaches, including many reported in this thesis. The first analysis is designed to replicate the taxometric analysis of problem gambling data in Chapter 2. The replication reported here focuses on the DSM-IV Pathological Gambling criteria, where there have been multiple latent class studies confirming the presence of a high severity latent class. The analysis in question used problem gambling status to determine which cases to assign to the putative taxon. In this first instance, analyses are conducted using the estimated base rate that is part of the output from taxometric procedures.

It is worth noting that the indicators in this analysis do not adhere to some of the best practices in the taxometric literature. Firstly, the use of single item indicators has been advised against. For demonstrative purposes only the dichotomous DSM criteria are reported here, but the analysis this attempts to replicate in Chapter 2 uses the best practices regarding indicator structure that are suggested in the literature.

5.5.a Method

5.5.a.i Sample

A total of 1,387 respondents were included for analysis in this study, the same as reported in Chapter 2. This is a subset of the 7,756 respondents to the British Gambling Prevalence Survey 2010 (Wardle et al., 2011b). The data from the survey is publicly available at the UK Data Archive (National Centre for Social Research, 2011). The most likely latent class membership was taken from the analyses reported in Chapter 3 and used to interpret the results. The analysis was restricted to cases endorsing one or more of the DSM criteria, as was the case in Chapter 2.

5.5.a.ii Measures

Two problem gambling assessments were administered to each subsample. The first was the Problem Gambling Severity Index (PGSI) (Ferris & Wynne, 2001), which was used as the input indicator for each of the taxometric analyses conducted. The PGSI is the predominant contemporary measurement of problem gambling (Williams et al., 2012a). Previous psychometric analyses of the PGSI indicate that it measures a mixed structure; there is strong evidence that high-severity gamblers form a latent taxon, as previous studies (including those reported in Chapter 2) find (Kincaid et al., 2013), but that the latent classes of PGSI data are ordered by severity, and that there is very little overlap between the classes on overall PGSI scores as subsequently shown in Chapter 3.

The output variables were dichotomised items from a questionnaire developed based upon the DSM-IV Pathological Gambling criteria. This measure was developed by (Fisher, 1996) to elicit the DSM indicators in a continuous fashion. This was validated on a nationally representative British sample prior to the administration of the original British Gambling Prevalence Survey (Sproston et al., 2000). Each of the ten items are probed on a four-point scale of frequency, which are then subsequently dichotomised. However, this approach does not produce consistent results, particularly for higher severity gamblers as Figure 7 in Chapter 3 demonstrates. The items were dichotomised in the same manner as a previous psychometric analysis of data from the same questionnaire (McBride et al., 2010); responses greater than zero were treated as present.

5.5.a.iii Analytic Procedure

Summed input MAXCOV and MAMBAC analyses were conducted on the dichotomous data. An initial check for indicator validity indicated that the MAXCOV analysis identified a low severity latent class with sufficient between groups separation and low nuisance covariance. As such the analyses proceeded on all ten indicators. Similar checks on the L-Mode Factor Analysis revealed that the left mode identified a relatively high severity base rate taxon, again with low nuisance covariance and sufficient between groups separation. Again analysis proceeded on these items as is. However, for the MAMBAC analysis base rates tended to cluster at 0 or 1, and it failed to validly identify an appropriate base rate. As such, two indicators (loss-chasing and preoccupation) were removed from the analysis. Previous latent class analyses of gambling data have shown these items fail to discriminate between those with a pathological gambling case status and those who do not. Three further items (committing crimes, risking important opportunities and borrowing money) were removed as these showed extreme levels of skew far beyond those modelled in the Monte Carlo analysis. (N.B. Analysis with these produced a dimensional finding (CCFI 0.33)).

5.5.b Results

All analyses corroborated previous studies that identified the presence of a taxon in problem gambling assessment data. The three analyses differed in the estimated base rates of taxon membership. MAXCOV analyses supported the presence of a very low base rate taxon, smaller than latent classes observed in the same or similar gambling prevalence data. This was similar to the taxon observed in a previous analysis of DSM data in Chapter 2. In contrast

MAMBAC analyses of the five most valid indicators found evidence for a taxon at a slightly lower level of gambling severity than DSM-IV case status, consisting of cases endorsing approximately four or more criteria. In further contrast still L-Mode Factor analyses marginally supported a taxon at an even higher base rate, classifying approximately 22% of the sample into a putative taxon. This included many cases that overlap with intermediate latent classes that have been previously observed in problem gambling prevalence data.

5.5.b.i Summed MAXCOV analysis

Analysis initially began by looking at the base rates and output for the summed input MAXCOV procedure. This identified a base rate of 0.041 similar to the one reported in Chapter 1, with a standard deviation of 0.02. All of the individual taxometric curves identified a small base rate taxon, comprising between 2.1% to 10.3% of the sample. Use of comparison data proceeded, and a comparison curves were generated, which revealed slight evidence for the presence of a taxon (CCFI = 0.547). However, three indicators had substantial levels of skew and kurtosis (8-10) on account of their limited endorsement. Additionally, one item (2; preoccupation) was extremely negatively skewed in the taxon and had a low between group separation (d = 0.509). As a result, these four items were excluded from subsequent analysis. The analysis was redone with the six valid taxometric indicators, which continued to support the presence of a taxon (CCFI = 0.579) (Figure 28). An examination of the final CCFI curve indicates that the taxonic comparison data is a better fit of the actual data for most parts of the dataset, apart from the central section.

5.5.b.ii Summed MAMBAC procedure

Again checks of item validity and indicator distribution were made prior to analysis. This first identified a very large base rate taxon (0.403, SD 0.514) This identified that all of the indicators had very small groups separation (all $d < 1.25$, mean = 0.721, SD = 0.325) and that many of the indicators were substantially skewed. Taxometric curves were then plotted for the five indicators that were used in the summed MAXCOV analysis. This identified acceptable levels of skew and sufficiently large between groups effect size, with a moderately larger base rate than identified in previous analyses (mean = 0.097, SD = 0.045). The CCFI showed slight, albeit ambiguous support for the presence of a taxon (CCFI = 0.524) (Figure 29). This identified slight support for the presence of a taxon, although given some indicator skew and the use of the summed input, a CCFI in this range is not entirely surprising.

5.5.b.iii L-Mode Factor Analysis

Initial checks revealed sufficient between groups differences on the factor scores ($d = 2.511$), but not on the individual indicators (mean $d = 1.168$, SD = 0.491). The estimated base rate of the left mode of the analysis was 0.201, larger than both MAMBAC and MAXCOV. The last three indicators were relatively skewed also. However, given the sufficient separation of the factor scores, it was decided to proceed with analysis as is. The analysis very marginally supported the presence of a latent taxon (CCFI = 0.51) (Figure 30).

It is worth noting that with removing any of the indicators, the findings tended to support the presence of a latent dimension. At the same time, the findings in Figure 14 show the ability of the L-Mode Factor Analysis to detect valid taxa is extremely sensitive to the number of indicators entered into the analysis, and that it requires a large number of variables to produce results that are valid on simulated data. At best, these findings provide equivalent support for the presence of a taxon, although given the base rates and levels of skew in the dataset, this is largely to be expected.

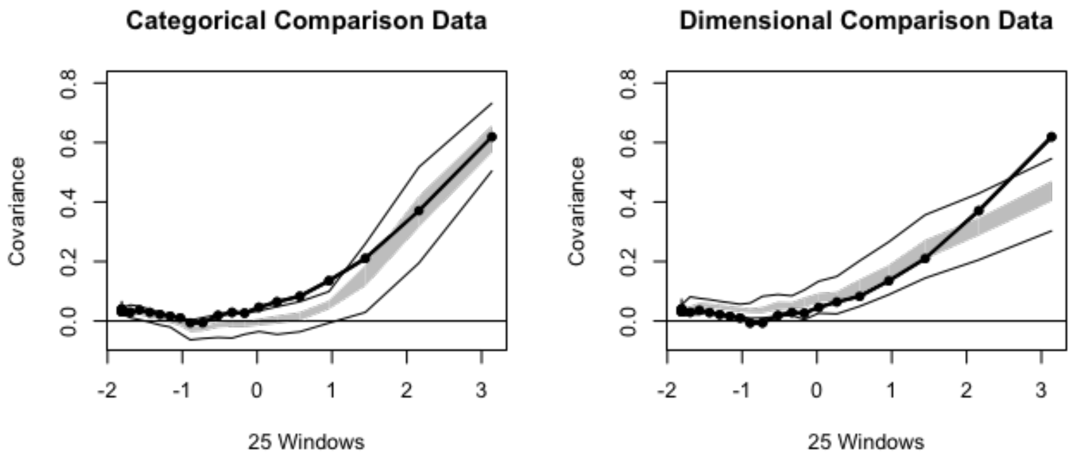

Figure 28

Categorical and dimensional comparison data compared against the observed data points for the summed input MAXCOV procedure (CCFI = 0.579). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAXCOV curve from the actual data observed.

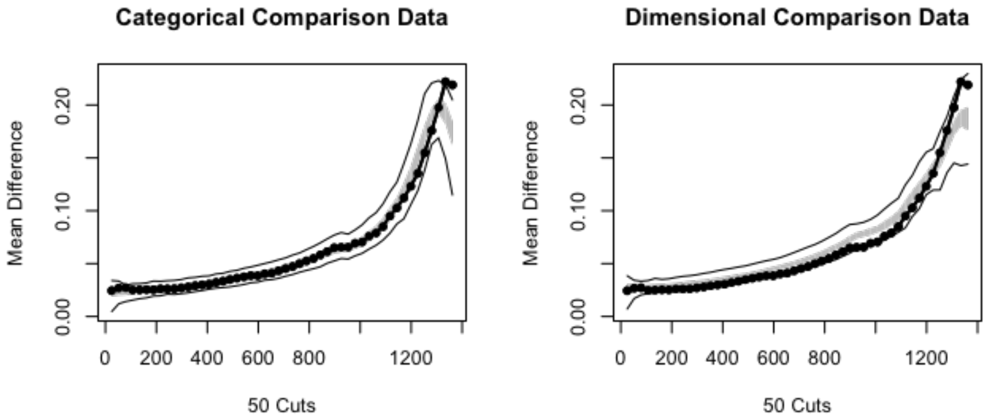

Figure 29

Categorical and dimensional comparison data compared against the observed data points for the summed input MAMBAC taxometric procedure (CCFI = 0.524). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAMBAC curve from the observed data.

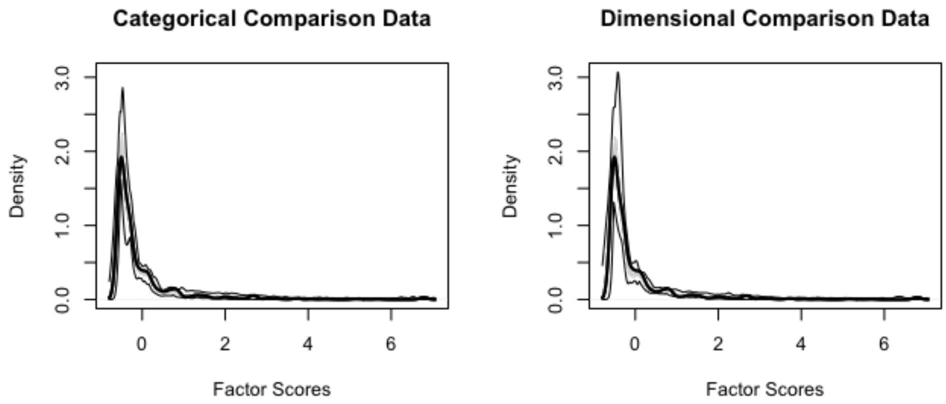

Figure 30

Categorical and dimensional comparison data compared against the observed data points for the L-Mode Factor Analysis taxometric procedure (CCFI = 0.51). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the distribution of the single latent factor estimated from the actual data observed.

5.5.c Discussion

Application of the most appropriate methods identified in the Monte Carlo analyses reported in Studies 1 and 2 replicated a previous taxometric analysis of problem gambling data. However the different taxometric analyses failed to converge on base rate estimation. This is possibly due to the presence of multiple latent classes in problem gambling data. This analysis directly replicates the taxometric analysis reported in Chapter 2, and does so using a scoring scheme that is congruent with the logic of the DSM approach to classifying psychiatric disorder.

5.6 – Extension to the South Oaks Gambling Screen

Having replicated the taxometric analysis conducted in Chapter 2, it is of benefit to further extend these findings. To this end, a taxometric analysis is reported of the South Oaks Gambling Screen, a frequently used assessment of pathological gambling. While the SOGS is now less frequently used in gambling prevalence surveys due to its substantial false positive rate in community samples (Stinchfield, 2002), the SOGS is still commonly used in experimental research as a screening tool or a measure of problem gambling severity. Thus, an understanding of the psychometric structure of the SOGS is informative to many gambling researchers. The SOGS has a number of weaknesses in its item content that are worth bearing in mind. The items are overly focused on money, particularly the borrowing of it; half of the questions in the SOGS pertain to borrowing in some form or another.

A previous analysis has indicated the SOGS might have a dimensional structure (Abdin, Subramaniam, Vaingankar, & Chong, 2015). However, as the previous sections have detailed, the use of dichotomous indicators is mildly problematic. Now, with the most efficacious means of identifying latent taxa identified, this exercise can be undertaken with a greater level of confidence in the subsequent findings.

5.6.a Method

5.5.a.i Sample

A nationally representative sample of 7,680 respondents to the SOGS is publically available from the British Gambling Prevalence Survey 1999 (Sproston et al., 2000) at the UK Data Archive. Analysis was restricted to cases scoring 1 or more on the SOGS. This left a total of 632 respondents, distributed across three latent classes.

5.6.b Taxometric analyses

5.6.b.i Summed MAMBAC analysis

Before any analysis was conducted, taxometric curves were plotted and the base rates were examined. The MAMBAC taxometric curves identified a base rate of 0.42 (SD = 0.487). As the standard deviation indicates, the individual taxometric curves differed markedly in the estimated base rates; in most cases, these were either 0 or 1. While there were acceptable levels of nuisance covariance, between groups differences on the putative indicators were minimal – the mean standardised between-groups effect size for the indicators was a *d* of 0.441. As such, the decision was made to start merging indicators (however still dichotomous). The first candidate for this was the set of items referring to borrowing money, 16a through 16j (see Appendix 1.D). These have very low levels of endorsement ~ 10-20 gamblers reported engaging in this behaviour in a sample in excess of 6000. Although some endorsed many of these items, most endorsed one or two. Thus, a composite borrowing item was create by assigning all cases that endorsed one or more of these indicators into a single dichotomous indicator. The first indicator (pertaining to loss-chasing) was also removed as it showed very little difference between groups (d = 0.215). Repeating checks of indicator validity revealed a lower base rate taxon (mean = 0.138, SD = 0.284 – again the standard deviation was high due to base rates at 0 or 1) and acceptable levels of between groups difference (mean d = 1.19, SD = 0.281) and a sufficient lack of nuisance covariance. Comparison curve indices conducted on this data revealed substantial support for the presence of a taxon (CCFI = 0.628) (Figure 31).

5.6.b.ii Summed MAXCOV analysis

In contrast, the summed input MAXCOV identified a small base rate taxon with the same *n* as the most severe problem gambling latent class identified in the analysis of the SOGS reported in Chapter 3. The MAXCOV curves tended to identify a small base rate taxon rather than the polarised base rates from the MAMBAC curves. As such, taxometric analysis with comparison data proceeded without merging or removing any indicators, which supported the presence of a taxon. A couple of the 20 indicators had lower than ideal between-groups separation, however, and the borrowing items were very substantially skewed. Consequently, the analysis was repeated with the merged borrowing item, which continued to support the presence of a taxon albeit only marginally (CCFI = 0.512) with a similarly low base rate (mean = 0.107, SD = 0.163, base rates ranged from 0.020 to 0.178, with a small number of extremely high base rates (> 0.4) making up the majority of the larger than perhaps expected standard deviation).

5.6.b.iii L-Mode Factor Analysis

The L-Mode factor analysis initially identified a low base rate taxon (0.112). However, although there was sufficient separation on the factor scores, very few of the indicators showed sufficient between groups differences. In addition, there were extreme levels of indicator skew and there was substantial nuisance covariance between the borrowing items. As such, the merged borrowing indicator reported in the MAMBAC analysis was used again. Further checks of indicator validity showed a higher base rate taxon (0.224), which still showed relatively low levels of between-group differences on the individual indicators but showed substantial differences on factor scores. Levels of skew were substantially reduced in this dataset.

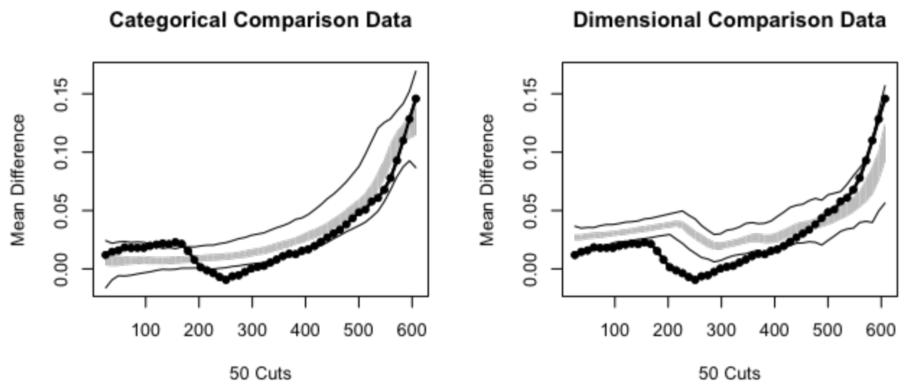

Figure 31

Categorical and dimensional comparison data compared against the observed data points for the summed input MAMBAC procedure (CCFI = 0.628). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAMBAC curve from the actual data observed.

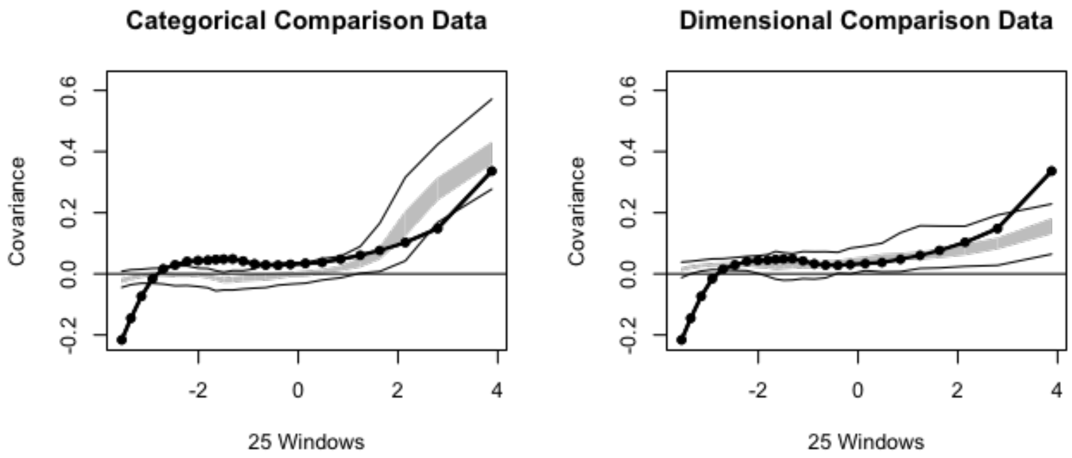

Figure 32

Categorical and dimensional comparison data compared against the observed data points for the summed input MAXCOV procedure (CCFI = 0.512). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the averaged MAXCOV curve from the actual data observed.

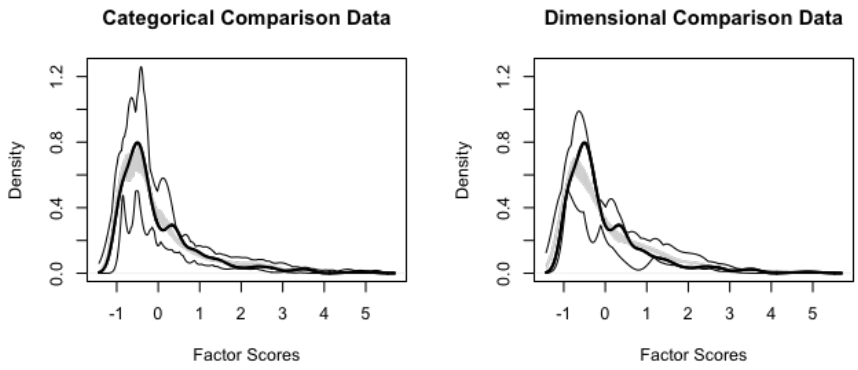

Figure 33

Categorical and dimensional comparison data compared against the observed data points for the L-Mode Factor Analysis taxometric procedure (CCFI = 0.637). The grey band represents the middle 50% of the data points from 100 bootstrapped samples (N = 100,000) with categorical and dimensional properties, with the same statistical distributions as the observed data. The two solid black lines represent the maximum and minimum points from the bootstrapped sample. The dotted black line is the distribution of the single latent factor estimated from the actual data observed.

5.6.c. Discussion

All three analyses, after checks of indicator validity, nuisance covariance and effect sizes, provided tentative support for the presence of taxon in SOGS data. These tended to be relatively small base rate taxa, so likely correspond to the SOGS' demarcation of probable pathological gambling. The advantage of using the BGPS 1999 data, despite its relative age, is that the approach taken in the British survey series has designed to minimise the number of false positives, an issue that has plagued the use of the SOGS on a population wide level, on account of the past year screen for gambling behaviour.

There are some drawbacks to the use of the British data, most notably the fact that it is nearly 20 years old. The data must be considered in the context of when it was collected: after the introduction of The National Lottery, and during a relative trough in the number of betting shops open and during the beginning of the considerable decline of activities such as football pools betting and bingo. It was collected just before the introduction of fixed odds betting terminals in 2001 that has been the major focus of gambling in the public eye, and at the very beginning of the period at which online gambling was available. While it has long been the contention by figures related to the gambling industry that the intervening years have seen remarkably little change in overall behaviour, it is a caveat that must be taken into account when interpreting these results.

The second is that its use of a past year rather than a lifetime frame (as was the norm with the SOGS) means it is unclear whether these findings generalise to a range of contexts where the SOGS is and was used differently. Many of the concerns about the use of the SOGS focused around its inflated estimates of probable pathological gambling, concerns that do not appear to be particularly relevant to this data given the relatively low population estimates observed in the BGPS 1999 (Sproston et al., 2000).

In the same manner as previous analyses (Abdin et al., 2015), the borrowing items had to be merged. This was in part due to each of them being substantially skewed, and in part because these often showed quite weak indicator validity. In most cases respondents endorsing a borrowing item only tended to endorse one or two, so the merging of these created a suitable dichotomous indicator that was much better suited for taxometric analyses and still captured the majority of the information contained within the individual indicators. Moreover the use of a composite borrowing behaviour makes analyses of the screen more congruent with the DSM model that the SOGS is designed to probe.

5.7 General Discussion

The analyses conducted in this chapter first sought to determine under what circumstances a taxometric analysis can be used on binary data, and then applied the findings of these to two sets of real gambling data, replicating the findings observed in Chapter 2 and extending them to another pathological gambling screen that was also analysed in Chapter 3. The majority of this discussion focuses on the implications that emerge from these analyses for the use of the taxometric method on binary data, with a particular focus given towards use on data derived from DSM criteria or similar. This is because this tends to be the prototypical scenario where the types of variable discussed here are utilised, and the findings are then used to draw conclusions about the nature of certain labels of mental disorder.

Using a 'traditional' taxometric approach, only the L-Mode Factor Analysis can be recommended on binary data, and even then only with a large number of variables. Moreover with modest effect sizes, this analysis is unlikely to produce a CCFI that exceeds the threshold of 0.6 that is typically used in the literature. As such, although the L-Mode Factor Analysis can discriminate between predetermined latent structures, it does so weakly on the quantitative measure of fit used most commonly in the literature. In the remaining approaches, MAMBAC performed exceptionally poorly in correctly identifying taxa, and MAXCOV/MAXEIG analyses were very sensitive to the identification of spurious taxa the data were skewed.

The Monte Carlo analyses found that the number of indicators was important in the accuracy of taxometric analysis; more indicators tended to be better, except specific types of data (i.e. dimensional data using a continuous input, dimensional data using a traditional MAXCOV/MAXEIG procedure). Typically it appears that a greater number of valid indicators are required for a taxometric analysis using dichotomous data relatively to the advice presented for ordinal or continuous data (Walters & Ruscio, 2009). It is recommended that seven or more valid indicators ought to be required if such an analysis is to be undertaken.

Under certain data conditions, the MAMBAC, MAXCOV and MAXEIG analysis either failed to identify taxa where the data was designed for them to exist, or had an unacceptable false positive rate. Two alternatives, a summed or continuous input, were subsequently put to the test. Both improved the performance of taxometric analysis substantially. A summed input approach with a sufficient number of indicators (> 7) correctly identified the pre-designed latent structure of a dataset 90% of the time or more regardless of whether the specification was for a taxonic or dimensional dataset. In contrast to advice previously given concerning the use of the summed input, for dichotomous data (and it appears dichotomous data alone) the use of the summed input is appropriate.

One of the paramount concerns that emerges from this analysis concerns the effects of skew on the interpretation. A number of studies of DSM data have make strong inferences rejecting the presence of a taxon or categorical latent structure on the basis of taxometric analysis with relatively fewer than optimal (< 7) variables and substantial indicator skew, as general population analyses of DSM data tend to be. The findings of these analyses strongly suggest that any strong conclusions rejecting the presence of a taxon drawn from these studies must be seriously qualified. The greater concern is that it is quite possible that the combined effect of the summed input and indicator skew are leading to such a criterion shift on certain data types (highly skewed, middling number of indicators) that in conjunction with the summed input, data that tentatively is ambiguously taxonic might be strongly inferred to be dimensional; with less than five indicators, a summed input taxometric analysis on MAMBAC data on average will produce a CCFI that rejects the presence of a taxon. These conditions are exacerbated with considerable positive skew.

The results in combination suggest, that with dichotomous data at least, there is something of a trade off between accuracy and interpretability. The use of the summed input increases the effectiveness of the CCFI as a statistic that discriminates between pre-specified latent structures as in this study. However, the summed input appears to make it harder to strongly infer the presence of a taxon in a dataset. Looking at the effects of the summed input (Figs x-y) the tendency appears to be that reduces the CCFI overall, meaning that it is more difficult to draw strong conclusions using this approach.

In the latter half of this chapter the findings of these were put to the test using real problem gambling prevalence data where taxa have been previously identified and the latent class structure of responding to the analysed indicators is well known. The results from these tend to identify valid latent taxa, the MAXCOV analysis in particular. In most cases these identified base rates larger than the high severity latent class extant in both of the datasets, but it is unclear whether this is due to the limitations of the procedures on dichotomous data or whether it was sensitive to an intermediate latent class in the data (which is present in both cases).

CHAPTER 6 -

MODELLING GAMBLING BEHAVIOURAL PROCESSES IN A SIMULATED SLOT MACHINE PARADIGM[1]

6.1 Overview

Having demonstrated that many of the differences found in problem gambling prevalence can be broadly attributed to the behaviourally conditioned problem gambling pathway, this chapter applies this work to the potential differences between mobile gambling and other technologies as hypothesized in the general introduction. In this report a slot machine paradigm is described in which the inter-trial interval and rate of reinforcement were systematically manipulated between groups. After participants had won a certain amount of money, they were then exposed to an extinction period in which they were forced to choose between gambling and skipping for a further fifty trials. Participants were subsequently asked to complete a medical decision-making task probing illusions of control. The results from the extinction data revealed a main effect of block (i.e. respondents extinguished), rate of reinforcement

[1] The findings of the PREE task have been published as James, O'Malley & Tunney (2016) "Why are some games more addictive than others: the role of payoff and timing in a slot machine task" in *Decision Neuroscience (Frontiers in Psychology)*.

and interactions between block and rate of reinforcement, and between rate of reinforcement and ITI. The chapter then goes onto look at the effects of individual differences in conjunction with perseverative behaviour and illusions of control. Finally, a secondary analysis of this data is conducted to model the effects of big wins' and 'near misses' on subsequent gambling cognitions and behaviours. These have historically been thought to underlie perseverative and problematic gambling, but a recent reinforcement learning model of addictive decision-making considers the importance of these on problem gambling behaviour.

6.2 Selecting indicators of problem gambling

Throughout the past four chapters the purpose of the analyses conducted was to study nationally representative data on problem gambling to generate indicators. This work raises two considerations. The first is which subtype of gambler to focus upon, and the second is the type of behaviours to experimentally model.

Although the thesis focuses on problem gambling, the remainder of the thesis focuses on the behavioural antecedents of problem gambling. These are of relevance to all gamblers, but particularly the 'behaviourally conditioned' problem gamblers Blaszczynski & Nower (2002) refer to. These gamblers are on a continuum with recreational gamblers, showing lower problem gambling severity and transition in and out of impaired control over their gambling. In terms of the latent classes estimated in Chapters 3 and 4, this primarily (but not exclusively) refers to those in Classes 1 and 2.

The first reason for doing so is that these models predict that for the most severe problem gamblers that there is some form of premorbid trait vulnerability, either in disordered mood or impulsivity, that motivates their gambling behaviour. The second is simply of numbers; modelling the general behavioural processes pertinent to mobile gambling will encompass a larger range of gambler than focusing on those who meet the criteria for a clinical disorder. In the latent class models estimated in Chapter 3, the ratio of gamblers in the intermediate to the higher severity subtypes were around 5-10:1. If, as the introduction argued, the primary differences in mobile gambling are behavioural or associative, the risks from mobile gambling are relevant to a much larger group of people.

Having selected the relevant portion of the population to focus down upon, it is then necessary to determine which indicators to model. By virtue of focusing on the first and second classes, two indicators immediately emerge. The first is loss-chasing. In the following studies within-session loss-chasing is modelled both in the lab and on phones using an extinction paradigm. While this is slightly different from the DSM indicator of pathological or disordered gambling, it has been argued there is an obvious connection with between session loss-chasing (Breen and Zuckerman, 1999), specifically that continuing to gamble for too long within-session must necessarily be related to between-session loss chasing. Lesieur (1984) makes an analogous distinction between the short and long-term chase, the former being a common part of the gambling experience, while the long chase is typical of the compulsive or pathological gambler. Lesieur (1984) specifically states that this is a part of recreational play, but may be characterised by occasional compromises or impairments in self-control. The difference between the two is less well explored, but appears to be treated as a continuum, with the demarcation between recreational and compulsive gambling hinging, in Lesieur's view, on whether within-session losses are discounted at the end of a gambling session or linked. Subsequent research has indicated that between-session loss-chasing appears to be relatively common among gamblers (Coventry & Brown, 1993; Orford et al., 2010).

However, while Breen and Zuckerman (1999) examine the individual determinants of within-session loss-chasing behaviour, the aim of this chapter is to study this in the context of the structural features of machine gambling play. The purpose of the following chapter is to explore how the structural features of gambling games, namely it's schedule of reinforcement, is related to the perseverant gambling that is typical of within-session loss-chasing. It has been previously noted that loss-chasing is comprised of two components: the *continuation* of the behaviour, and often of its *escalation* within session (Dickerson, 1984; Lesieur, 1979). The study of perseverance as a measure of within-session loss-chasing has been previously identified, with simple persistence a potential marker of impaired control in machine gambling play (Dickerson, Hinchy, & Fabre, 1987; O'Connor & Dickerson, 2003). In using a perseverance approach, the aim is to look at the role of the gambling product (i.e. its schedule of reinforcement) in the continuation of a gambling session in spite of a continued string of unavoidable losses. Furthermore in the app studies reported in Chapter 7 the longitudinal nature of the study allows a direct test of whether between-session chasing is found in mobile gambling.

The second is preoccupation. The construct of preoccupation has been identified as somewhat problematic as it appears to be treated as a catch-all for the range of cognitive distortions, biases and phenomena in a number of behavioural addictions (King & Delfabbro, 2014a). In this experiment an additional task probing the illusion of control was included after the slot machine paradigm. It is important to note that preoccupation refers to an increased cognitive salience and cue reactivity toward a reinforcer (i.e. an attentional bias), whereas illusory control refers to a bias or distortion in decision-making. In a number of instances (Grant & Chamberlain, 2013; King & Delfabbro, 2014a, 2014b) it has been argued that preoccupation is indicative of a wider cognitive dysfunction, which includes domains like decision-making where distortions such as the illusions of control occur. Experimental and neuroimaging approaches that have considered preoccupation (Goudriaan, Yücel, & van Holst, 2014) note the relationship between preoccupation and impulsivity, analogous to incentive sensitization theories of addiction (Robinson & Berridge, 2008). Moreover the illusion of control is included within the Pathways Model as one of the general cognitive and behavioural processes that underlie all problematic gambling behaviour, and operates on a continuum with recreational gambling behaviour. To model this, in the following chapter an adaptation of a previously published contingency judgement task in the context of a medical decision-making game is reported as a probe of the illusion of control, a cognitive bias thought to be instrumental in reinforcing problematic gambling behaviours.

Additionally, to ensure that covariates across the entirety of the gambling spectrum are being accounted for, psychometric measures of disordered mood and impulsive personality traits are included in both of the experimental chapters.

6.2 Introduction

The emergence of new gambling technologies comes with the concern that novel reinforcement schedules might increase the risk of harm to gamblers. Models of problem gambling assume there are a set of common behavioural and cognitive processes underpinning the development of addictive behavior (Blaszczynski & Nower, 2002; Sharpe, 2002). This chapter reports an experiment investigating the effects of partial reinforcement and timing on perseverative gambling behavior, as these may underpin part of the transition to problem gambling. Deficits in processing partial reinforcement have been previously observed in heavy gamblers (Horsley et al., 2012), while increasing inter trial intervals (ITIs) facilitates the acquisition of conditioned behavior (Gallistel & Gibbon, 2000).

6.2.a Delay, Trial Spacing and Inter Trial Intervals.

Increasing the interval between gambles might be instrumental in encouraging continued play and may be a component behind the popularity of certain games. Lottery games for example have extended delays between gambles and are often the most popular and frequently played games (Wardle et al., 2011b). While this might be because lotteries are highly available (amongst numerous considerations), in some jurisdictions (e.g. the UK) other games are offered alongside lottery tickets (e.g. scratchcards), controlling for availability. Despite this, many more people play the lottery than similarly available games, and do so more frequently. However, the perceived risk of harm is very low, although it is unclear whether the ‘addictiveness’ of gambling lies in specific games (Afifi et al., 2014) or specific behavioral features (Griffiths & Auer, 2013). Some mobile video games exploit similar effects by enforcing delays between plays of gambling-like games. In-play betting, which is associated with mobile (Hing et al., 2014) and problem gambling (Gray et al., 2012; LaPlante et al., 2014), combines continuous and discontinuous play. Understanding the role of timing and latency on gambling behaviour has important consequences for newer forms of gambling, such as mobile gambling (where in-play betting is heavily promoted), as the manner in which people use smartphones is likely to increase latencies between gambles. In-play refers to bets made on an event (e.g. a soccer match) while the event itself is occurring whereas in traditional forms of betting the wager is made prior to the event. Griffiths and Auer (2013) argue in-play betting might be more addictive because it is more continuous. However, considerable discontinuities persist in play as betting remains constrained within an event. Real data on in-play betting (LaBrie, LaPlante, Nelson, Schumann, & Shaffer, 2007) reveals mixed findings: although there is a clear risk of problem gambling, the findings do not decisively conclude this is because of its continuous nature; in-play gamblers placed fewer bets and there was little difference in daily levels of betting. Although in-play bettors wagered more money overall, the median wagered was lower than traditional sports betting, and in-play bettors had a lower net loss. Gray et al. (2012) suggest the immediacy between wager and outcome may be instrumental in attracting risky or impulsive gamblers to in-play gambling.

The associative learning literature indicates that increased latencies between reinforcements facilitate acquisition of conditioned behaviors (Gallistel & Gibbon, 2000). Gallistel and Gibbon's timing model hypothesizes that a decrease in the ratio between reinforcements and ITI in classical and operant conditioning reduces the number of reinforcements to acquisition. This is claimed to be independent of partial reinforcement, which increases the number of *trials* but not *reinforcements*. The literature on the 'trial spacing' effect, primarily studied in the context of classical conditioning (Barela, 1999; Miguez, Witnauer, Laborda, & Miller, 2014; Moody et al., 2006; Stout, Chang, & Miller, 2003; Sunsay & Bouton, 2008; Sunsay, Stetson, & Bouton, 2004), has found that dispersed trials facilitate conditioning.

It is less clear whether greater latencies in extinction affect performance. Gallistel and Gibbon (2000) claim that the interval without reinforcement rather than non-reinforcing events is key, and that omitted reinforcements in extinction are unaffected by partial reinforcement. Other research has identified ITI effects on extinction, with greater suppression of responding observed with shorter ITI's (Mackintosh, 1974; Moody et al., 2006).

Timing is thought to be an important component of the illusion of control (Baker, Msetfi, Hanley, & Murphy, 2010; Msetfi, Murphy, & Simpson, 2007; Msetfi, Murphy, Simpson, & Kornbrot, 2005), a cognitive bias that is prevalent in problem gambling (Fortune & Goodie, 2012). Illusions of control, operationalised as an overestimation of the relationship between a response and outcome, can be induced using a contingency judgement task in which these events are unrelated but the outcome occurs very frequently. Standard examples of this task include a button pushing task associated with the activation of a light (Alloy & Abramson, 1979), or a medical decision-making task judging the relationship between an experimental drug and patient improvement (Orgaz, Estévez, & Matute, 2013). The extent to which non-depressed individuals show illusions of control is affected by the latency between trials: longer ITI's are associated with stronger illusory control in non-depressed individuals (Msetfi et al., 2005). Problem gamblers show stronger illusions of control in contingency judgement paradigms (Orgaz et al., 2013), although the causal direction of this relationship remains unclear: extensive exposure to certain schedules of reinforcement increases illusions of control, or individuals susceptible to illusions of control may be more likely to develop gambling problems. A task derived from the same paradigm as Orgaz et al. (2013) was included, in which participants were asked to complete after the slot machine task. Depression was also measured as depressed individuals appear to make more calibrated judgements in this paradigm (Alloy & Abramson, 1979) with a longer ITI (Msetfi et al., 2005). Disordered mood has also been identified as a potential pathway to problem gambling (Blaszczynski & Nower, 2002).

6.2.b Partial Reinforcement Extinction Effect and Impulsivity

The partial reinforcement extinction effect (PREE) is a behavioral paradox in which weakly reinforced behaviors persist for longer without reinforcement relative to more consistently occurring reinforcers (Bouton et al., 2014; Mackintosh, 1974), such as during an extended period of losses in gambling (Dickerson, 1979; Fantino, Navarro, & O'daly, 2005; Horsley et al., 2012). . Partial reinforcement deficits have been identified in high frequency gamblers[2], who take longer than recreational gamblers to extinguish these assocations (Horsley et al., 2012), a change that might occur from chronic exposure to the schedules of reinforcement in gambling. Horsley et al. (2012) report that although partial reinforcement is hypothesized to be an important component in gambling, the evidence base is sparse. Failure to extinguish has been identified as a marker of problem gambling (Weatherly, Sauter, & King, 2004). Failure to extinguish also directly (e.g. unsuccessful efforts to stop gambling, gambling more than intended to) or indirectly (e.g. chasing losses) corresponds onto indicators for Gambling Disorder (American Psychiatric Association, 2013) or problem gambling (Lesieur & Blume, 1987).

It is unsurprising that the PREE has been linked with gambling, and considerable attention has been devoted to studying this in slot machines. Slot machines tend to have a very low rate of reinforcement (although this varies on computerized machines), and gamblers persevere in play despite mounting sequences of losses. There is a literature that has used slot machine tasks to probe the effects of partial reinforcement on operant learning. Lewis and

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[2] This study reports that their sample of high-frequency gamblers (n = 19) contained only three pathological gamblers, and the mean number of DSM-IV Pathological Gambling criteria endorsed was 2.3, indicating this is a difference found in low to moderate levels of problematic gambling.

Duncan (1956, 1957, 1958a, 1958b) conducted a series of experiments using simulated gambling to test theories of partial reinforcement, finding that lower reward probabilities were associated with greater perseverance. Poon and Halpern (1971) used a similar paradigm to test Capaldi's (1966; Capaldi & Martins, 2010) partial reinforcement theories by manipulating trial order in a slot machine task with a small number of acquisition trials. Kassinove and Schare (2001) manipulated big wins and near-misses in perseverative behavior in extinction in a similar slot machine paradigm, finding that near-miss density affected the extent to which participants persisted gambling but not big wins.

Different schedules of reinforcement potentially affect how behaviors extinguish (Haw, 2008a; Madden, Ewan, & Lagorio, 2007) Gambling operates on a random ratio schedule of reinforcement, a subset of the variable ratio schedule. Less well understood than variable ratio schedules, it is informative to contrast how random ratio schedules differ from variable ratio schedules. The typical distribution the number of trials until a response is reinforced on a random ratio schedules follows an L-shaped pattern; the number of trials rapidly drops off after a small number of plays but continues indefinitely at very low probability. In contrast on a variable ratio schedule it is usually (but not necessarily) the case that the probability of the number of trials to reinforcement is evenly distributed, and there is an upper limit on the number of trials before a behaviour is reinforced (Haw, 2008a). Studies comparing these schedules have not shown clear differences; Hurlburt, Knapp, and Knowles (1980) found no difference between variable and random ratio schedules in gambling, although weaknesses with this study have been identified (Haw, 2008). Crossman, Bonem, and Phelps (1987) found no difference between three ratio reinforcement schedules (variable, fixed and random) in animals. Recent studies have suggested that random-ratio schedules demonstrate more perseverative behavior compared to fixed-ratio schedules, particularly when the number of trials to reinforcement is very large (Madden et al., 2007)

The slot machine task outlined in this chapter was designed so that participants were asked to risk money they had won during the experiment, but the amount of money won would gradually increase. The low-reinforcement conditions attempted to create a situation similar to real-money gambling. One criticism of many slot machine experiments was that these studies tended to utilise a high rate of reinforcement relative to real slot machines (Harrigan, 2007; Kassinove & Schare, 2001). A mechanical three-reel slot machine has a win probability of 9%, but this varies on computerized machines (Harrigan & Dixon, 2009). In gambling research (e.g. Dixon et al., 2011; MacLin, Dixon, Daugherty, & Small, 2007) higher rates of reinforcement (20%) have been used in extinction paradigms. A rate of reinforcement of 30% was used, operating on a random ratio schedule of reinforcement similar to real slot machine gambling (Dixon, MacLaren, Jarick, Fugelsang, & Harrigan, 2013b).

Self-reported impulsivity was measured in this experiment. Trait impulsivity has been shown to predict perseverative gambling in the face of mounting losses, and is a pathway to problem gambling. Breen and Zuckerman (1999) found that impulsive gamblers 'chased' losses for longer in a gambling game where the win probability decreased as the experiment continued. Impulsivity has been identified as risk factor for problem gambling, problem gamblers (Kräplin et al., 2014; MacLaren, Fugelsang, Harrigan, & Dixon, 2011) show higher self-reported impulsivity.

To test whether these behavioral effects encourage perseverative gambling, a two-part experiment was conducted in which ITI and rate of reinforcement were manipulated. Participants were assigned to one of four groups and exposed to a high or low rate of reinforcement, and a long or short ITI between gambles. Associations were extinguished after a certain amount of money had been won. Participants subsequently completed a contingency judgement task in which they judged the efficacy of an experimental drug. The literature on partial reinforcement predicts that individuals exposed to a lower rate of reinforcement will persevere longer. Trial based accounts of extinction predict that massed extinction trials should suppress responding faster, as opposed to a timing-based account where there ought to be no difference. Impulsive gamblers should persevere for longer in extinction as well, on the basis of previous experiments looking at perseverance in loss-chasing.

6.3 METHOD

6.3a DESIGN

The experiment was a 2 x 2 between-subjects factorial design, the rate of reinforcement and the interval between trials (ITI) were between subjects-factors. The rates of reinforcement were 0.7 and 0.3. ITIs were either long (10 seconds) or short (3 seconds).

On every trial the participants were given the choice either to gamble or not. The number of trials in which participants decided to gamble was the dependent variable. The outcome of the gamble and the amount of money participants had won was also recorded. The extinction phase was divided into blocks of 10 trials for analysis. Participants were also administered a contingency judgement task. In the contingency judgement task measures were of the proportion of trials in which the drug was administered, and the contingency judgement made by participants. Impulsivity and depression were measured using the Barratt Impulsiveness Scale (BIS-11) (Patton, Stanford, & Barratt, 1995) and Beck Depression Inventory (BDI) (Beck, Ward, Mendelson, Mock, & Erbaugh, 1961) respectively. The BIS-11 is a 30-item measure that measures three higher order factors of attentional, non-planning and motor impulsivity (Patton et al., 1995). The BDI is a 24-item measure that measures multiple levels of depression severity, discriminates depression from anxiety and has strong internal consistency (Beck, Steer, & Carbin, 1988). No further measurements of individual difference or behaviour were taken apart from the ones reported herein. Participants were not assessed on their prior gambling experience, nor screened for problem gambling prior to the start of the study.

6.3b PARTICIPANTS

A total of 122 participants were recruited from the University of Nottingham community to take part in this study (Mean age = 22.63, *S.D.* = 3.96, gender – 69 females and 53 males). This study was carried out in accordance of, and with ethical approval by the University of Nottingham School of Psychology Ethics Review Committee. All participants gave written consent prior to the beginning of the experiment.

Two additional participants were collected in the long ITI, high reinforcement and the short ITI low reinforcement groups. This was because in two cases participants had completed the PREE task but not the illusion of control or questionnaire parts of the study.

There was no evidence of any trait differences between the groups. A one-way Analysis of Variance (ANOVA) was conducted on both questionnaires, and the ANOVAs for the BIS ($F(4, 166) = 1.543$, $p = .192$) and the BDI ($F(4, 166) = .662$, $p = .619$) were non-significant.

A number of participants across conditions dropped out ($n = 18$). Participants who withdrew were resampled. All the participants who dropped out completed measures of depression and impulsivity. The majority of these dropouts (82%) were in the low rate of reinforcement, high ITI condition. Non-parametric tests were carried out to test whether the participants who dropped out differed from other participants from the same condition in any regard. No significant differences were observed in impulsivity or depression scores, nor the rate they were gambling prior to dropping out (Wilcoxon's signed rank test, $p > 0.05$). All participants were debriefed upon withdrawal from the experiment. Participants who dropped out reported that they withdrew from the experiment because the length of the study conflicted with other engagements (e.g., lectures).

6.3c PROCEDURE

Participants were randomly assigned to one of four conditions. For the first part of the experiment, participants were asked to participate in a partial reinforcement extinction effect paradigm in the context of a simulated slot machine (Figure 34). Participants were told how the slot machine worked, and the magnitude of the payoff for each type of winning outcome. The simulated slot machine was a simple one-line slot machine with three reels. Participants won money if the icons on three reels matched. There were five different icons (lemon, cherry, pear, orange and lucky seven), with winning values of 10p, 15p, 20p, 25p and 30p. The likelihood of each winning outcome occurring was the same, so the mean winning outcome was 20p ($0.35).

For each trial, participants were given the choice between gambling and skipping. The buttons were highlighted so that participants were aware of the two choices they had. Regardless of whether they chose to gamble or not, the images on the three reels presented on the screen refreshed every 500ms to give the appearance of movement. At 1500, 3000 and 4500 milliseconds, one of the reels (from left to right) stopped reeling. If the reels matched and the participant gambled, the participants was awarded money correspondent to value of the icons on the reel. If the reels did not match, they lost the wager they had made, which was fixed at 3p (£0.03, equivalent to around US$0.05). Wins and losses were accompanied by visual and auditory feedback which differed for each outcome. These noises were different if the participants skipped the gamble. Throughout the task participants were informed of their current balance. Between each trial, the buttons on the screen remained red, signifying that the participants were unable to make another wager. The ITI for the short ITI condition was 3000ms, and 10000ms for the long ITI condition.

Participants were presented with 10 practice trials before the game began crediting or deducting money from the player. Participants were informed when the practice trials had ended. Once the experimental trials began, participants played until they reached criterion, set as having won than £10.00 (US$15.40) in the bank. Once participants reached criterion, they were exposed to fifty trials of extinction, where it was not possible to win any money from the slot machine, and then the task ended automatically. Extinction was measured by the suppression of their gambling behavior; participants were not informed of the extinction phase at the end of the experiment. The practice trials had winning trials (which did not pay out), and the extinction phase had no wins or money. The practice and extinction phases were identical in each condition, bar the different ITI's participants were exposed to.

After completing the partial reinforcement extinction effect paradigm, participants were asked to make a series of contingency judgements about the effectiveness of a fictitious experimental drug related to patient recovery. The contingency judgement paradigm was adapted from a previously published study (Orgaz et al., 2013). In this paradigm participants were presented information about a fictional drug that was designed to cure a fictional infectious skin disease that had unpleasant consequences when an outbreak/crisis occurred. Participants were given the option of choosing between administering the drug and not administering the drug, and they were given feedback concerning the outcome immediately afterwards (whether the patient's situation had improved or not). The paradigm was designed to elicit illusions of control by having a high outcome density – the base rate of the desired outcome (patient recovered) was high (0.8), and was completely independent of the users decision. After making their decision, the participants were informed of the outcome of the choice, and there was a small pause (3500ms) before being presented with the decision again.

After each set of 10 trials, participants were asked to judge the effectiveness of the drug. Participants were asked to judge the effectiveness of the drug on a scale from zero to 100. This was represented by a shaded bar in the middle of the screen, on which they were given feedback about the number they chose, determined by how far along the bar they clicked. Participants could repeat clicking along the slider until they were happy with their choice, and were asked to confirm their choice using a separate button.

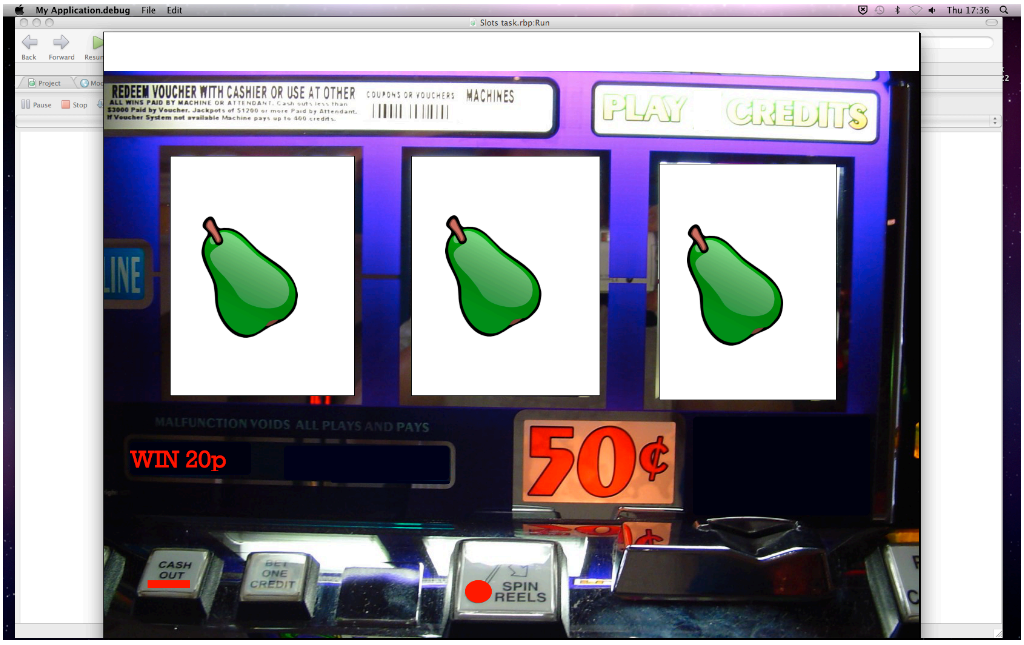

Figure 34

Screenshot of the slot machine display participants were given during the partial reinforcement task

6.4 ANALYTIC APPROACH

To assess the length of extinction for each group, the proportion of gambles made were averaged across five blocks of ten trials. Data analysis proceeded in two stages. Firstly, factorial ANOVAs were conducted on the extinction and contingency judgement data, with a 5 (block) x 2 (ITI) x 2 (Rate of Reinforcement) mixed design ANOVA being conducted. A 10 x 2 x 2 mixed design ANOVA was carried out on the 10 contingency judgements participants made. To test the effects of individual differences on gambling behavior and perseverative gambling, a series of poisson regression models were estimated on the number of trials participants gambled on during acquisition and extinction. This was conducted in three steps. First, an initial model was constructed where no covariates were entered into the model. Then, a second regression model was constructed in which ITI, rate of reinforcement, BIS scores, BDI scores and an interaction term between ITI and rate of reinforcement were included. ITI and rate of reinforcement were dummy coded (high ROR = 1, low = 0; short ITI = 1, long = 0), and BIS/BDI scores were rescaled with a mean of 0. This was compared against a null model using a likelihood ratio test (LRT). LRT's are typically used in latent variable modelling to compare between two nested models, for example in latent class analysis (Collins & Lanza, 2010), or between the fit of two regression models, as in this case. This was then compared against a full model in which interaction terms were modelled across each covariate.

At this point, the data was tested to examine whether the data fit a poisson distribution. Crucially, poisson regression assumes that the conditional mean and variance are equal. While deviations from this assumption have little effect on the overall regression coefficients, when overdispersion (the variance being larger than the mean) is substantial this tends to depress standard errors, increasing the risk of false positive findings. Initial examination using Cameron & Trivedi's test for overdispertion indicated both acquisition and extinction data were overdispersed. While robust standard errors can be used to adjust these (Cameron & Trivedi, 2009), an alternative is to estimate a negative binomial regression model, which includes a random effect to model overdispersion. For the acquisition data, this approach was taken as the index of overdispersion on the negative binomial model suggested that the data was extremely overdispersed (θ = 50.61, *S.E.* = 8.47). This is likely because the experiment continued , and so the data was a relatively weak fit of the count distribution. For the extinction data, while the data was overdispersed the level of dispersion was considerably less (θ = 3.103, *S.E.* = 0.511), and so robust standard errors were applied to the poisson regression model. Comparisons between the negative binomial and overdispered poisson models revealed very little difference in the models.

A number of outliers were found in the low rate of reinforcement extinction data. An examination of the data indicated that a number of gamblers in the low reinforcement, long ITI condition stopped gambling less than two gambles into extinction occurring and that these were outlying data points. These participants (*n* = 3) reported in debrief they treated £10 as salient, either stopping immediately after they won £10 or stopped to remain above £10, independent of any change in contingency. These participants were excluded from further analysis.

6.5 RESULTS

6.5.a Gambling Behavior

Full descriptive statistics are reported in Table 35. To study the effect of behavioral and trait variables on acquisition behavior, an offset negative binomial regression model was used to control for differential effects of exposure, where the same variables were used for the restricted and full factorial models as the extinction data. These revealed that the restricted model (Table 36) was a better fit than the null model ($G^2 = 22.74$, $p < .001$), but that a full factorial model was no better fit than the restricted model ($G^2 = 6.359$, $p = 0.784$). This revealed that participants exposed to a higher rate of reinforcement gambled more frequently in acquisition.

Table 35

Descriptive statistics for performance in the PREE task.

Group		Mean gambles in acquisition (SD in brackets)	Mean gambles in extinction (SD in brackets)
High	Short	78.20 (7.24)	10.26 (8.70)
	Long	76.16 (7.21)	7.74 (5.55)
Low	Short	261.33 (51.43)	23.00 (14.16)
	Long	256.16 (53.49)	30.19 (11.75)

Note: With the outlying cases (n = 3) included in the Low/Long condition, the mean number of gambles in extinction is 27.27.

Table 36

Offset negative binomial regression model of acquisition data.

Indicator	*b*	*S.E.*	*z*	*p*
Intercept	-0.224	0.031	-7.245	<.001 ***
ITI	-0.032	0.042	-0.758	0.448
ROR	0.122	0.046	2.689	0.007 **
BDI	0.001	0.002	1.097	0.273
BIS	0.000	0.002	0.059	0.953
ITI * ROR	0.049	0.064	0.772	0.440

6.5.b PREE Task

The ANOVA conducted on the extinction data revealed main effects of block, F (2.541, 292.187) = 131.095, p < .001, η_p^2 = .533, where the linear contrast was significant, F (1, 115) = 229.457, p < .001, η_p^2 = .666, and the rate of reinforcement, F (1, 115) = 82.912, p < .001, η_p^2 = .419, but no main effect of ITI, F (1, 115) = 1.455, p = 0.23. There was an interaction between block and rate of reinforcement, F (2.541, 292.187) = 22.801, p < .001, η_p^2 = .165, and a further interaction between the rate of reinforcement and ITI, F (1,115) = 6.317, p = 0.133, η_p^2 = .052. There was no interaction between block and ITI, F (2.541, 292.187) = 1.124, p = .334, or a three-way interaction, F (2.541, 292.187) < 1. The main effect of block indicated that responses decreased as the block number increased (i.e. participants extinguished). This interacted with rate of reinforcement, as participants exposed to a higher rate of reinforcement extinguished more quickly, suggesting the presence of a PREE. The main effect of rate of reinforcement signified the same finding. The rate of reinforcement and ITI interaction indicated that when there was a low rate of reinforcement with a long ITI, participants gambled for longer in extinction (Figure 35). The block and rate of reinforcement effects, and the interaction between block and rate of reinforcement were all large in size ($\eta_p^2 > 0.12$), whereas the interaction between rate of reinforcement and ITI interaction was a small to medium effect.

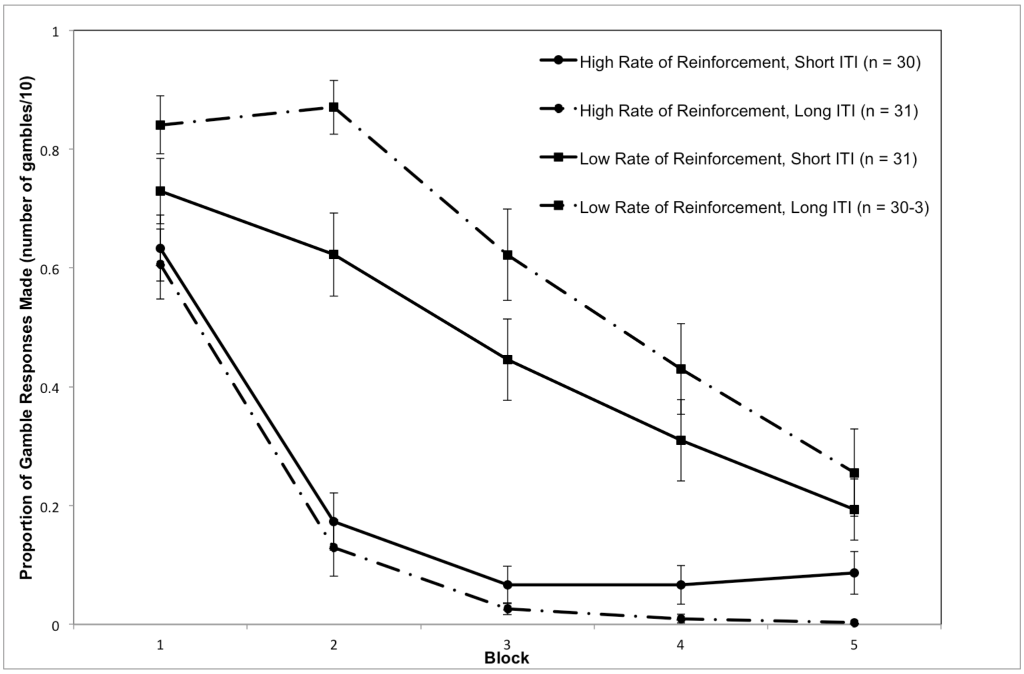

Figure 35

Plot of extinction data for all groups, in blocks of ten trials.

6.5.c Individual Differences

Both the BDI (α = 0.87) and BIS (α = 0.82) showed good internal reliability. To test the role of individual differences in perseverative gambling, a poisson regression procedure was used on the number of gambles in extinction. The LRT indicated that the initial restricted model was a better fit of the data compared to the null model ($G^2 = 581.15$, $p < .001$). The restricted regression model (Table 37) indicated that lower rates of reinforcement and longer ITI's predicted longer perseverative gambling. These terms interacted in the same manner as the factorial ANOVA. A further regression model including interaction terms between the different covariates was subsequently conducted (Table 38) with the same variables as the regression in Table 1. A LRT comparing the restricted and full factorial regression models indicated that the full factorial model was a better fit of the data ($G^2 = 66.44$, $p < .001$). This revealed the same significant effects as previously, but also that higher self-reported impulsivity predicted longer perseverative gambling. There was a trend suggesting that this interacted with rate of reinforcement, with less impulsive individuals appearing to persevere less in low reinforcement conditions. Scores on the two psychometric measures interacted, and there was a three way interaction between ITI, rate of reinforcement and BDI, with more depressed individuals in the high rate of reinforcement, short ITI group gambling for longer in extinction (Figure 36).

Table 37

Restricted poisson regression model of extinction data with robust standard errors.

Indicator	*b*	*S.E.*	*z*	*p*
Intercept	3.245	0.070	48.751	<.001 ***
ITI	-0.291	0.127	-2.303	0.021 *
ROR	-1.385	0.144	-9.587	<.001 ***
BDI	-0.010	0.004	0.931	0.134
BIS	0.004	0.006	-1.498	0.352
ITI * ROR	0.565	0.239	2.366	0.018 *

Table 38

Full poisson regression model of extinction data with robust standard errors.

Indicator	*b*	*S.E.*	*z*	*p*
Intercept	3.471	0.068	51.191	<.001***
ITI	-0.329	0.126	-2.620	0.009 **
ROR	-1.457	0.130	-11.208	<.001***
BDI	-0.011	0.008	-1.396	0.163
BIS	0.013	0.006	2.218	0.027 *
ITI * ROR	0.620	0.237	2.617	0.009 **
ITI * BDI	-0.012	0.016	-0.751	0.453
ROR * BDI	-0.009	0.023	-0.383	0.701
ITI * BIS	-0.011	0.011	-1.006	0.314
ROR* BIS	-0.026	0.014	-1.911	0.056
BDI * BIS	-0.002	0.001	-2.388	0.017 *
ITI * ROR * BDI	0.068	0.031	2.184	0.029 *
ITI * ROR * BIS	0.027	0.018	1.474	0.141
ITI * BDI * BIS	0.000	0.001	0.005	0.996
ROR * BDI * BIS	0.000	0.002	-0.058	0.954
ITI * ROR * BDI * BIS	0.000	0.003	-0.037	0.971

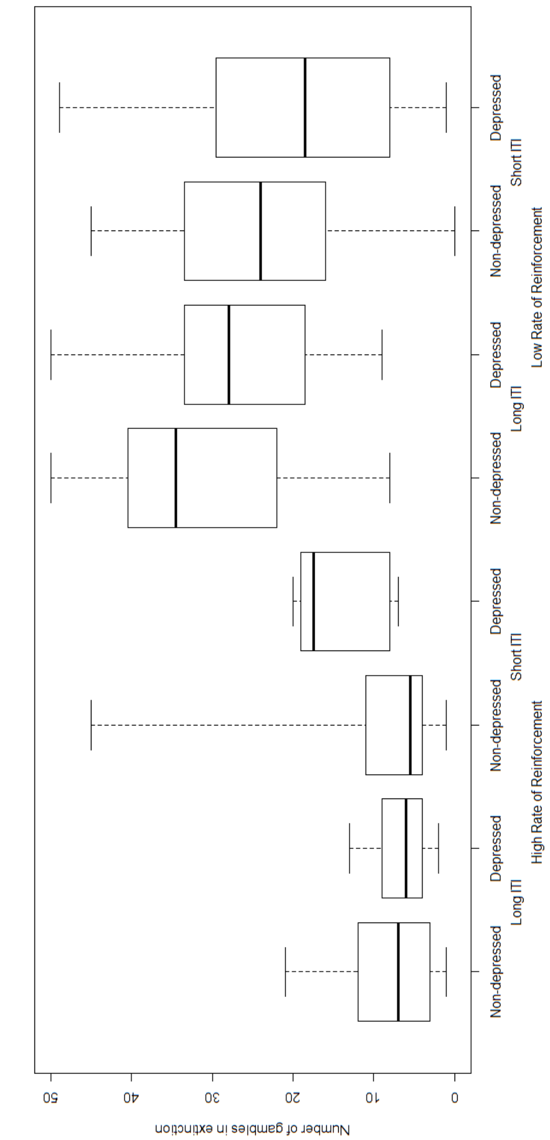

Figure 36

Boxplot of depression status and proportion of gambles in extinction for each of the four conditions.

6.5.d Contingency Judgement Task

Analysis of the contingency judgement data revealed that a significant main effect of block, F (6.526, 737.416) = 3.735, p = .001, η_p^2 = .032, was observed. The main effect of block also included a significant linear contrast, F (1,113) = 10.312, p = .002, η_p^2 = .084, indicating that participants became better calibrated during the task (Figure 37). Please note the smaller degrees of freedom than the PREE ANOVA's; this is because some participants (n = 2), both from the low ROR, low ITI condition, did not have a complete dataset for this task and were excluded. Main effects of ITI, F (1,113) < 1, and rate of reinforcement, F (1,113) < 1, were not observed. Interactions between block and ITI, F (6.526, 737.416) < 1, block and rate of reinforcement, F (6.526, 737.416) < 1, and ITI and rate of reinforcement, F (1,113) = 1.109, p = .295, were not significant. A three way interaction between block, rate of reinforcement, F (6.526, 737.416) = 1.048, p = .399, was not significant either.

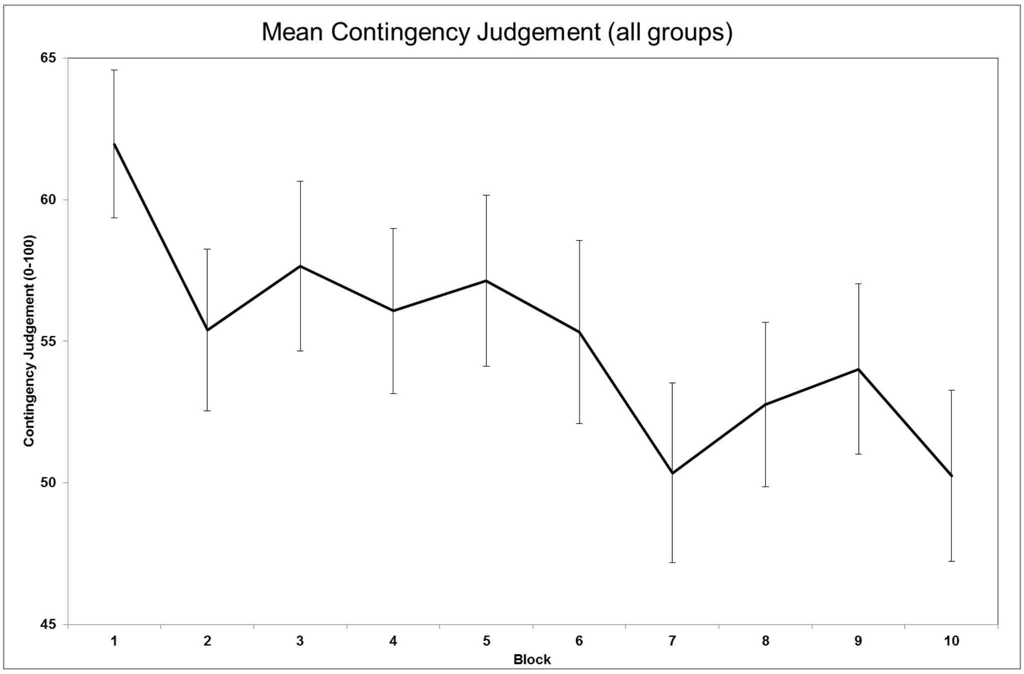

Figure 37

Plot of mean contingency judgements across the ten judgements participants made.

6.6 DISCUSSION

The results of this experiment demonstrate how different schedules of reinforcement affect behavior during a simulated gambling task, and can produce extended gambling in the face of continued losses. This also extends findings from a number of behavioural paradigms measuring perseverance to situations where participants are asked to name a specific preference. Both rate of reinforcement and ITI were instrumental in affecting how long participants gambled for when associations were extinguished, and these interacted. There was evidence that individual differences affected behavior under these conditions, with more impulsive individuals gambling for longer in extinction. In terms of rate of reinforcement, the findings of this study mirror an extensive literature that has repeatedly found that a leaner schedule of reinforcement is associated with greater perseverance in extinction. The findings concerning ITI (and the interaction term), have been predicted in the past, and a couple of studies have identified trial spacing effects in extinction with animals, but to it appears human research on this issue is somewhat limited. This also highlights how the effects of timing on perseverative gambling have potential implications for gambling practice, particularly with newer gambling technologies being likely to alter the latencies between gambles. The impulsivity related findings speak to a literature that has previously suggested that impulsive individuals persevere for longer when the amount of money lost This furthers research that highlights the importance of behavioral processes on gambling behavior, and has implications for gambling games and technologies, particularly those that encourage intermittent patterns of play.

These findings broadly mirror a number of studies that used simulated slot machine paradigms to test partial reinforcement (Lewis & Duncan, 1956, 1957, 1958a, 1958b; Poon & Halpern, 1971). Extinction was measured slightly differently to previous studies, asking participants to choose whether to continue or not rather than when they walked away from the machine. Similar effects have been observed previously when asking people to choose between one of two machines (Dymond et al., 2012). It is important to note that it has been contested whether gamblers are able to discriminate between machines with different rates of reinforcement, measured in terms of preference (e.g. time spent on machine) between two or more simulated slot machines (Coates & Blaszczynski, 2014; Dixon et al., 2013a; Haw, 2008b; Weatherly et al., 2004). Higher rates of reinforcement were associated with a higher level of engagement on the simulated machine. This is broadly consistent with the literature, which has found that differences emerge but only when there is a sufficiently large enough gap in reinforcement. These results extend these to when different groups are exposed to different machines.

Both of the low reinforcement groups displayed extensive perseverative gambling. This continued gambling is potentially a behavioral marker of loss-chasing. Chasing losses is the often the first criterion of Disordered Gambling to emerge (Miller et al., 2013; Orford et al., 2010), and in models of problem gambling is theorized as a tipping point towards problem gambling. The extinction paradigm probes within-session continuation, a phenomena thought to be very closely related loss-chasing in problematic gambling (Breen & Zuckerman, 1999). Partial reinforcement has previously been suggested as an alternative explanation for the phenomenon of loss-chasing (Dickerson, 1984), particularly for the continuation of gambling. Other explanations for loss-chasing tend to invoke the gamblers fallacy (Campbell-Meiklejohn, Woolrich, Passingham, & Rogers, 2008). The results of this study provide support for the role of, albeit being limited to the perseverative aspects of chasing. Further research would need to be conducted on wager size to. It should be noted though that in terms of clinical criteria (e.g. for Gambling Disorder in the DSM), there is a greater emphasis on perseverance. Similarly impulsive individuals gambled for longer in extinction, a finding that has been previously observed in the literature (Breen & Zuckerman, 1999), and interpreted as demonstrating that impulsive individuals chase losses for longer.

Considering ITI, while individuals persisted for longer in extinction with a longer ITI, their gambling behaviour did not systematically differ in acquisition. The extinction finding appears to be somewhat more consistent with a trial based account of the PREE (Mackintosh, 1974), although the two accounts were not directly tested. This finding somewhat contrasts with studies that have found that shorter latencies are associated with greater engagement (Linnet, Rømer Thomsen, Møller, & Callesen, 2010) and greater risk preferences (Hayden & Platt, 2007). Individuals did not appear to prefer the longer ITI machines, but they did gamble for longer on them when forced to make a choice. A key qualification is that the development of slot machines indicates that machines have tended to speed up rather than slow down. However the way in which individuals interact with devices that can be used for gambling such as smartphones tends to increase latency, and is occasionally used within mobile video games for a similar purpose; players are offered the opportunity to gamble for an in-game valuable with large intervals (e.g. once a day), and can play again for real money. A similar concern is that some interventions aimed at reducing the harm caused by gambling intervene by forcing pauses within a gambling session. While this affects timing between sessions rather than trials, associative accounts of timing indicate a similar outcome. The findings of this study imply that care should be taken with these interventions. Moreover, this concern is not without empirical support, as a recent study has found that forcing breaks without including content to target gamblers' attitudes or behaviours increases individuals' motivations to continue gambling (Blaszczynski et al., 2015). Although this study explains these findings in the context of behavioral completion, an associative interpretation that is closely aligned with the present findings can be postulated.

The main effect of block (and a significant linear contrast) showed that participants' gambling behavior was suppressed as extinction proceeded, and that extinction continued the longer that participants continued to lose. A main effect of rate of reinforcement was found. This is the classic PREE effect that has been observed in many studies since Humphreys (1939). These two main effects also interacted; behaviorally this is a restatement of the PREE, as the speed at which participants extinguished was faster with a high rate of reinforcement.

An interaction between the rate of reinforcement and inter trial interval was also observed. The analyses strongly suggest that this interaction was driven by the low reinforcement, long ITI group, which appeared to show a resistance to extinction in the first two blocks (although no interaction with block was observed). Moody et al. (2006) found a similar pattern of results manipulating ITI in a partial reinforcement paradigm, albeit with much larger gaps between trials. This finding also appears to be consistent with Mackintosh's (1974) review of extinction. This finding is particularly interesting in the context of newer gambling technologies, such as smartphone gambling, where larger gaps between gambles are anticipated because of how these devices are used. The Pathways Model (Blaszczynski & Nower, 2002), a well-supported model of problem gambling, predicts there are three pathways to problem gambling that share common associative learning and cognitive bases, and in particular that there is a 'behaviorally conditioned pathway' driven purely by this, compared to others which emphasise emotional vulnerabilities and antisocial/impulsive traits.

The only difference observed in the contingency judgment task was a main effect of block: participants' judgments became better calibrated as the task progressed. The linear contrast on this was also significant, confirming the direction of the finding. Participants showed an illusion of control, as contingency judgements were substantially greater than relationship between response and outcome. There were no effects of ITI and rate of reinforcement. Given the unclear causal mechanisms underlying illusions of control (Orgaz et al., 2013), it might be that a behavioural processing deficit poses a risk factor for problem gambling. Consequently it would be interesting to examine whether performance on this task, taken prior to a gambling task, subsequently predicts gambling behavior.

Depressed individuals were found to gamble for longer in the highly reinforced, short ITI group. Depressed individuals often prefer rapid, random games (e.g. slot machines) that produce negative reinforcement from poor mood (Blaszczynski & Nower, 2002). Problem gambling theories emphasise the importance of negative reinforcement in individuals experiencing traumatic life events or disordered mood; negative reinforcement is strongly hypothesised to be an important component in dependence related behaviours. With regard to ITI, resistance to expectancy changes observed in depressed and individuals (Abramson, Garber, Edwards, & Seligman, 1978), in conjunction with changes in learning in depression due to ITI that has been used to explain the depressive realism effect might explain this finding. Specifically, the ITI and illusion of control literature identified that in positive contingencies, increases in ITI did not affect contingency judgement, but in depressed individuals these were inhibited in the same manner as non-contingent associations (Baker et al., 2010; Msetfi et al., 2007; Msetfi et al., 2005) Given this line of research strongly suggests that ITIs affect behaviour different in depressed people, it might be the case that increasing ITI has the same effect on expectancy changes as it does on contingency judgements, which might explain these findings. However this is primarily speculative, and would require further research to investigate..

This study highlights how different schedules of reinforcement affect gambling behavior. Participants exposed to a lower rate of reinforcement persevered for longer. This interacted with ITI, as participants exposed to a longer ITI and a low rate of reinforcement gambled for longer in extinction. Participants with higher self-reported impulsivity gambled for longer in extinction. The results demonstrate that manipulating behavioral features in a simulated gambling game can produce longer perseverative gambling.

CHAPTER 7 -

UNDERSTANDING MOBILE GAMBLING BEHAVIOUR[1]

ABSTRACT

Having piloted the behavioural effects that might underlie problematic mobile gambling, this chapter reports an initial field experiment in which users were given a smartphone gambling application in the form of a scratchcard style game. Participants were asked to play on this over the course of 12 weeks, in which the probability of reinforcement was kept constant at 0.3 for 9 weeks, after which they were placed into extinction. The study revealed that participants engaged in a considerable amount of perseverative gambling, associated with their level of engagement in the study. Furthermore there appeared to be a number of effects related to timing; a post reinforcement pause after wins was observed that correlated with the magnitude of reinforcement. Moreover, participants were more likely to prematurely cease gambling after a win, which also tracked alongside win magnitude.

7.1 Recap on mobile gambling

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[1] The data and analyses reported in this chapter have been adapted and are in the process of being submitted for publication at the time of thesis submission.

Mobile gambling is an emerging form of play that has the potential to profoundly affect human behaviour. There is ample evidence that the schedules of reinforcement present in gambling, a combination of random ratio and fixed interval schedules, are highly resistant to extinction and is associated with perseverative play even in the face of considerable adverse outcomes as Chapter 6 demonstrated. Gambling is commonly believed to be addictive to a portion of the population and Gambling Disorder is recognized as the sole behavioural addiction in the DSM-5 (American Psychiatric Association, 2013); models of Gambling Disorder emphasize the role of operant and classical conditioning in the transition towards addictive behaviour (Blaszczynski & Nower, 2002). There has been a continual concern with the emergence of gambling technologies; electronic gaming machines in the late 1980's, internet gambling in the 1990's and now mobile gambling, that these new technologies are more addictive than those that came before them. As such, research literatures have similarly emerged studying the effects of these technologies on gamblers and the wider population. The potential concern with mobile gambling is that changes in the gambling behaviour engendered by how phones are interacted with might reinforce harmful patterns of play.

Mobile gambling is becoming increasingly popular worldwide. Even though it is restricted alongside online gambling in some jurisdictions, the mobile gambling market is anticipated to show considerable growth over the next five years (H2 Capital, 2013). Evidence from gambling regulators suggests that a larger proportion of mobile gambling is conducted by younger adults (The Gambling Commission, 2016a), a group already generally at risk for the development of addictive behaviour (Health and Social Care

Information Centre, 2015; Wardle et al., 2011b). In areas where gambling regulation is more permissive, live action betting is heavily promoted on mobile gambling apps. The preponderance of gambling activity on smartphones is on sports betting. There are additional issues concerning the convergence between gambling and forms of gaming on social media and mobile, as a number using gambling games or mechanisms to help monetize a product (Gainsbury et al., 2012b). As there is continued pressure towards the liberalisation of internet gambling laws worldwide, understanding the risks associated with one of the main means of accessing the internet, mobile phones, is necessary.

Mobile technology is characterised as involving short, interspersed bouts of interaction that have been compared with to snack-like engagement (Bohmer et al., 2011). The behavioural literature predicts that the increases in the latency between reinforcements are associated with increased acquisition of learned behaviours (Moody et al., 2006; Sunsay & Bouton, 2008). It has been previously contended that the interaction of these two behavioural phenomena has the potential to make mobile gambling especially harmful to at least a portion of the wider population. It is unclear whether this is a group already engaged with or at risk of problematic gambling, or whether it is a novel group at risk of addictive behaviour. However there is little extant literature on mobile gambling, and no direct research studying the behaviour of the individual while gambling on a mobile phone. One of the aims of this study is to collect data to try and start answering these questions.

Mobile apps have been used extensively in health and medical research to deliver interventions designed to change behaviour. This has ranged from interventions for acute physical illness, long-term conditions (i.e. obesity, diabetes) and psychiatric conditions such as mood disorder (Depp et al., 2015). Many of these make use of functions such as self-monitoring and recording, goal-setting and context sensitive functionality alongside a component designed to induce behaviour change. Others have more explicitly used or enhanced psychological therapies. Other interventions have made use of more phone-based functions, such as text messaging, to prompt behaviours or remind participants to attend sessions or appointments. What has been less explored is the use of app studies in understanding behaviour; while these studies may collect a wide variety of self report data on health behaviours, these typically do not measure the behaviour itself. More broadly a wide range of research in associative learning studies the effects of stimulus and reinforcement on animal behaviour with significant latencies (i.e. of hours or days) between trials. The use of mobile technology has the potential to be highly informative for translational research in this area.

One area of particular interest to gambling and mobile in particular is the role of timing. The gambling literature has already looked at the role of post reinforcement pauses in a range of gambling outcomes, finding that typically gamblers engage in greater latencies between gambles after a win relative to a loss (Belisle & Dixon, 2016; Delfabbro & Winefield, 1999; Dixon et al., 2013b; Templeton, Dixon, Harrigan, & Fugelsang, 2015). These findings have been extended to scratchcards (Stange, Grau, Osazuwa, Graydon, & Dixon, 2016a; Stange, Graydon, & Dixon, 2016b) and mobile video gaming (Larche, Musielak, & Dixon, 2016), both of direct relevance to the study reported here. In addition, forcing changes in post reinforcement pause appears to affect perseverance at gambling when reinforcement is suppressed; the data in Chapter 6 showed that gamblers exposed to a low reinforcement, long latency (in the form of an ITI, or a forced pause between plays) persevered for longer in a simulated slot machine game. The role of timing has been expanded elsewhere, utilised to explain why under certain circumstances, there appears to be a 'depressive realism' effect in contingency judgements. Instead of depressed individuals making better calibrated judgements however, it appears that depressed individuals integrate latencies between reinforcements differently, affecting their subsequent judgements (Msetfi et al., 2007; Msetfi et al., 2005).

The paradigm utilised in this study is a simulated gambling approach that has previously shown typical behavioural and individual difference related effects in gambling behaviour. The manipulation rate of reinforcement (payout rate) and timing between gambles on a simulated slot machine game in Chapter 6 demonstrated a partial reinforcement extinction effect, a trial spacing effect in extinction and interaction between the two; the low-payout, long latency schedule of reinforcement typical of mobile gambling was associated with increased perseverance in play. Additionally, more impulsive participants played for longer in extinction, following previous research on loss-chasing behaviour (Breen & Zuckerman, 1999).

This chapter explores how participants engaged with a mobile gambling app based off the principles that emerged from the previous chapter in this thesis. Participants were asked to play a simulated gambling game that had a fixed rate of reinforcement operating on a random ratio schedule of reinforcement, and multiple levels of reward. After a pre-specified period of engagement with the app, participants were placed into extinction, during which it was no longer possible to win any more money. The experiment in Chapter 6 provided the basis for modelling the effects of timing, reinforcement and impulsivity on perseverance in gambling behaviour. Where this study differs is that in previous uses participants were given a forced choice between wagering and observing (skipping) on the simulated machine. In this study, participants were given a free choice as they could simply not engage with the app should they have chosen not to. After this, participants were debriefed. Contextual information was taken during the study. At the beginning of each session, information about where the participant was, which apps they had used before (i.e. since activating the phone) the gambling app, and which apps they intended to use after. In addition, behavioural and location (GPS) data was taken each time a gamble was made. For the interaction with the app itself, the interactions involved were through the touch screen. While this does not cover the wide range of interactions a smartphone allows, it does not appreciably differ from the interactions utilised by most gambling apps as the General Introduction noted.

7.2 METHOD

7.2.a Participants

Thirty participants were initially recruited from the University of Nottingham student community. Of these, 18 were female and 12 were male, with a mean age of 24.167 (*S.D.* 3.55, range = 20-37) at pre-test. Two participants did not complete the follow up at the end of the study; in one case the participant did not respond to requests for the follow up, and in the second the participant changed employment and was not available to follow-up. In one further case that was followed up, the participants' phone was destroyed during the experimental period. The destruction of the phone was unrelated to the study. Data from the latter two participants is reported in the results section. Participants were reimbursed based on their performance on the app. Average reimbursement was £34.50, but ranged from £0.10 to £93.00. Because the game itself was random, payouts varied although correlated with engagement (r = 0.96). As the scatterplot indicates, although extravagantly linear, often the small deviations from the linear effect correspond in relative terms of a significant amount of gambling – between 300 and 500 extra plays for equivalent cash payments. Ethical clearance was obtained from the School of Psychology, University of Nottingham Ethics Committee prior to data collection.

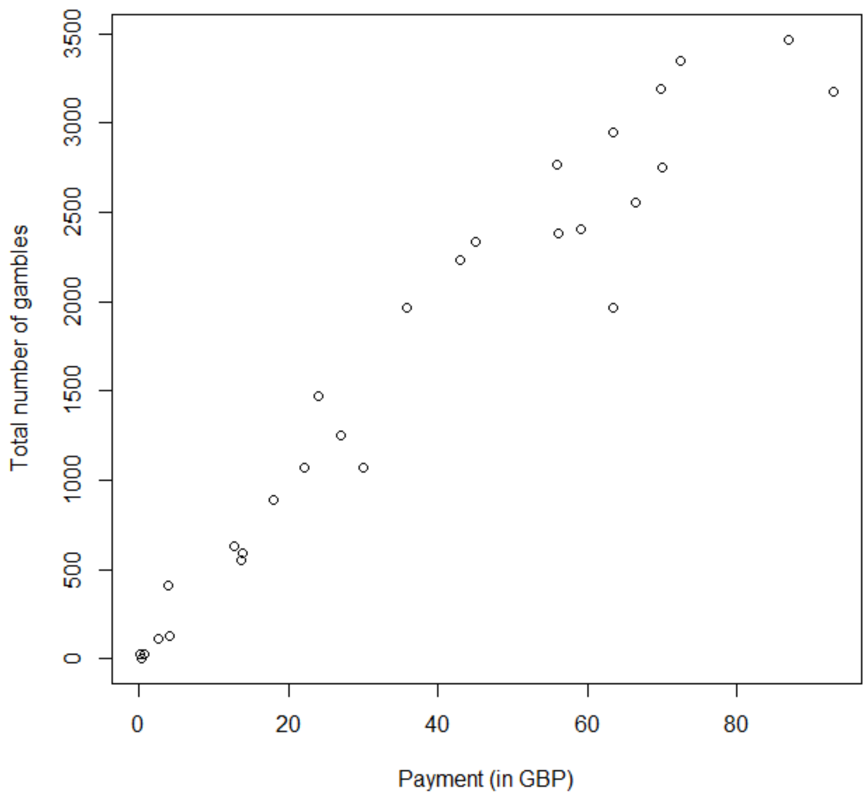

Figure 38

Scatterplot of the relationship between gambles over the course of the acquisition phase and monetary reimbursement.

7.2.b Measures

At the beginning and the end of the study participants were asked to complete a battery of psychometric assessments measuring constructs directly relevant to gambling and problem gambling. Depression and negative affect were assessed using the Beck Depression Inventory (BDI) (Beck et al., 1961) and the Positive and Negative Affect Scale (Watson, Clark, & Tellegen, 1988). Models of problem gambling identify the role of negative reinforcement and disordered mood as a causal factor in the development of problem gambling behaviours (Blaszczynski & Nower, 2002; Jacobs, 1986). Constructs related to risk taking and impulsivity were measured using the Sensation Seeking Scale Form V (SSS-V) (Zuckerman, Eysenck, & Eysenck, 1978) and the Barratt Impulsiveness Scale (BIS-11) (Patton et al., 1995). Again. Further constructs directly relevant to gambling, problem gambling and gambling cognitions, were measured using the Problem Gambling Severity Index (Ferris & Wynne, 2001) and the Gambling Related Cognitions Scale (Raylu & Oei, 2004). In addition questions about gambling behaviour querying the type of game played, levels of expenditure, frequency of access and modality the game was played on were also administered. In the second questionnaire session a series of open ended questions were given to participants about their experiences with the app, reflections on their own behaviour, the contexts in which they gambled and whether they noticed any changes in the app or their behaviour as the study progressed.

A range of behavioural measures was collected over the course of the study. The primary behavioural measure was the number of gambles in extinction, followed by gambles in acquisition and within each session. The app also includes timing information that allow exploration of the latencies between different types of outcome. The associative literature on gambling frequently measures post reinforcement pauses. This potentially has a mutual effect on behaviour; forcing a longer PRP on participants increased their gambling in extinction, as shown in Chapter 6.

The third primary class of data collected in this study was contextual data, concerning location, activity and other app usage. This was collected via a series of self-report questions included. In addition on every gamble GPS co-ordinates were recorded from the phone. Participants had to explicitly opt-in to the taking of this data, and were informed they could change the settings on the phone to prevent the app from taking this data. A small number of participants (n = 7) had some contextual data missing. For most of these participants, this was isolated to the final session of gambling in extinction. In most of these cases, location could be interpolated based on corresponding GPS co-ordinates with previously reported locations. In two further cases, again due to a bug with the reporting of the contextual data, the location a participant reported using the app was ambiguous. GPS co-ordinates and other factors were used to guide decision-making on determining which location the participant was at when they gambled.

7.2.c Stimuli

The stimuli for the app study consisted of 19 different scratchcard style stimuli. These involved three different icons placed beneath a grey overlay. There were five different types of outcome (orange, lemon, pear, cherry, lucky

7). Five of the cards had a winning outcome. Four had a near miss outcome, counterbalanced so that in half the stimuli the near miss was XXO, and in half OXX. Near misses in slot machines tend to involve the first two of the three icons, but because participants could swipe from left to right or right to left, it was decided to counterbalance this. Previous studies of non-classic near misses have tended not to find any effects of timing on the OXX style near miss (Dixon et al., 2013b), but the use of a scratchcard means that participants could begin from the left or right of the screen (unlike a slot machine). Previous studies of scratchcard gambling have instructed participants to reveal the card from left to right (Stange et al., 2016a; Stange et al., 2016b). The remaining 10 cards were losses. Wins were set at 30%, with losing outcomes being randomly drawn. Accounting for the 30% win rate, this means the rate of near misses was set at 20%. The app was written in AppFurnace, a platform for designing apps that combines visual coding for the designation of screens and the placement of objects, as well as additional coding in JavaScript.

7.2.d Procedure

Participants initially completed the battery of questionnaires (order: Gambling Questions, PGSI, GRCS, BIS, BDI, PANAS, SSS-V) by themselves in the laboratory. Subsequently they completed a computerised contingency judgement task that is a probe of the illusion of control, a cognitive bias in gambling and problem gambling. The paradigm adopted was similar that used in Chapter 6, which found no effects of prior gambling exposure on illusory control. These were completed in laboratory settings in the School of Psychology at The University of Nottingham. Then, whilst still in the lab, participants were instructed on how download the AppFurnace app onto their phones via the iOS or Google Play Store, and then how to load the gambling app onto their phone via AppFurnace. The process of doing so was completed whilst they were still in the lab. Upon doing so, participants were instructed on how to enter their participant number on the first use of the app, and given instructions concerning how the gambling app worked (specifically how to uncover the scratchcard, how to upload data etc.).

The app itself was designed as a 'scratchcard' style game. Scratchcard or instant win games are a common form of gambling, in person and online, in the United Kingdom where they are legally available to gamblers over the age of 16 (Wardle et al., 2011b). Participants were presented with a grey overlay on the screen, and they were required to swipe or tap the overlay off (swiping functionality was limited to participants using an iOS phone – this was controlled for in the statistical analysis), to reveal a one-line scratchcard underneath. Participants were allowed to engage with the app freely, and were not instructed to gamble at any specific rate. The app itself however had a pre-specified upper limit, preventing users from playing more than one hundred times per day (resetting at 12.01AM GMT every day). Participants engaged with the app in this phase of the experiment for approximately six weeks from the commencement of the study.

At the beginning of each session (either the first play of the day or any gamble when gambling had not been previously conducted in the two hours prior to a play on the same day), participants were asked three questions: where they currently were whilst playing the app, what types of app they had used prior to opening the gambling app, and which type of app they were planning to use after they had finished playing the gambling game. After this was completed once they were presented with the scratchcard overlay.

The home screen consisted of two pieces of information on the top left (current number of plays on a given day) and the top right (total balance from playing on the app) of the screen, and three buttons: play, to initiate play of the app; upload data to trigger the sending of data via a JSON loop to a server held in the School of Psychology in The University of Nottingham, and a settings button that allowed the experimenter (via the use of a code) to reset data on participants' phones or enter the participants' number if not entered or had been done so erroneously[2].

At this point, after a pre-specified date it was no longer possible for participants to win any further money on the app. Participants were put into extinction, and their perseverative gambling behaviour was measured. The approach was modelled directly on that taken in Chapter 6, and is more directly analogous to a wider range of behavioural research partial reinforcement and extinction using gambling (specifically slot machine) paradigms.

After approximately two weeks of this had passed, participants were then invited back into the lab, and asked to complete the same series of

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[2] Neither of these functions was used during the course of the experiment. In piloting work, where participants were asked to download and initiate the app remotely, difficulties were reported with adding a participant number. This functionality was added so that data could be attached to a participant number *post-hoc*.

questionnaires and the contingency judgement task. They then were fully debriefed as to the purpose of the study, and reimbursed for their participation.

7.3 RESULTS

7.3.a BEHAVIOUR

A total of 904 gambling sessions were initiated over the course of the experimental period, comprising a total of 45,749 gambles from the 29 participants who either a) could be followed up (n = 28) or b) could not be followed up but had uploaded data (n = 1). These sessions were distributed across 651 gambling days, meaning participants on average initiated 1.39 sessions over the course of a typical gambling day. Participation of the app varied markedly between participants; there was evidence that engagement with the app was bimodally distributed (Figure 1). Four participants gambled less than 100 times. In a small number of cases (n = 4), the participant had stopped gambling before reaching extinction. In these instances the participant was asked to play on the app prior to the debrief session. The data from these gambles are not included in the descriptive statistics reported here nor in the participants or trial level analyses reported elsewhere within these results. Psychometric data is reported in Table 39. At the time of writing the thesis these had not been formally analysed. It is intended that these will be used as covariates in mixed effects models similar to those reported in this chapter, especially given the impulsivity related findings in Chapter 6.

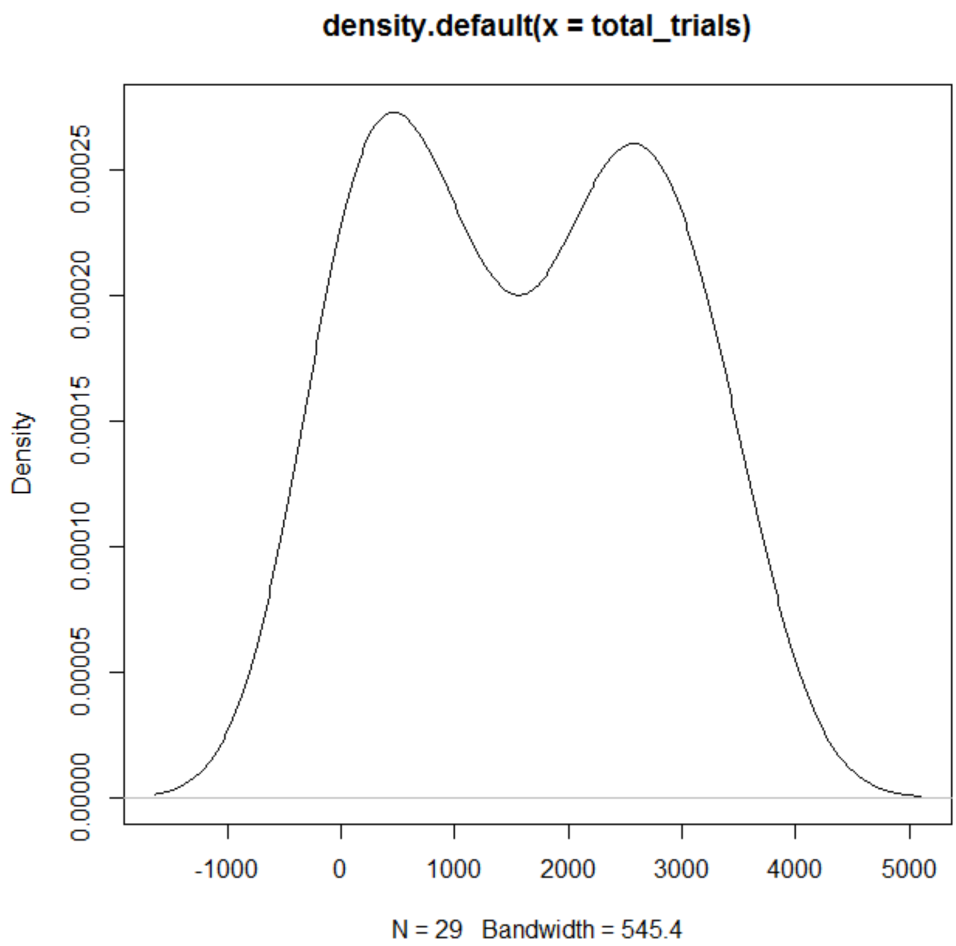

Figure 39

Density plot of the distribution of the total number of simulated gambles each participant played in over the course of the app study.

On average, participants made 1,635.25 gambles over the course of the study (S.D. = 1168.3). The data was highly non-normal, with some evidence of a bimodal distribution (Figure 1). The number of gambles ranged from 0 to 3,467 and the median number of gambles was 1,474. The payout rate during was 30.2%, in line with the probability coded in the app. The distribution of payouts was evenly spread between the five possible outcomes. Near misses occurred 20.22% of the time, roughly evenly distributed between XXO and OXX outcomes (10.27% vs 9.95%).

7.3.b CHANGES WHILE PLAYING THE APP

Two phenomena were of interest in looking at participants' engagement with the app. The first was the number of sessions people played over the course of a day, the second the number of gambles in each session.

In the 'timing' section the effect of the number of gambles within a session and across the course of the experiment in relation to their roles as indicators of latencies between gambles is discussed. Essentially, while both are significant as fixed effects, inserting random slopes for the number of gambles (or specifically the quartile of the experiment the game was placed in) removed any effect on gambling latency, whereas this did not appear to affect the effect on session length[3]. However, it is unclear whether this is because a) there is no effect of b) the effect is nonlinear, particularly for the relationship between the first and second quartiles of the experiment. Figure 40 reports the mean latencies across each quantile with error bars reporting one standard error of the mean. What appears to occur is that participants take longer (~ 0.5 seconds) to gamble in first quarter of their gambles, before rapidly dropping off and then slowly increasing latencies as the experiment progressed,

[3] Strictly speaking it is difficult to tell, as the linear mixed model failed to converge when modelling session number as a random slope. However, the *t* value associated with the effect (-2.5), indicates the effect is probably significant regardless.

increasing to a rate approximately 125ms slower than gambles in the first quartile of the experiment.

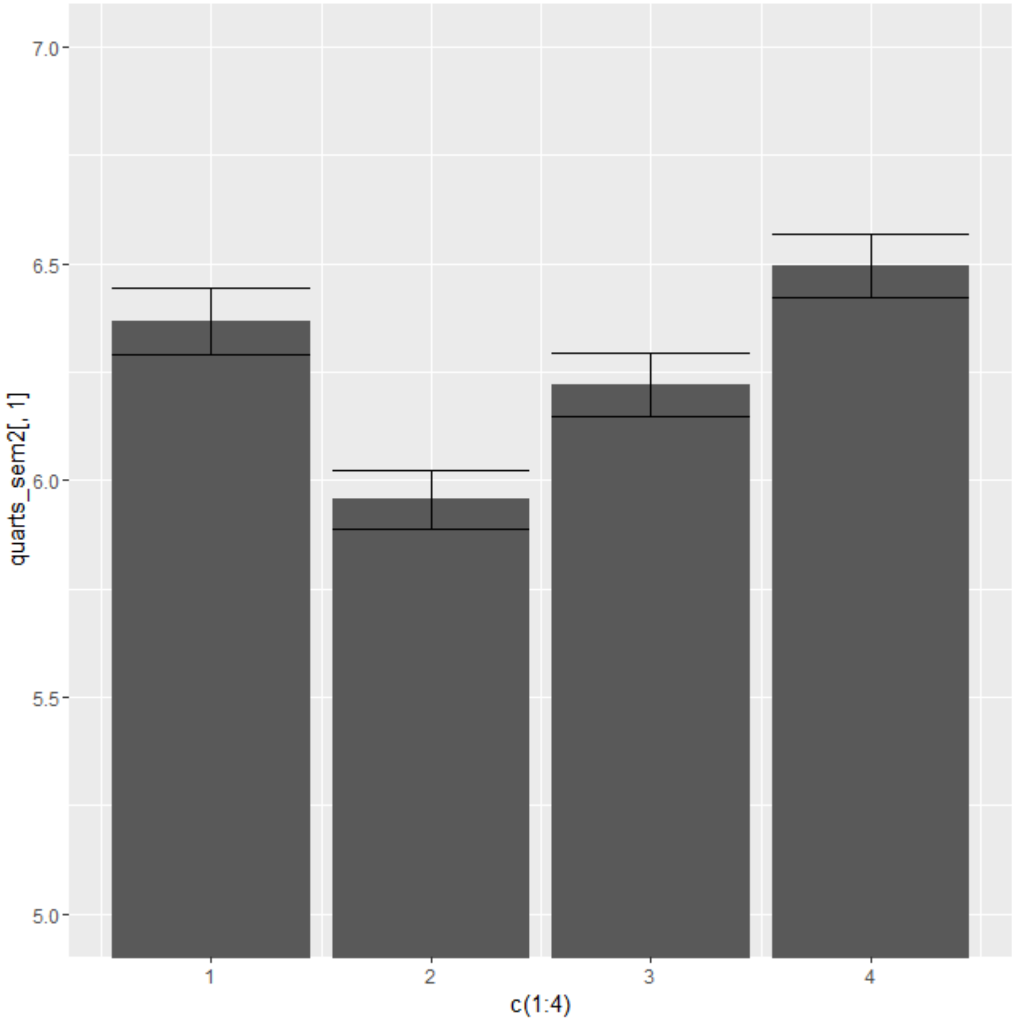

Figure 40

Bar chart of latencies between gambles across quartiles of the study.

Concerning the number of gambles with a gambling day (or session number), the effect was relatively straightforward. There was a clear negative correlation between the number of gambles one has played and PRP (Figure 41) (r = -0.396, p < .001). People within session accelerated their gambling as they continued to play, on average having latencies between gambles between a quarter and half a second faster at the end of a gambling session than at the beginning.

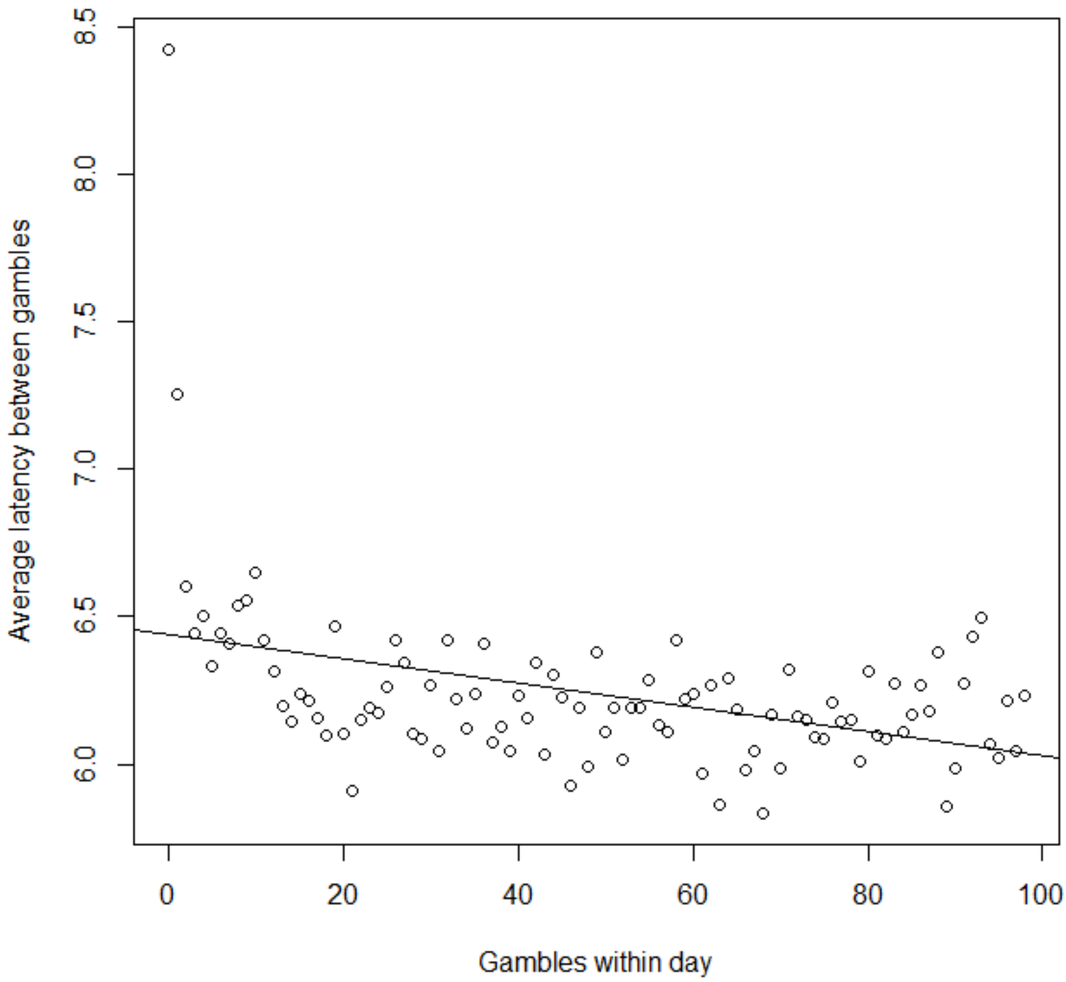

Figure 41

Scatterplot of the relationship between the average latency between gamble, and the number of gambles made within a day, including the regression line on the scatterplot.

7.3.c PERSEVERATIVE GAMBLING

Participants on average gambled 58.08 times in extinction (SD = 49.86). Excluding the participants who had ceased playing the app before extinction, this increased to 65.65 (SD = 48.01). The median number of gambles in extinction was 40. The range of gambles in extinction ranged from 0 to 177.

Initially, a linear regression model was estimated to model the effects of prior gambling behaviour (as a general index of associative strength) on gambling in extinction. Two participants whose data were analysed at a trial level were excluded from this analysis. In both cases this was because their behaviour in extinction was unknown; in one case the participant's phone was destroyed during the experimental period, and in the second the participant could not be followed up (did not respond to requests for follow up). The amount of gambles made during acquisition significantly predicted the number of gambles during extinction (b = 0.02139, SE = 0.0079, t = 2.722, p = .0119, Multiple R^2 = 0.236, Adjusted R^2 = 0.2041)[4]. The scatterplot of the relationship between these data is reported in Figure 42, including the regression line. Essentially, what this shows is the amount of gambles in extinction for low gamblers is relatively clustered together, whereas there appear to be three clusters for higher engagement gamblers of roughly equal size. One of these cluster gambles at around the same rate in extinction as the low frequency gamblers, one gamblers at a higher rate in extinction than the low frequency

[4] Intercept – $b = 22.3097, SE = 15.77, t = 1.414, p = 0.1701$

gamblers, and a final group does so at a substantially higher rate. The regression line, which is also plotted, goes through the second of these clusters.

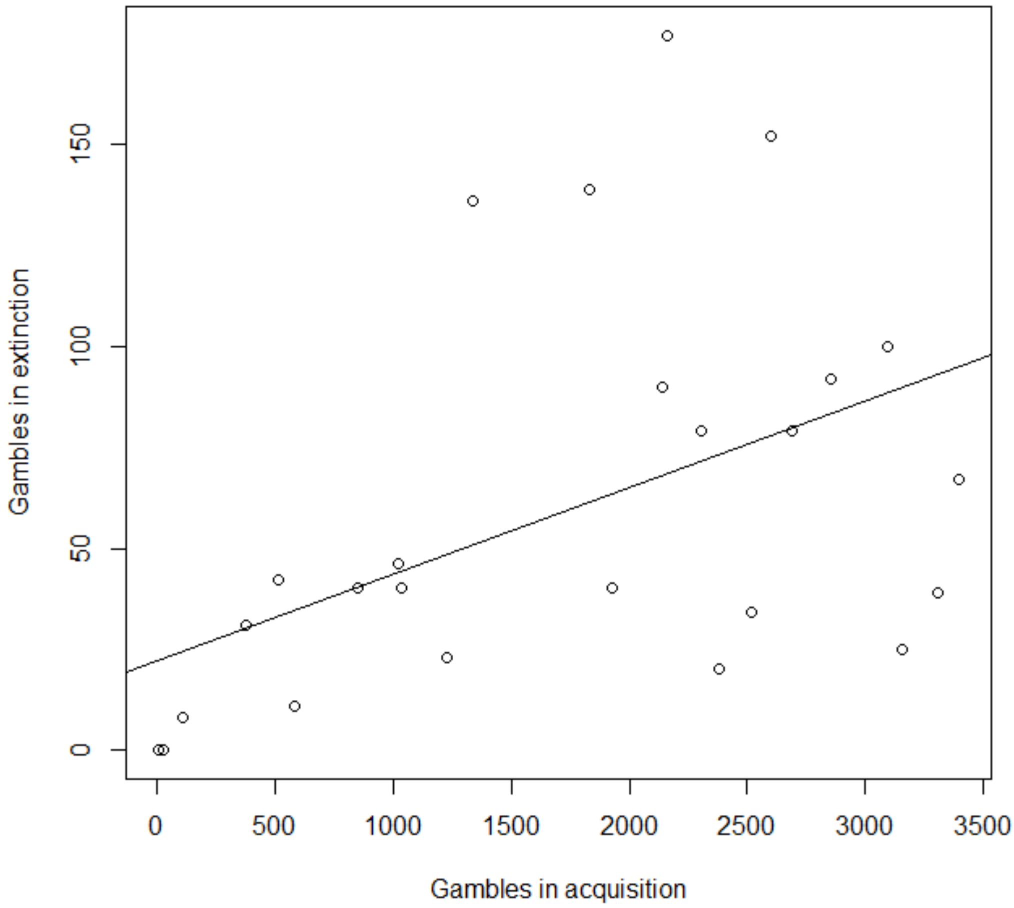

Figure 42

Scatterplot of the relationship between the number of gambles in acquisition and extinction, including the regression line from the linear regression predicting gambles in extinction from gambles in acquisition (n = 26).

Predictors of perseverative gambling were modelled on a trial level using a binary variable to capture the last gamble within a session, except where participants had reached the upper limit. This meant the variable captured the instances where participants elected to stop playing on the app. This was then modelled using a mixed effects logistic regression model, with outcome and context as fixed effects, and participants and phone operating system (iOS/Android) as random effects[5]. This revealed (Table 40) that participants were relatively more likely to stop playing after a win. Decomposing this effect by looking at the different types of near miss and magnitudes of reinforcement, this effect is driven by the two winning cards with the highest magnitude of reinforcement (the orange and the lucky seven, which paid £0.25 and £0.30 respectively) (Table 41).

It is important to consider this effect in the wider context of the data; only around half (*n* = 445) of gambling sessions ended before the maximum. Despite this, the final session was equally likely to be a win or a loss. This is despite losses occurring 2.33 times more than wins and participants being exposed to a period of unavoidable losses in extinction, in which most ceased playing before reaching 100 gambles in multiple sessions.

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[5] Note for these analyses and the subsequent linear mixed modelling of timing in the next section, different datasets were generated. Because within-session latencies could not be computed for the final gamble in each session, these were excluded from any timing analysis, whereas these are central to the analysis reported here.

Table 39

Scores on measures of individual difference. The figures in second set of brackets on the second, third and fourth measures report the ranges.

Measure	Mean Pre (SD)	Mean Post (SD)	α (Pre, Post)
Gambling activities**	1.1	0.33 (0.71)	N/A
Illusion of control – Mean	61.09 (26.88) (0-93.7)	56.51 (30.63) (0-97.6)	N/A
Illusion of control – Final	58.37 (30.91) (0-99)	54.61 (33.23) (0-99)	N/A
PGSI	0.5 (0.9) (0-3)	0.46 (0.88) (0-3)	0.57, 0.61
GRCS	37.60 (13.64)	36.82 (11.24)	0.84, 0.82
Expectancy	6.93 (2.79)	6.54 (2.56)	0.28, 0.43
Illusion of Control	5.90 (3.20)	5.00 (2.40)	0.65, 0.83
Predictive Control	11.00 (6.09)	11.50 (5.99)	0.77, 0.71
Failure of Control	5.30 (0.84)	5.14 (0.45)	0.12, NA
Interpretive Bias	8.47 (5.12)	8.64 (4.27)	0.78, 0.63
BIS-11 (Total)	59.53 (8.46)	61.36 (10.24)	0.8, 0.82
Attentional Impulsivity	16.93 (2.42)	17.36 (3.09)	0.15, 0.47
Motor Impulsivity	22.27 (4.35)	22.64 (4.75)	0.67, 0.71
Nonplanning Impulsivity	20.33 (4.29)	21.36 (4.95)	0.73, 0.77
BDI	6.5 (5.65)	5.52 (5.13)	0.86, 0.85
Positive Affect	28.70 (8.10)	26.79 (7.96)	0.91, 0.91
Negative Affect	13.13 (3.54)	14.85 (5.00)	0.74, 0.82
Sensation-Seeking (Total)	17.73 (6.59)	17.71 (6.62)	
Boredom Susceptibility	2.3 (2.11)	2.29 (1.65)	0.67, 0.43
Disinhibition	4.6 (2.5)	4.89 (2.39)	0.72, 0.68
Experience Seeking	5.17 (2.15)	5 (1.76)	0.63, 0.45
Thrill and Adventure Seeking	5.63 (2.79)	5.54 (3.10)	0.77, 0.83

** - Please note gambling activities were queried for the year prior to the study at pre-test, and during the course of the study post-test. They are not directly comparable.

Notes on alphas: Please also note the PGSI α values are especially low as 4 and 6 items had to be deleted from them as all respondents scored zero on them. Given the comments in the discussion of Chapter 3 this is not surprising. As such the confidence intervals on these α statistics are substantial (0.28 – 0.91 at pre-test, 0.17 – 1.01 at post-test). For the GRCS, three and four items were deleted at pre and post-test from the alpha calculation as there was no variance between respondents on these items (i.e. all respondents scored the item at 1). These items were: “I can’t function without gambling”, “My desire to gamble is so overpowering”, “I’m not strong enough to stop gambling” and “I will never be able to stop gambling”. Again with the GRCS subscales there is the confidence intervals are notably high (+/- 0.3-0.4) For the failure of control subscale, 3 and 4 of the 5 items were removed due to zero variance. This meant at post-test alpha could not be calculated for this subscale. For the BDI, one participant failed to answer nine of the BDI questions. They were removed from the statistics reported here, but including them makes little difference to these summary numbers (M = 5.35 ($S.D.$ = 5.11). At post-test, one item (querying the extent to which the respondent had cried more than usual) was removed as everyone gave the same answer i.e. that they hadn’t cried more than usual. Statistics for the SSS total score could not be calculated because the number of items exceeded the number of cases.

Table 40

Mixed effect logistic regression model of the predictors of prematurely ending a gambling session, with participant and operating system as random intercepts.

Effect	Estimate	SE	*z*	*p*
Participant (random effect)	1.426	1.194		
OS (random effect)	0.072	0.268		
Intercept	4.579	0.335	13.664	$p < 1 * 10^{-5}$
Outcome:				
Near-miss	0.082	0.139	0.588	0.5567
Win	-0.535	0.104	-5.133	$p < 1 * 10^{-5}$
Context:				
Other	-0.468	0.237	-1.970	0.0488
Pub	-0.450	0.289	-1.555	0.1199
Social	0.093	0.391	0.237	0.8128
Travelling	-0.212	0.158	-1.342	0.1797
Work	-0.209	0.121	-1.725	0.0845

Note - 1 = participant gambled again, 0 = participant did not.

Table 41

Mixed effect logistic regression model of the predictors of prematurely ending a gambling session, with participant and operating system as random intercepts, modelling different types of outcome (i.e. type of near miss, magnitude of reinforcement).

Effect	Estimate	SE	*z*	*P*
Participant (random effect)	1.450	1.204		
OS (random effect)	0.068	0.261		
Intercept	4.576	0.335	13.656	$p < 10^{-5}$
Outcome:				
£0.10 win	-0.332	0.196	-1.696	0.090
£0.15 win	-0.039	0.220	-0.177	0.859
£0.20 win	-0.490	0.187	-2.618	0.009
£0.25 win	-0.723	0.174	-4.155	$3.26 * 10^{-5}$
£0.30 win	-0.902	0.157	-5.733	$p < 10^{-5}$
L-R near miss	0.083	0.181	0.456	0.648
R-L near miss	0.079	0.184	0.431	0.667
Context:				
Other	-0.456	0.238	-1.914	0.056
Pub	-0.457	0.290	-1.574	0.116
Social	0.094	0.396	0.238	0.812
Travelling	-0.211	0.158	-1.332	0.182
Work	-0.205	0.121	-1.687	0.092

Note - 1 = participant gambled again, 0 = participant did not.

7.3.d TIMING

The app collected data that allows for the analysis of timing related processes. The time each gamble is initiated is recorded for each trial (in hours, minutes, and seconds). Over the aggregate data, this allows modelling of the effect different outcomes have on the time it took to uncover the scratchcard and the post-reinforcement pause within a session. The effects of timing were modelled using a linear mixed effects model, using the 'lmer' package in *R*. In addition, interpretation of the model was guided using the 'lmertest' package. This is because there is a concern that interpreting *t* values from a linear mixed model as being normally distributed has a tendency to be anti-conservative and increase the probability of identifying a false positive. The mixed effects model was estimated using a restricted maximum likelihood (REML). Significance was assessed using an ANOVA model with Sattherwaite's approximate for the degrees of freedom for each effect. This has been shown to demonstrate acceptable levels of Type 1 error, even with relatively small sample sizes (Luke, 2016). The last trial from each session was omitted from trial level analyses as PRP's could not be calculated for these.

Model building began by estimating random intercepts for each participant (Tables 42 and 43)[6]. Pauses exceeding three minutes were excluded from the analysis. The dependent variable was the number of seconds between the initiation of a gamble, and the number of second elapsed until the next gamble was initiated. Participant was modelled as a random effect. Outcome (loss, near miss, win, loss as referent), context (home, other, pub, social, travel, work, home as referent), number of gambles within session[7] and number of gambles overall were included as fixed effects.

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[6] Operating system was not estimated in this analysis as the estimated random intercept was 0.

[7] Note for session length in this contrast this only covers the number of gambles within a day. It does not reset if someone initiates multiple session

However, it has been noted that this approach is potentially associated with an unacceptable false positive rate (Barr, Levy, Scheepers, & Tily, 2013), and that maximal models should be estimated. This process began by focusing on the outcome variable (near misses and wins), and modelling random slopes (or random coefficients to be precise as these are categorical predictor) for these outcome predictors and each participant. The first test of this removed any effects of outcome on the PRP, but also an extremely large estimate for the win random coefficient. The plot of the fitted versus residuals, reported in Figure 43, revealed substantial levels of fitting error on a small number of trials. These were a small number of trials (n = 63) where the participants' pause exceeded 60 seconds, and produced very large residuals on the fitted regression model. As such the decision was taken to exclude these. Re-modelling of the random coefficients recovered the same effects as observed with the random intercept, with a slightly larger effect size (Table 44), the same emerging the magnitude of outcome (Table 45).

The next decision to make was how to model contextual variables such as location. There is an argument for modelling them purely as fixed effects and fixed and random effects (the latter as a random intercept). The model reported in Table 46 does so, modelling random intercepts for these variables. The primary difference in t values between modelling type of location as a fixed (Table 42 & 43) or fixed + random effect (Table 46 & 47) is in the former there are statistically significant differences in PRP in certain contexts

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within a day. Also, more importantly note that these session breaks *were* modelled in the quitting analysis reported above.

(other locations, whilst travelling and while at work) in the former, whereas in the case of the latter none of these meet statistical significance.

Finally, intra-session and intra-experimental effects were accounted for using the number of gambles played within a day as a covariate for the former, and dividing each participant's total number of gambles into quartiles for the latter. These were first maximally modelled using random slopes and intercepts, but the model could not be identified, with specific difficulties emerging with the 'lmertest' package that meant adjusted p-values could not be estimated. The final model that could be estimated without the model failing to converge modelled session number with a random intercept and quartile also as a random intercept nested at the participant level. While both were significant as fixed effects (expected given the large degrees of freedom on the model) only session number was significant with a random intercept. The final model is reported in Table 48.

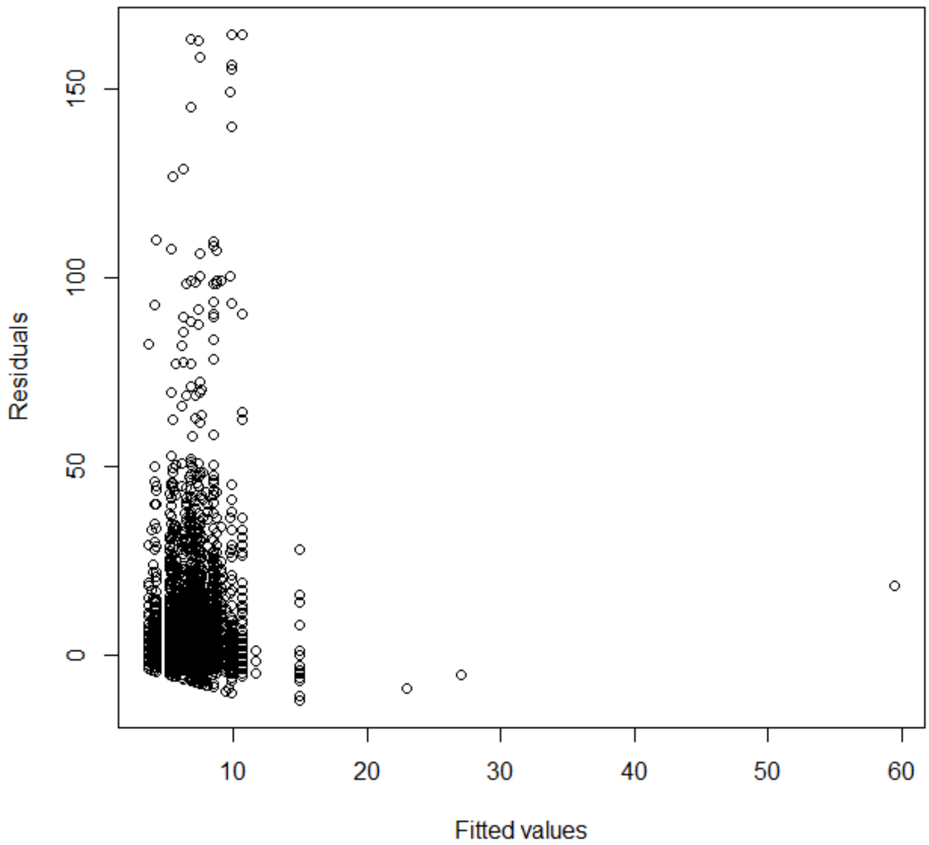

Figure 43

Scatterplot of fitted versus residual values for the first mixed effect model with different types of outcome modelled as random slopes.

The mixed effects model (Tables 47 & 48) shows that there was a significant effect of the type of outcome upon the combination of the trial length and post reinforcement pause. Participants took longer to initiate a new gamble (or complete a gamble) when the outcome was a win rather than a loss or a near miss. In addition, participants had greater latencies in certain contexts – they took greater time in work or other (see 'context of use' section for more details) environments, and gambled more quickly whilst travelling (e.g. on a train or bus). There were also interesting effects regarding engagement with the app. As a gambling session progressed, participants had shorter latencies between their gambles i.e. their gambling accelerated. However, this did not appear to be related to their overall engagement with the app; as the experiment progressed, they experienced a larger composite trial time and post reinforcement pause.

Table 42

Linear mixed effect model predicting latencies between gambles, with participant modelled as a random intercept.

Effect	Estimate	SE	*T*	*p*
Participant (random effect)	18.46	4.297		
Intercept	7.410	0.822	9.015	$p < 10^{-5}$
Outcome:				
Near-miss	0.019	0.066	0.295	0.768
Win	0.212	0.058	3.627	<.001
Context:				
Other	0.468	0.147	3.192	0.001
Pub	-0.191	0.179	-1.071	0.284
Social	-0.199	0.182	-1.097	0.273
Travelling	-0.290	0.087	-3.346	0.001
Work	0.445	0.063	7.041	$p < 10^{-5}$
Session Number	-0.004	0.001	-4.702	$p < 10^{-5}$
Gamble Number	0.000	0.000	4.790	$p < 10^{-5}$

For gamble number, the *b* is 0.000165, and the standard error is 0.000034. The *p* value on the win effect is $p = 0.0003$.

Table 43

Linear mixed effect model predicting latencies between gambles, with participant modelled as a random intercept, additionally modelling different types of outcome (i.e. magnitude of reinforcement, type of near-miss).

Effect	Estimate	SE	*T*	*P*
Participant (random effect)	18.62	4.315		
Intercept	7.414	0.825	8.982	$p < 10^{-5}$
Outcome:				
£0.10 win	0.034	0.111	0.310	0.757
£0.15 win	0.054	0.108	0.499	0.617
£0.20 win	0.264	0.111	2.382	0.017
£0.25 win	0.364	0.111	3.283	0.001
£0.30 win	0.352	0.110	3.201	0.001
L-R near miss	-0.022	0.086	-0.254	0.800
R-L near miss	0.062	0.087	0.712	0.476
Context:				
Other	0.467	0.147	3.183	0.001
Pub	-0.189	0.179	-1.058	0.290
Social	-0.199	0.182	-1.096	0.273
Travelling	-0.290	0.087	-3.347	0.001
Work	0.444	0.063	7.034	$p < 10^{-5}$
Session Number	-0.004	0.001	-4.687	$p < 10^{-5}$
Gamble Number	0.000	0.000	4.790	$p < 10^{-5}$

Note. For gamble number, the *b* is 0.000165, and the standard error is 0.000034.

Table 44

Linear mixed effect model of the outcome based predictors of the PRP and latency between gambles, with the two types of outcome modelled with a random slope (nested in participant).

Effect	*b*	*SE*	*t*	*p*
Participant (random intercept)	3.047	1.742		
Win (random slope)	0.086	0.293		
Near miss (random slope)	0.00015	0.012		
Intercept	6.667	0.337	19.795	$p < 10^{-5}$
Win	0.333	0.074	4.513	0.002
Near miss	0.075	0.045	1.694	0.099

Table 45

Linear mixed effect model, modelling the effect of different types of gambling outcome on the latency between gambles. These different types of outcome (differing in magnitude of reinforcement and type of near miss) are modelled as random slopes for each participant. Participant is additionally modelled with a random intercept.

Effect	*b*	*SE*	*t*	*p*
Random effects:				
Participant (random intercept)	3.937	1.714		
Win £0.10	0.287	0.536		
Win £0.15	0.035	0.188		
Win £0.20	0.130	0.361		
Win £0.25	1.554	1.247		
Win £0.30	1.109	1.053		
Near-miss L->R	0.006	0.076		
Near miss R->L	0.011	0.103		
Fixed effects:				
Intercept	6.645	0.331	20.046	$p < 10^{-5}$
Win £0.10	0.322	0.133	2.416	0.072
Win £0.15	0.093	0.085	1.097	0.291
Win £0.20	0.355	0.108	3.298	0.017
Win £0.25	0.796	0.265	3.003	0.033
Win £0.30	0.722	0.226	3.190	0.016
Near-miss L->R	0.101	0.061	1.645	0.107
Near miss R->L	0.015	0.063	0.230	0.820

Table 46

Linear mixed effect modelling of the effect of different types of outcome and different contexts on latencies between gambles. Different types of outcome are modelled as random slopes. The different contexts are modelled with random intercepts, nested at the participant level. Participant is additionally modelled as a random intercept.

Effect	*b*	*SE*	*t*	*p*
Random effects:				
P:Other	0.421	0.645		
P:Pub	0.319	0.565		
P:Social	0.437	0.661		
P:Travel	0.451	0.672		
P:Work	0.817	0.904		
Participant	1.120	1.059		
Win (slope)	0.073	0.270		
Near miss (slope)	0.004	0.060		
Fixed effect:				
Intercept	6.545	0.369	17.741	V small
Win	0.313	0.070	4.460	0.001
Near Miss	0.066	0.047	1.422	0.162
Other	0.356	0.306	1.165	0.271
Pub	-0.305	0.328	-0.931	0.387
Social	0.421	0.382	1.099	0.306
Travel	-0.171	0.226	-0.754	0.462
Work	0.324	0.263	1.231	0.231

Table 47

Linear mixed effect modelling of the effect of different types of outcome and different contexts on latencies between gambles. Different types of outcome are modelled as random slopes. The different contexts are modelled with random intercepts, nested at the participant level. Participant is additionally modelled as a random intercept. Additionally, number of gambles within session and quartile are modelled as fixed effects.

Effect	*b*	*SE*	*t*	*P*
Random effects:				
P:Other	0.482	0.695		
P:Pub	0.299	0.547		
P:Social	0.482	0.694		
P:Travel	0.455	0.675		
P:Work	0.810	0.900		
Participant	0.928	0.964		
Win (slope)	0.072	0.269		
Near miss (slope)	0.003	0.051		
Fixed effect:				
Intercept	6.495	0.370	17.705	$p < 10^{-5}$
Win	0.319	0.070	4.553	0.001
Near Miss	0.068	0.046	1.466	0.148
Other	0.320	0.323	0.989	0.345
Pub	-0.270	0.320	-0.842	0.431
Social	0.479	0.397	1.205	0.265
Travel	-0.153	0.228	-0.674	0.511
Work	0.340	0.262	1.299	0.208
Session Num	-0.004	0.001	-6.256	$p < 10^{-5}$
Quartile	0.074	0.017	4.465	$p < 10^{-5}$

Table 48

Final linear mixed effect model predicting latencies between gambles, with the different contextual variables and quartile of the experiment estimated as random intercepts (nested within participant), participant and gambles within day estimated as a random intercepts, and the different types of outcome estimated with random slopes.

Effect	*b*	*SE*	*t*	*P*
Random effects:				
Session Num	0.050	0.224		
P:Quartile	0.545	0.738		
P:Other	0.596	0.772		
P:Pub	0.180	0.424		
P:Social	0.302	0.550		
P:Travel	0.429	0.655		
P:Work	0.595	0.771		
Participant	0.780	0.883		
Win (slope)	0.083	0.288		
Near miss (slope)	0.001	0.029		
Fixed effect:				
Intercept	6.726	0.385	17.458	V. small
Win	0.327	0.073	4.497	0.001
Near Miss	0.079	0.045	1.757	0.082
Other	0.438	0.352	1.244	0.237
Pub	-0.584	0.268	-2.180	0.068
Social	0.068	0.333	0.204	0.844
Travel	-0.003	0.224	-0.012	0.991
Work	0.381	0.229	1.665	0.112
Session Num	-0.003	0.001	-2.796	0.006
Quartile	-0.057	0.070	-0.819	0.415

7.3.e CONTEXT OF USE

The average gambling session consisted of 51.53 plays. Most gambling was conducted in the participant's home, with 46.87% of gambling sessions initiated there. Almost three in ten (29.31%) of sessions were initiated at work/university, and 15.44% while the participant was travelling. Fewer sessions were initiated while the participants were at a pub or bar (2.57%), at a social gathering or event (1.9%) or somewhere else/engaging some other form of activity (3.91%). In the previous section the latencies between gambles was reported, considering the context of use. There was limited evidence of a difference in latencies between contexts, any effect disappearing. The final model put the p value of one environment (pub) close to significance but ultimately is not.

7.3.f ENGAGEMENT WITH OTHER APPS

In addition to the location where people used the app, they were also asked to report whether they used any other apps (Tables 49 and 50). On any given session, participants reported engagement with an app prior to gambling around 12% of the time. However, there are two caveats associated with this. One is that one type of app use (social media) was far more common than any other – social media use was reported prior to 39% of session, whereas the remainder were below 12%. The second is that there were some notable variation between individuals, as a number engaged with apps frequently and others did not. Some participants repeatedly engaged with certain kinds of app (> 33-50% of sessions).

Table 49

Reported engagement with different types of app prior to the gambling app by participant

	Game	News	Web	Sport	Work	Music	Social Media	Other	Number of sessions	Mean
1	0	0	0.67	0.33	0	0.33	0.33	0	3	0.21
2	0	0	0	0	0	0	0	0	32	0
3	0	0	1	0	0	0	1	1	1	0.38
4	0.93	0.26	0.04	0	0	0.04	0.89	0	27	0.27
5	0	0.02	0	0.12	0	0	0.27	0	48	0.05
6	0.02	0.08	0.06	0	0.04	0.06	0.06	0	48	0.04
7	0.07	0	0	0	0	0	0.27	0	45	0.04
8	0.24	0	0	0	0.82	0.24	0.03	0	38	0.16
9	0	0	0	0	0	0	0.24	0	29	0.03
10	0	0	0	0	0	0	0	0	2	0
11	0	0.14	0	0.14	0.14	0	0.43	0	7	0.11
12	0	0.08	0	0	0	0	0.42	0	12	0.06
13	0	0.1	0.05	0	0.1	0.1	0.19	0.05	21	0.07
14	0.17	0.17	0.17	0.08	0.33	0.08	0.17	0	12	0.15
15	0.03	0	0	0	0	0	0	0	38	0
16	0	0	0	0	0	0	0.95	0	21	0.12
17	0.03	0	0.03	0	0.16	0.03	0.03	0.08	37	0.04
18	0.03	0.36	0.61	0	0.61	0.33	0.97	0.12	33	0.38
19	0	0	0.02	0	0.04	0	0.28	0.22	50	0.07
20	0	0	0	0	0	0	0.23	0	22	0.03
21	0	0	0	0	0	0	0.11	0	36	0.01
22	0	0	0.07	0	0.13	0	0.6	0	15	0.1
23	0.06	0	0.53	0	0.47	0.03	0.75	0.06	32	0.24
24	0	0	0	0.07	0	0	0.14	0	42	0.03
25	0	0	0	0	0	0	1	0	8	0.12
26	0	0.53	0.03	0	0.42	0.53	0.89	0	36	0.3
27	0	0	0.16	0	0	0.35	0.41	0	37	0.11
28	0.11	0	0.22	0	0.19	0.05	0.22	0	37	0.1
Mean	0.06	0.06	0.13	0.03	0.12	0.08	0.39	0.05	27.46	0.12

Table 50

Participant level intentions to engage with different types of app after the gambling app

	Game	News	Web	Sport	Work	Music	Social Media	Other	Number of sessions	Mean
1	0	0	0.33	0	0	1	0.67	0	3	0.25
2	0	0	0	0	0	0	0	0	32	0
3	0	0	1	0	1	0	1	0	1	0.38
4	0.89	0.07	0	0	0	0.04	0.89	0	27	0.24
5	0	0.19	0	0.29	0	0	0.19	0.02	48	0.09
6	0	0	0.04	0	0	0.02	0.02	0	48	0.01
7	0.02	0	0	0	0	0	0.07	0	45	0.01
8	0.26	0	0	0	0.42	0.47	0.03	0	38	0.15
9	0	0	0	0	0	0	0.07	0	29	0.01
10	0	0	0	0	0	0	0	0	2	0
11	0	0	0	0	0	0	0	0	7	0
12	0	0	0	0	0.08	0	0.25	0	12	0.04
13	0	0.05	0.05	0.05	0.05	0	0.19	0.05	21	0.05
14	0.08	0.25	0.08	0.08	0.42	0.08	0.25	0	12	0.16
15	0	0	0	0	0	0	0	0	38	0
16	0	0	0	0	0	0	0.95	0	21	0.12
17	0.14	0.03	0	0	0.03	0	0	0.03	37	0.03
18	0.42	0.12	0.85	0	0.76	0.3	0.91	0.03	33	0.42
19	0	0	0.02	0	0	0	0.04	0.02	50	0.01
20	0	0	0	0	0	0	0.09	0	22	0.01
21	0	0	0	0	0	0	0	0	36	0
22	0	0.07	0.07	0	0	0.13	0.47	0	15	0.09
23	0.15	0.03	0.64	0	0.67	0.03	0.7	0.09	33	0.29
24	0	0	0	0	0	0	0	0	42	0
25	0	0	0	0	0	0	0.62	0	8	0.08
26	0	0.72	0	0	0.67	0.81	0.86	0	36	0.38
27	0	0	0.14	0	0	0.41	0.27	0	37	0.1
28	0.08	0	0.16	0	0.19	0.08	0.16	0	37	0.08
Mean	0.07	0.05	0.12	0.02	0.15	0.12	0.31	0.01	27.5	0.11

7.4 DISCUSSION

When exposed to a simulated gambling game on their smartphones, participants showed evidence of considerable persistence in the face of losses. Over the course of multiple days of unavoidable losses, most participants returned for multiple days of play. Participants generally reported being aware of a chance in contingencies but this did not necessarily seem to cease their gambling. Similar findings have been reported in interviews with mobile gamblers (Deans, Thomas, Daube, & Derevensky, 2016).

Participants had greater latencies between their gambles after a win relative to other outcomes. Moreover, there was consistent evidence that this magnitude of this effect broadly increased in line with the magnitude of reinforcement. This replicates a number of findings in the gambling literature using simulated slot machines (Delfabbro & Winefield, 1999; Dixon et al., 2013b; Templeton et al., 2015) and scratchcards (Stange et al., 2016a; Stange et al., 2016b). Moreover these findings extend beyond the previous literature; whereas it has been typical to aggregate pauses by participant, this study demonstrates how this effect remains meaningful on a trial by trial basis.

The finding of this study that has the greatest implication concerns the manipulation of different types of timing on subsequent behaviour. The wider behavioural and social sciences literature has explored how behavioural contingencies can be manipulated to maximise responding on an operant level. The key finding of this study is to entrench how timing between reinforcements is another variable that can be manipulated and controlled in the same fashion. In the mobile sphere, different types of responding can be manipulated to maximise responding in a manner such that the typical schedules of reinforcement existing in a behaviour such as gambling might interact with mobile phone use in such a manner that it expedites the acquisition of certain learned behaviours. When scaled up to a behaviour that occurs, for some, at such frequency as gambling, mobile phone use has the potential to moderate the relationship between one's engagement with gambling and the subsequent development of an addictive behaviour.

This raises important implications for the development and design of games, both gambling and video games, particularly on mobile phones. In conjunction with this, Chapter 6 showed that manipulating the post reinforcement pause leads to greater perseverative gambling, given an equivalent exposure to simulated gambling and varying rates of reinforcement. In addition, studies of losses disguised as win. It is clear that the rates of reinforcement and latency can be fine tuned by designers to elicit the maximal desired behaviour by someone using their app, even in the face of unsuccessful and frustrating outcomes. These implications are particularly exacerbated in mobile gambling, where latencies punctuate periods of reinforcement both a) as part of the way in which people interact with smartphones (Oulasvirta et al., 2012) and b) directly under the control of the designer in the manner of stamina systems and similar mechanisms to space out reinforcements.

What was not found was any evidence for an effect of latency on the near-miss. When modelling different types of outcome in depth, the effect of classic over non-classic near miss tended to be substantially greater but neither appeared to be significant. Studies of the post-reinforcement pause have identified mixed findings. Some have found no effects of the near-miss on pause (Dixon et al., 2013b; Stange et al., 2016b), some have found indications that near-misses accelerate play in *post-hoc* analyses (Dixon et al., 2013b), and others have found that near-misses are quantitatively interposed between wins and losses (Daly et al., 2014; Stange et al., 2016a). The findings on scratchcard play thus far have been equivocal (Stange et al., 2016a; Stange et al., 2016b). It is difficult to make any strong conclusions regarding the effect of the near-miss on latencies in this data but given the typical difference between losses and near-misses in the literature has typically been in the 200-400ms range, it is quite possible that measuring latencies by calling on the internal clock of participants' smartphones isn't sensitive enough to pick up any effect if it exists.

There was also evidence for a second type of post reinforcement pause. In the logistic regression modelling it appeared that participants were more likely to prematurely cease gambling after a win, and the magnitude of the logistic regression coefficient correlated with the magnitude of reinforcement. People were equivalently likely to stop after a win than a loss, despite losses (near misses aside) being almost twice as likely to occur, and participants being exposed to an extensive sequence of unavoidable losses should they have chosen to gamble in the final part of the experiment. This also raises an interesting hypothesis for the relationship between the big win and disordered gambling, which was originally thought to be instrumental in the development of pathological gambling (Custer, 1984) but evidence since has been mixed (Kassinove & Schare, 2001). Recent models have argued that the effect of the big win is due to the effect of statistically improbable wins leading to a qualitatively distinct categorisation of the big win to typical gambling experiences, meaning it is particularly resistant to extinction (Redish et al., 2007). The data in this study raises the proposition that, instead, big wins are associated with gambling problems on account of gamblers not subsequently experiencing the regular, unsuccessful outcomes of gambling after their big win. With the advent of mobile gambling, which is thought to be particularly attractive to younger gamblers (The Gambling Commission, 2016a), it is now the case that these hypotheses can be tested.

There was evidence that the gambling app was used in a sequence alongside other apps by a number of participants. In some cases participants used a certain kind of app before or after the gambling app with moderate (> 33%) or heavy (> 50%) frequency. The use of gambling apps in habitual sequences is potentially one of the greatest concerns that might emerge from mobile gambling. There is already evidence that mobile phone users engage in habitual patterns of behaviour e.g. from a social media app, to a game, to checking emails, in regularised sequences (Oulasvirta et al., 2012). The inclusion of gambling, an addictive behaviour, in such sequences has the potential to be harmful over and above other behaviours such as gaming or social media that might in the future found to be addictive. The combination of heavy engagement on an intermittent schedule of reinforcement is likely to speed acquisition of behaviour and potentially accelerate the transition between recreational and addictive play identified in models of gambling addiction.

Although this highlights some of the behavioural and contextual considerations relevant to gambling, it is important to acknowledge wider environmental and individual considerations that may also be of interest. Mobile gambling advertising focuses on different games from traditional gaming, showing preponderance towards betting and live-action (or ‘in-play’) betting. In addition there might be additional considerations that contribute to stimulating mobile gambling; for instance drinking and smoking behaviours weren’t measured, both of which are likely to have an effect on gambling.

There are a multiple limitations that must be considered with these findings. First, the range of cues associated with the game itself were relatively restricted; gambling games tend to have much richer environments, and in the longer run these have been shown to be instrumental in the conditioned reinforcement of gambling behaviour. To an extent this is associated with mobile gambling as a whole, as intimated in the General Introduction. Models of gambling addiction also highlight the role of physiological arousal as especially important for addictive behaviour, part of which is triggered by gambling related cues and stimuli. This is thought to mirror behaviours in drug consumption modelled on a second order schedule of reinforcement. Second the game was designed so that there was a positive expected value in the long run, even if on each individual trial participants were more likely to lose than to win. While it has been previously shown this can model behavioural effects found in gambling well, validating these results with a game that has a closer schedule to other forms of gambling would be beneficial. Giving users free gambles at the beginning of the experiment might help in this regard; betting companies frequently offer free bets at enhanced odds, and mobile games with stamina systems are designed for a larger bout of play at the beginning of the experience (either by making earlier levels use less stamina or awarding more stamina for completing tasks at the start). Typically in the UK free bets are set up so that bettors can only release any winnings after a certain amount has been subsequently wagered. It would be useful to use either of these approaches to corroborate these findings. Additionally there was some attrition from the study, as noted in the Methods.

It is also necessary consider the boundaries on these findings; it is the case that some have suggested that mobile phone use might be problematic in of itself (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015a). These findings at present ought to be restricted to gambling and perhaps internet gaming based upon its schedule of reinforcement. The indication from this study is that there is a behavioural basis to start considering how mobile phone use moderates the relationship between the individual and an addictive behaviour. Although it is seductive to suggest that there is something addictive about mobile phones, it is imperative to note that are conceptual issues concerning whether a device can be addictive that render such a suggestion premature. Mobile phones are conductive to the production of habitual behaviour, as previous studies and this one have shown. The effect of smartphone use in the context of other behaviours is of great interest, but further research needs to be done in this area, and also to determine whether mobile phone use in general or specific activities (e.g. gaming, social media) are the locus of concern in those cases. The behavioural addictions literature including problematic smartphone use has a general problem with a lack of specificity that mean additional research needs to be conducting before interpolating that this study has any implications for a wider smartphone addiction.

In conclusion, this chapter reports an initial study into mobile gambling behaviour. Participants showed considerable engagement with the app, which was associated with the level of engagement participants continued with once the possibility of winning money had finished. This showed preliminary finding. Studying whether these findings can be replicated using different methods of reimbursement (particularly a free bet style approach) would be particularly interesting.

GENERAL DISCUSSION[1]

ABSTRACT

The general discussion focuses on two issues that emerge from this thesis and are relevant to a wider area. The first is the application of the approaches reported in the first and second half of the thesis, synthesising them toward developing typologies of in-play gambler. The advantage of studying in-play betting is that data will be held at the trial and individual level as seen in the app study in Chapter 7. The second part focuses more on the behavioural implications that emerge from this thesis, and looks toward the growing debate on behavioural addictions. Specifically, the discussion highlights how behavioural elements of gambling may be different from other potential behavioural addictions, and how a behavioural approach (like the one explored in this thesis) may prove fruitful in determining whether some of these excessive behaviours are ultimately addictive.

Different typologies of gambler and problem gambler

[1] The content contained within the first half of the discussion is currently being adapted into a manuscript, with a view towards submission for publication. Content contained within the second half of this chapter has been adapted and published as James and Tunney (2017) "The need for a behavioural analysis of behavioural addiction" in *Clinical Psychology Review*.

It has become widely accepted that problem or disordered gambling is a heterogeneous phenomenon, with multiple subtypes or latent classes existing within the population of problem gamblers. The two commonly adopted contemporary models of problem gambling (Blaszczynski & Nower, 2002; Sharpe, 2002) attempt to capture some of these distinctions. In addition to this, there is increasing evidence that are multiple subtypes of gambler across the population that differ in their range of engagement with gambling, measured in terms of the number of gambling activities they have undertaken (Lloyd et al., 2012; Lloyd et al., 2010; Wardle et al., 2014). This section is designed towards reviewing the literature on different attempts to subdivide gamblers and problem gamblers, particularly research using latent class analysis that has been out of the focus of previous studies, and shown considerable growth over the past ten years. These analyses cut across a range of latent variable modelling techniques such as cluster, latent class and taxometric analyses.

The most recent review on the subtyping of gambling was conducted by Milosevic and Ledgerwood (2010), which looked at the subtyping of problem and pathological gambling, synthesising findings from a number of analyses and theoretical models in the area. This reviewed a number of studies, primarily using cluster analyses in clinical samples, finding three subtypes of problem gambler. The review restricted itself. Through the lens of the Pathways Model (Blaszczynski & Nower, 2002), their review of the literature indicated the presence of three subtypes of problem or disordered gambler. These broadly identified one subtype that was characterised by the lack of pre-existing psychopathology, a second group endorsing severe problem gambling and disordered mood and a third cluster of very severe disordered gamblers reporting markers of impulsivity and a greater incidence of comorbid substance addiction.

The aim of the present exercise is in part to provide an update of research in the intervening years, but primarily to report on the growing literature using other psychometric techniques that build on previous findings, which are primarily based on cluster analyses. Moreover whilst Milosevic and Ledgerwood (2010) restricted their review to subtypes of problem or pathological gamblers, subsequent analyses have increasingly looked at subtypes of gambler across the population. In particular a number of studies using taxometric and latent class analyses in community and general population samples have provided a number of interesting findings that are worth reflecting upon. On doing so, I apply the findings from these, the psychometric modelling contained within this thesis and the findings from the mobile literature to develop typologies of in-play bettors that can be experimentally tested.

Subtypes of gambler in the general and gambling populations

Several analyses of gamblers and the general population have used latent class and latent growth modelling to capture different subtypes of gambler (Goudriaan, Slutske, Krull, & Sher, 2009; Lloyd et al., 2012; Lloyd et al., 2010; Wardle et al., 2014). These have typically focused on modelling different types of gambling activities in certain population (the general British population, internet gamblers, university students), but have predominantly used different types of gambling activity as indicators in a latent class model before subsequently regressing covariates such as demographics, problem gambling status, and indicators of harm or mental illness onto these classes. These studies have identified between four and eight groups that differ systematically in their engagement with different forms of gambling play. However, these identify a number of commonalities that it is worth briefly exploring.

Wardle et al. (2014) used data from the Health Survey for England 2012 and the Scottish Health Survey 2012 (Rutherford et al., 2013a; Wardle & Seabury, 2013) to derive different latent classes of gambler by gender. These analyses both revealed eight latent classes, with greater differentiation at different levels of gambling involvement for men and women. In addition to a class of non-gamblers, each analysis identified three subgroups of low intensity gambler, primarily differentiating on their engagement with products run by the National Lottery, either exclusively playing lottery games, or minimal levels of engagement differing on the presence of National Lottery products or not. There was then a band of moderate gamblers (2 classes for women, differentiated by variation of engagement, 1 for men) and a band of high intensity gamblers. For women, class membership appeared to be differentiated by age, with older women less likely to gamble and who were underrepresented in the high engagement and moderate higher variability groups, but overrepresented in the low variability, moderate engagement group. This group tended to engage in lottery play, with a third activity from either scratchcards, bingo and horse racing. For men, differentiation between latent classes was primarily related to alcohol consumption; higher levels of engagement were associated with a greater incidence of alcohol consumption.

Lloyd et al. (2010) identified five latent classes of gambler, again modelling differences in types of gambling engagement. The latent class model first identified a subgroup of low intensity gamblers, with little propensity for gambling and a minor probability of engaging in casino and table games such as poker. The model next assigned cases to a subgroup of gamblers whose gambling was almost exclusively limited to lottery games (and a moderate conditional response probability of playing casino style games). Next, there were a group of gamblers who extensively engaged in sports betting and little else, and a second group that extensively bet on sports but also played on casino games and poker to a slightly lesser extent. Finally, a group of highly engaged gamblers was identified that gambled across many different types of game.

Using a different approach, Goudriaan et al. (2009) studied the gambling behaviours of American university students using a combination of latent class and latent transition analyses. Across participants' college experiences, there was consistent evidence for a four latent class model which first captured low intensity gamblers. Next, two moderate intensity subgroup; one with a particularly high probability of playing card games and a moderate probability of engaging in activities such as lottery play and sports betting, one primarily engaging in activities commonly found in the casino such as table games and slot machines. Finally, a subgroup of highly, extensively engaged gamblers were identified that engaged in wide range of gambling activities. Across the different time points (1st, 2nd, 3rd and 4th years of college) there are a number of findings that are of note. The first is that the number of casino/slot machine gamblers increase almost tenfold in the second half of the study, at the expense of low engagement gamblers. This is because most college students in the US would be turning 21 or 22 in their third year of university, the age at which casino gambling becomes legal in the state that the university that was studied was located (Missouri). Second is that in the third year the prevalence of the highest engagement group trebled but fell back in the final year of the study.

What is common across all of these classes is that there is a subtype of multi-activity gambler that is vastly overrepresented in their prevalence of problem gambling, using indicators such as the DSM-IV Pathological Gambling criteria (American Psychiatric Association, 2000). These gamblers typically engage in anywhere from a minimum of four to eight different kinds of gambling, depending on the sample and the range of questions asked about gambling behaviour. These groups as well as those discussed before, in developing typologies of in-play betting further on in this section, are used to begin determining the different typologies of gambler. In addition to the different subtypes identified, many of these analyses also consider the predictors of these different groups, which the next section expands upon, reflecting upon previous research and the analysis reported in Chapter 4.

Subtypes of problem gambler in the general population

A number of studies have used forms of latent class analysis to model the number of subtypes of gambler emerging from responses to problem gambling assessments such as the DSM-IV Pathological Gambling Criteria in the general population. These have identified a consistent set of three or four classes of responding to these assessments (Carragher & McWilliams, 2011; McBride et al., 2010; Xian et al., 2008), in a similar fashion to those in Chapter 3.

The analyses conducted as part of this thesis, alongside other papers (Carragher & McWilliams, 2011; McBride et al., 2010), strongly suggest that there is a common structure to population wide assessments of problem gambling. The data in Chapter 3 in particular explores this in depth. Taken together, there is substantial evidence that assessments of problem and pathological gambling capture three or four broad subtypes of gambler, arrayed along a dimension of severity but with a categorical difference between intermediate and highest severity groups. Studies identifying a fourth latent class of gambler (Xian et al., 2008) additionally modelled non-gamblers alongside gamblers, and the additional class comprises those individuals that do not gamble.

The first group of gamblers have a very small probability of endorsing any of the problem or pathological gambling criteria. Respondents classified into this group that do tend to endorse the items with the least item difficulty, namely the loss-chasing and preoccupation items that do not appear to discriminate between disordered and non-disordered gamblers. This unsurprisingly makes up the vast majority of respondents to gambling prevalence surveys; between 75 and 90 per cent of gamblers do not endorse any gambling criteria, varying by survey frame and assessment. Where these gamblers do endorse a problem gambling indicator (and it usually is only one), it tends to be items that do not discriminate between different levels of gambling severity, such as loss-chasing or preoccupation. These gamblers have varying levels of participation with gambling, but tend to play the lottery more frequently than others.

The second group of gamblers have been referred to as ‘preoccupied loss-chasers’ on account of their tendency to endorse two of the DSM-IV Pathological Gambling criteria of those names. In addition they endorse the third at a middle conditional response probability. These gamblers almost invariably endorse one or more DSM criteria but do not endorse enough to meet the criteria for Pathological Gambling. Some meet the prerequisite for Gambling Disorder in the DSM-5.

The third group of gamblers comprise the individuals endorsing 5/6 or more of the problem gambling criteria. These gambles endorse a significant number of DSM criteria, but in almost every instance exceed the clinical cutoff of 4 criteria for Gambling Disorder or of 5 for Pathological Gambling. One consideration is whether this is distinction is best represented as quantitative as McBride et al. (2010) contend, or whether there is a latent taxon, as the findings in Chapter 2 suggest. The implication from the findings of Chapter 3 is that there are both. This class quantitatively differs from the others on symptom count, but appears to qualitatively differ in the emergence of a cluster of 4-5 criteria probing loss of control. The substantial difference between these groups is characteristic of a qualitatively difference and almost certainly explains the taxon identified in Chapter 2.

Sociodemographic predictors of problem gambling in the general population

These groups not only differ in their endorsement of pathological gambling indicators, but also appear to do so in their sociodemographic backgrounds. McBride et al. (2010) found that certain predictors (odds of being male, from an ethnic minority, being divorced, current smoking status) tracked alongside these three class and thus problem gambling severity. Additionally, a number of indicators (being < 25, a current drinker) predicted membership of the second but not the third latent class. Further modelling by Carragher and McWilliams (2011) found broadly similar effects: males were overrepresented in the moderate latent class (but not the pervasive class), certain ethnic minorities were overrepresented (black Americans, Asian/Native Hawaiian/Pacific Islander) and underrepresented (American/Alaskan Native) in certain latent groups. Younger adults were overrepresented in the intermediate class. Alcohol but not substance use disorders tracked alongside problem gambling severity, as did phobias. Mania and antisocial personality disorder were predictive of the most severe gambling class.

In a slightly different vein, Xian et al. (2008) nonetheless found similar findings in their latent class model of middle aged men; from the three gambling classes, the probability of belonging to an ethnic minority increased with problem gambling severity, as did coming from the younger half of the samples and less likely to be married and less likely to be in full or part time employment. The absence of comorbid psychiatric disorder fell alongside problem gambling severity,

Relatively similar findings were observed in Chapter 4 when pooling data from the BGPS 2007, 2010 and HSE/SHS 2012 datasets. A number (being from an ethnic minority apart from British Asian, being divorced, never married) did not track latent class membership (apart from between the first and second class) when scaled up. Additionally, being widowed predicted membership of the most severe latent class in the pooled data. The findings in Chapter 4 additionally identified that certain economic groups (semi-routine occupations, intermediate occupations) and people self-reporting worse general health were overrepresented in the intermediate group.

Translation to other cultures and jurisdictions

There is clear evidence that measurements of problem gambling have a common structure, which is generally invariant across time and survey frame in the UK at the very least, as shown in Chapter 3. There is some evidence this translates to a number of different cultures and jurisdictions; analyses of data in South Africa provide evidence for a distinction between the second and third class (Kincaid et al., 2013). Additionally, latent class analyses of NESARC and other data in the USA have found similar evidence for the three-class structure among gamblers (Carragher & McWilliams, 2011; Xian et al., 2008).

Taxometric analyses of gambling

The last five years has seen a number of taxometric analyses of problem gambling data (Abdin et al., 2015; Braverman et al., 2011; Kincaid et al., 2013). In addition to this, the findings from Chapters 2 and 5 also add to our understanding of problem gambling assessment data using the taxometric method. From the perspective of the taxometric and the gambling literatures the findings here are of considerable interest. From the taxometric perspective, there is stronger evidence relative to other psychiatric disorders that there is a taxon in problem or disordered gambling screening data. Taxometric research that has adopted a model fitting approach to interpreting taxometric analysis (Ruscio et al., 2006; Ruscio & Marcus, 2007), has generally found evidence against the presence of taxa in psychopathologies that are conceptualized in a categorical fashion (i.e. disorders taken from the DSM) (Haslam et al., 2012). While interpreting the absence of a taxon as indicative of a dimensional model is potentially problematic, these findings mirror the shift in thinking among many mental health researchers towards the nature of psychopathology. The presence of a taxon in gambling is therefore rather unusual, and particularly interesting given that addictions are one of the other exceptions to this trend. As Chapter 5 enunciates, addictions as a whole are an interesting area as one of, if not the, solitary areas where a taxon emerges without the presence from birth. Eating disorders may be an exception to this, but the literature has raised the possibility of an overlap here, particularly with binge eating disorder. In addition eating and substance use disorders are highly comorbid, with many individuals with an eating disorder also having a substance use disorder. However, this is based on an ageing literature; more recent studies, including the latent wave of the NESARC, did not study comorbidity between eating and substance use disorder due to the low base rate of the former.

Including the two sets of taxometric analysis reported in this thesis, there are presently five analyses of gambling data either in the published or conference literature. These have broadly suggested the presence of a taxon in problem gambling data, ambiguous findings among the behavioural data across a sample of European betting site gamblers and dimensional findings in the Asian SOGS data (although there are serious issues associated).

Limitations

One key limitation is that the distribution of problem gambling assessment indicators is highly skewed in the general population. Even with the most liberal screens using methods designed to account for screens such as the PGSI having a substantial false negative rate, only 10-15% of the population typically endorse any criteria on these sort of screens. This is best represented in Table 8 in Chapter 3. In part this is because the most common reference point in the UK for comparing problem gambling prevalence against, past year gambling, is somewhat misleading. Only around a quarter of the population gamble on any given week (Wardle et al., 2011b), and around half in the previous month (The Gambling Commission, 2016a). While the studies reported are informative about other subtypes of gambler, it means that there is rather little to say about the group endorsing very few gambling indicators (except what they are not). Behaviourally these are likely to be considerably more diverse in their gambling behaviours, attitudes and cultures. On account of the fact that for many gamblers their engagement is limited to frequent or intermittent play on the lottery, many of the gamblers in class 1 will have very limited engagement with gambling otherwise.

The second is the causal mechanisms differentiating intermediate and severe problem gambling groups are unclear. Whereas in clinical samples there are clear hypotheses to explain, the nature of the data collected in problem gambling prevalence data rarely allow, and in health surveys due to differences in framing (Williams & Volberg, 2010), there are likely to be fewer surveyed problem/pathological gamblers, thus typically reducing the probability of finding an actual effect. Moreover these data aren't typically collected in problem gambling prevalence surveys, meaning that making strong conclusions on these mechanisms in general population data is rarely feasible.

The third is that while this captures the various subgroups that fall onto a combination of categories and a dimension which appears to be defined by impaired control, it is almost taken for granted that there will be a substantial number of non-disordered or problematic gamblers that experience considerable harm from gambling. In other addictions it is taken for granted that addiction and harm should be treated separately, but in the gambling literature these concepts have been treated often in opposition. One of the issues identified in Chapter 2 was that a) these were frequently seen as contrasting (one indicative of a dimension, the other a category, measured using the same instrument), and b) that instruments derived from measures of addiction were being designed to measure 'harm'. Since then the debate has moved towards actually identifying gambling harms, which in some cases map onto clinical characteristics of gambling addiction, but in many cases do not e.g. see indicators from Browne et al. (2016).

The fourth issue has been that the very small numbers of problem gamblers that emerge from problem gambling prevalence screens. As discussed above, a number of findings identified in the latent class modelling of individual populations do not appear to scale up when this data is pooled together, as the discussion of these results in contrast to the findings in Chapter

4 identifies. Using the British prevalence survey series' cut-off's for problem gambling (either using PGSI or DSM-IV), the survey typically identifies around 60-90 gamblers as 'problem gamblers' from samples of 6000-9000. This means that identifying robust differences between groups can be difficult, although the analyses in Chapter 4 were tasked with remedying this using a pooled data approach.

Reconciling clinical and general population studies of problem gambling

Contrasting the findings reported from the studies contained here and previous attempts to subtype problem gamblers immediately reveals that population studies identify a smaller number of subtypes of problem or pathological gambler than clinical studies. One consideration might be this is due to idiosyncrasies associated with problem or pathological gamblers recruited through clinical settings; it is estimated that a very small proportion of problem and pathological gamblers end up seeking treatment (Ronzitti, Lutri, Smith, Clerici, & Bowden-Jones, 2016). However, latent class modelling of general population data from the NESARC (Nower et al., 2013) suggested that the relationship between the emotionally vulnerable and antisocial impulsivist classes might be quantitative rather than qualitative.

The simpler explanation is simply a lack of problem gamblers in population wide datasets. The analyses reported in Chapter 4 required the pooling of several datasets to observe sociodemographic trends among problem gambling. A number of the effects, especially among widowed adults, would not be observable without pooling data on simple account of the very low number of respondents. Using more conservative cut-off's (e.g. PGSI 8+) from the same three datasets leads to barely more than 200 problem gamblers from a sample of over 18,000 gamblers (and over 25,000 respondents). Population-wide studies have generally not found multiple sub-types of disordered gambler, but this is most likely because. In addition, these studies don't include the covariates that are present in clinical samples, and which appear to discriminate more between these subtypes than specific indicators of disordered or pathological gambling.

There is reason to believe that the intermediate (pre-occupied loss-chasers) gamblers can be transposed onto the behaviourally conditioned pathway; the Pathways Model predicts these problem gamblers are on a continuum with recreational gambling and show the lowest problem gambling severity. Nower et al. (2013) found that the mean number of DSM criteria for this group was a) significantly lower than the other two observed latent classes and b) lower (3.84) than the DSM cutoff for Pathological Gambling. The analysis further suggested that many of the differences between classes were quantitative, a finding that notably emerges from other latent class analyses of population wide gambling data.

Further directions

There is a potential for additional modelling of problem gambling assessment data. In particular factor mixture modelling of problem gambling assessment data in a general population sample would be highly beneficial because combining latent class and latent factor modelling, given the data reported in Chapter 3, is likely to produce a more parsimonious model. The research reported in this thesis and more widely in the literature strongly hypothesize that, when modelled, a two or three class model with a single latent factor would be the best fit of the data. This might work towards reconciling clinical and populations subtyping of problem gambling somewhat, especially as the relationship between the second and third classes identified in the problem/pathological gambling literature has been described as quantitative rather than qualitative (Nower et al., 2013).

It would be beneficial to model the heterogeneous motivations for different types of gambling. Models of problem gambling have tended to identify different subtypes across types of engagement, but have rarely focused on a specific type of gambling. Research in alcohol has started to use latent class modelling to develop different typologies of drinker (Ally, Lovatt, Meier, Brennan, & Holmes, 2016), and while some of the analyses perform a similar function, it is also worth noting these only capture gambling activities and have limited insight into the wider gambling culture. Perhaps moreso than with drinking, it is widely assumed that there are different types of motivation driving the use of certain types of gambling play.

In the following section of the discussion, the evidence presented in this section is applied to a relatively new form of gambling play, in-play betting. The reasons for doing so are straightforward. Firstly, it neatly captures the different aspects of the thesis into a single passage; the psychometric work modelling different subtypes of gambler, the experimental work studying latency and the overall aim of the thesis to probe mobile gambling (as in-play, as the introduction highlights, is a stereotypical form of mobile play). Second, unlike many other forms of gambling, a lot of the data that can be used to test these different typologies is already held. The app study data reported in Chapter 7 show how this trial level data can be used to understand mobile gambling behaviour. Similar principles can be applied to data held by gamblers or operators.

Creating different typologies of in-play or live action bettor

The rise of mobile gambling, and the increasing use of sports as a way of normalising gambling, has seen an increased focus on sports betting opportunities. One of the more controversial of these opportunities is in-play, or live-action, betting. This is a form of betting play where gambles are made during an event, typically a sports match, in contrast to more traditional betting where wagers are made prior to the start of an event. With in-play betting the odds, either on the outcome of the sports event in question or a vast array of events in the game (next goal, throw-in, foul etc), fluctuate over the course of the game, match or event.

The Gambling Commission, in their position paper on the activity (The Gambling Commission, 2016b), note that in-play betting occurs in one of two forms. The first is an extension of more traditional betting, where a set of fixed odds are offered by a bookmaker once an event has started, but fluctuate over the course of a match in response to events. For instance, if odds are being offered on a football match and one team scores, a betting site or app would typically respond by lowering the offered odds on the conceding team winning. The other is in the form of a betting exchange, which is becoming increasingly popular. Here, the odds are offered by another bettor/s and the bookmaker acts as an intermediary, taking a commission.

Although restricted worldwide, this form of play has reached particular prominence in the United Kingdom, and there a number of factor that necessitate discussion of the issues concerning in-play betting. This chapter outlines the context around in-play betting as it is currently played in Great

Britain, before ultimately considering the different clusters or patterns of behaviour that might exist among in-play betting. The particular advantage with studying in-play betting, relatively to other forms of gambling, is that there is the potential for particularly rich data at the level of the individual, session and gamble.

In-play betting in the UK and worldwide – Prevalence and problem gambling

Recent estimates of prevalence suggest that around one in four online gamblers, of whom 14-15% of the population are comprised, have bet in-play in the past month (The Gambling Commission, 2016a). In-play betting is heavily advertised alongside mobile apps, typically in breaks during sporting matches, and most frequently alongside live odds on the current match. In-play is treated by betting adverts as a prototypical form of mobile betting, more or less. In-play betting tends to be advertised most frequently during football matches, particularly the English Premier League, but is rapidly expanding to television coverage of other leagues and other sports (such as Sky's coverage of La Liga). In-play betting is particularly profitable for the bookmaking industry in the UK; although engaged in by around a quarter of online gamblers, estimates from the Gambling Commission indicate it yielded around one third of gaming profits in the previous (15/16) financial year. The Gambling Commission's position paper on in-play betting notes how in-play bettors appear to gamble more frequently in a relatively short amount of time. Such findings were similarly observed in European live action sports betting data on desktop computers (LaBrie et al., 2007).

Typically in-play betting offers the opportunity for wagering on a wide array of different outcomes. While betting prior to an event increasingly offers a large array of potential bets, in-play betting typically extend these and adds the allure of being able to potentially wager at the point where a bet has the highest odds. In tennis for example, it allows for the live wagering on the outcome of each individual point within a match. The ability to watch a sports match and see the odds of a certain event wax and wane, and being able to wager at which point the tide will turn, or when one is certain is part of the attraction of in-play betting. In addition, the rapid variability of the odds alongside offers by bookmakers are also likely to be attractive to certain types of gambler.

Increasingly this is integrated with more 'traditional' betting, where the bets are offered on the same page but start updating when a match begins. This also means that the type of bet offered in-play (each on certain types of event) are increasingly offered prior to the match as well. In-play betting is frequently subject to offers concerning free bets to encourage gamblers to play on them, making a certain level of wager that is matched by the bookmaker. These typically offer exaggerated odds on a relatively likely outcome, and in the terms and conditions lock any winnings in, preventing the gambler from withdrawing the winning from the introductory bet until a certain amount has been wagered.

In-play betting is illegal in a number of jurisdictions around the world, either because all online sports betting is prohibited or severely restricted (United States, Canada), or because it is explicitly banned in its own right (Australia). In a number of jurisdictions it is legal or at least feasibly to in-play bet by using a bookmaker not based in the jurisdiction in question (e.g. New Zealand). In cases where in-play betting has been explicitly banned, such as in Australia, the reasoning behind this has been directly related to the potentially addictive nature of this form of play.

There is evidence from analyses of actual sports betting data collected in Europe that in-play (or live-action as it has been referred to in the literature) betting is associated with problem or disordered betting. A number of studies analysing data from *bwin* (Braverman et al., 2011; Gray et al., 2012; LaBrie et al., 2007; Nelson et al., 2008; Xuan & Shaffer, 2009), a European sports betting operator, found that in-play betting was associated with a greater likelihood of activating self-exclusion and corporate responsible gambling mechanisms. In addition, live-action betting was also associated with markers of problem gambling using the lie/bet scale, even when controlling for involvement.

Despite this association, the literature on in-play betting remains largely absent, or is restricted to descriptions of decision-making behaviour on betting markets. The live-action, variable-odds betting offered by bookmakers has not been adequately explored. This might be due to lack of prevalence; apart from the UK, engagement with in-play betting appears to be scant, if those data are collected in the first place due to its illicit nature. The second is that attention from the media and pressure groups towards gambling has been primarily focused on fixed-odds betting terminals.

One of the reasons to consider the role of in-play betting now is in the context of the intense debate on another gambling product, the fixed odds betting terminal, and the potential similarities between the two in the UK at least. In both cases, problem gamblers are over-represented among the population of gamblers playing these products, even when adjusting for wider involvement in gambling (Gray et al., 2012; LaPlante et al., 2014; LaPlante, Nelson, LaBrie, & Shaffer, 2011; Nelson et al., 2008). Second, both are very highly visible; the media and gambling pressure groups focus on betting terminals as the face of betting shops across the country, in-play betting is almost ubiquitously presented alongside mobile gambling and commonly across sports betting as a whole. Since the relaxation of regulations on gambling advertisement with the Gambling Act 2005, the number of gambling adverts has increased exponentially, most of them advertising sports betting and increasingly in-play. Additionally, both forms of play are highly profitably for the bookmaking industry despite relatively low levels of engagement across the population. In both cases this raises the prospect that these products are only viable on account of a population of addicted gamblers; population engagement with these products outside of these groups tends to be rather minimal. While this is true for all behaviours that are addictive and legal, such as gambling as a whole and alcohol consumption (Orford et al., 2013; Sheron & Gilmore, 2016), it is likely that concern will focus more on products where the proportion of gaming yield is drawn from those at risk of harm.

The second is the nature of the sort of data available with in-play betting. Concerning the debate on fixed odds betting terminals, the issue has tended to be that while data on the gambles made on such a machine is stored on the terminal, the lack of individual level data has made it difficult to provide much, if any, details about any differences that aren't within a gambling session (i.e. escalation of gambling, cessation etc.). Additionally, this limitation has, until recently, made the appeal of releasing such data unattractive because the questions operators are interested in (i.e. role of product versus individual in problem gambling) cannot be answered with the data available. On the other hand, betting terminals and electronic gaming machines are licensed products, and researchers in other countries have had considerable difficulties obtaining structural data from them (Harrigan & Dixon, 2009). That being said, changes in regulations to the stake size in B2 gaming machines over the past couple of years have meant that gamblers betting more than £50 in a single play on an FOBT are required to use one of a number of identification mechanisms to access higher stakes wagers on an FOBT. While this has generally meant that gamblers have switched to wagering more on the £40-£50 bet level (Woodhouse, 2016), one of ways in which gamblers could access these gambles was by signing up to a loyalty scheme. This allowed some of these questions to be empirically tested, an exercise undertaken by Featurespace (Excell et al., 2014) via the Responsible Gambling Trust.

Few of these difficulties apply to in-play betting; the individual, gamble level data can if desired by tied to an individual account, and certainly for mobiles a range of contextual data can be obtained either through the gambler, or via the sensing functionality of a phone, as the General Introduction alludes to, and the GPS data collected as part of the app study in Chapter 7 confirms. Mobile phones have a much wider array of sensors than other forms of online gambling, which if used appropriately can be used to capture some of the contextual and dispositional differences that might emerge. The literature on mobile gambling has considered the role of latencies in the development and maintenance of gambling behaviour. Not only is wagering behaviour likely timestamped, but the range of bets offered in relation. One of the speculations concerning in-play betting was that the short delay between bet and outcome might. With bet level data for a sporting event it is possible to model how bettors' selection of bets captures their need for a certain latency between wager and reinforcement (or frustration). Among the range of bets available frequently include wagering on a certain event (first goal, number of goals etc.) occurring within a certain time frame (first 30 mins, 30-60 mins, last 30 mins of a football match). Both in relation to mobile gambling and in-play betting in particular, this has the potential to be a highly interesting variable to measure, especially as the latency between gambles is a key variable of interest for mobile gambling, as both the General Introduction and the findings in Chapters 6 and 7 identify. It also means that, alongside gamble level contextual data, the effect of certain types of in-play outcome can be statistically modelled (i.e. subsequent betting behaviour if a bet time-locked to the first 30 minutes of a football match comes off).

What remains unclear though are the specific mechanisms that underlie different patterns of in-play betting. Such data has the potential to uncover different patterns of behaviour that can be used to assess different risk profiles, inform responsible gambling practices/programmes or tailor content towards the gambler. As the discussion of different subtypes of gambler noted, these tend to produce restricted numbers of subtypes in large part on account of the lack of responding to many of the indicators put into cluster and latent class analyses. Many of the indicators are substantially skewed, particularly problem gambling indicators, in part because very few respondents on a population wide level endorse them. For gambling engagement, this is because although many people gamble, the majority do so on a small number of games, more often than not limited to the National Lottery (Wardle et al., 2011b). Therefore population wide analyses of gambling behaviour only capture some of the distinctions within gambling behaviour. It is of utility also to study these in a smaller sample of highly engaged gamblers. Particularly with in-play betting, the data that is already typically recorded allows contrasts to be made between gamblers and between different types of play. To this end, starting to consider the different typologies of in-play. The other utility of discussing it here is that it synthesises much of the work in the thesis; the first half is tasked at using problem gambling indicators to look at different typologies of gambler. The second in part uses these to look at mobile gambling behaviour. It makes sense to finish the thesis by looking at the different typologies of one of the more prototypical forms of mobile gambling play.

The potential typologies contained herein cut across the role of the product and different motivation. It is important to address the continuing debate concerning whether the locus of problem gambling is seated within individual psychopathology or the product. To an extent this distinction can be deeply unhelpful. Even in addictions where the role of the product is well known in both the development of physiological dependence and subsequent harm, people have multiple motivations for engaging in said behaviour. Some are peculiar to the individual, such as self-medication related hypotheses of addiction where there is some, albeit controversial, evidence to support this model in addictions such as those related to opiates (Darke, 2013; Khantzian, 2013; Lembke, 2013). Models of problem gambling account for the possibility that a significant number of problem gamblers are motivated by dispositional factors such as disordered mood. Some are controlled. In the next session of the discussion the role of different cues and reinforcers on perseverative behaviour, and how in gambling and video gaming these are more manipulated, both in the environment and within a gambling/gaming session is reflected upon. Putting those two extremes aside, even for personality traits such as impulsivity the picture presented is not as simple as often presented in the gambling literature. The substance addiction literature has started to consider the role of state impulsive behaviour in stimulating continued engagement with a potentially addictive behaviour (de Wit, 2009). In Chapter 4, the regression modelling of pooled gambling prevalence data showed that regular drinking and smoking behaviours tracked alongside problem gambling severity. Overall, this can be attributed to both state and trait effects, as studies of smoking have shown how the state impulsive effects of smoking appear to be distinguishable from those related to trait (i.e. BIS) impulsivity (Hogarth et al., 2013b). In the app study reported in Chapter 7, evidence for state effects on the latency between gambles was observed, as participants accelerated their gambling as a gambling session progressed.

In the first set of groupings different groups are highlighted whose distinctive features are likely their vulnerability to gambling disorder or high stakes live action betting. In the case of some (Group 2), their vulnerabilities to gambling problems may be more frequently observed in-play betting due to a combination of the nature of live-action play, differential engagement using the product and platform due to wider demographic variation, and population wide vulnerabilities to addictive gambling. In others (Group 3) the risk factors may be common to several forms of gambling play. The relationship between previous histories may be important in distinguishing Group 4 from other gamblers.

Cluster 1: Individuals with a Gambling Disorder

Previous studies of in-play betting have found that problem gambling is more common among in-play betters than other games while controlling for involvement. However, controlling for involvement in analyses of the relationship between a type of gambling play and problem gambling almost invariable reduces the size of the relation. In other words, there are likely to be a number of in-play bettors who gamble across many types of play, and are more likely than any other group to endorse indicators of disordered gambling. Many of these gamblers are likely to have difficulties across a range of different platforms. One of the continued challenges associated with research studying the relationship between online and problem gambling has been whether online problem gamblers are also gambling in person as well. Given the low base rate of internet gambling in the population, gambling on the internet might not be directly related to problem or disordered gambling. This is generally what the literature has found; the overrepresentation of problem gamblers among online gamblers has been among those who are 'mixed use' gamblers (Gainsbury et al., 2016; Wardle et al., 2011a) – people who gamble in person and online have a much greater risk of. The risk of problem gambling among those who gamble online is negligible or highly attenuated, although it is worth pointing out very few gamblers only gamble online. This is not the case for in-play betting, but a proportion of in-play bettors are likely to be extremely engaged in gambling across a large number of contexts.

The key distinguishing feature for this group compared to the other subtypes within this is the number of gambling activities they engage in. It is likely to be much higher than the other groups. A number of latent class analyses of gambling involvement have suggested the presence of a group of gamblers that engage in a wide range of gambling activities (Wardle et al., 2014; Lloyd et al., 2012; 2010). They also have a much higher risk of an addiction to gambling.

Cluster 2: Populations vulnerable to disordered gambling

Certain demographic groups have a higher risk of problem gambling that is well explored in the problem gambling literature. In Chapter 4 data was pooled from the 2007 and 2010 British Gambling Prevalence Surveys, the Health Survey for England 2012 and the Scottish Health Survey 2012, to study the sociodemographic predictors of different latent classes of problem gambling severity. This analysis identified that relative to a group that endorsed minimal levels of problem gambling indicators (measured by the DSM-IV measure used in the survey series), higher levels of problem gambling (particularly for an intermediate group) were more likely to be younger (< 35), male, from an ethnic minority and a smoker. They were more likely to e.

The importance of this is that many of these demographic features correspond to groups with increased levels of mobile phone ownership and the belief held by many bookmakers about the gamblers that mobile gambling is capturing. In dispositions to The House of Commons Culture Media & Sport Select Committee (2012), British operators indicated their belief that many mobile gamblers are novel punters. This is a finding supported by a business analysis by Deloitte, on behalf of the British remote gambling sector, finding minimal evidence for 'cannibalisation' of betting shop profits from mobile gambling (Pietkanien, 2014). Similarly, in-depth surveying of online gambling on behalf of The Gambling Commission indicated the relative popularity of mobile and in-play gambling among younger adults (The Gambling Commission, 2016a). It is also important to consider this alongside an interesting paradox in the prevalence of problem gambling; problem gambling is most common in adolescents and young adults, despite the prevalence of gambling behaviour being smaller. In short, mobile and in-play betting appears to be stimulating gambling among a population who is a) vulnerable to gambling problems and b) has until recently gambled less frequently than most of the rest of the population.

The distinguishing feature of this group is its demographic characteristics, but these are likely to differ quantitatively from Clusters 1 and 3 rather than qualitatively. These gamblers' gambling history will also be interesting to consider. Problem gambling appears to often by transitory (Konkolÿ Thege, Woodin, Hodgins, & Williams, 2015), and the data from the British Gambling Prevalence Survey 2010 succinctly captures relatively lawful changes in population across the lifespan, in the form of a 'L' shaped pattern that drops off sharply after over 25's (Wardle et al., 2011b). What is most interesting about this group is their subsequent gambling behaviour. Most are likely to continue gambling, but some might migrate to gambling across many different types of play, and show evidence of a gambling disorder. Studying these specific gamblers prospectively is likely to be highly informative in looking at the risk and protective factors in the development of disordered gambling.

The relative exposure to fixed odds (pre-event) and live odds is worthy of interest, particularly for this cluster. The *bwin* data (LaBrie et al., 2007) indicated that the ratio of fixed-odds only, fixed and live odds, and live odds only was 37.78% fixed odds only, 59.30% both, and 1.92% live odds only. It would be interesting to examine whether, for the UK at least, the increased prominence of in-play betting and the increased integration between the two on gambling websites and apps has changed this distribution in the 10 years since the collection of the *bWin* data.

Cluster 3: Impulsive Gamblers

The distinction between this group and the first is worth bearing in mind. In large part, it is likely to differ in part on the extent of engagement in various gambling activities, and the type of games played. The typical profile of Group 1, based on prior typologies, is a desire to seek as many ways as possible to gamble. Group 3, on the other hand, are likely to seek out certain types of gambling game if they are particularly exciting. Whilst they might migrate into the pattern of behaviour typical of Group 1 (and are probably the group most liable to do so), this pattern has yet to be instantiated among these gamblers. In terms of previous typologies of gamblers, the distinction between this group and other clusters might be similar to those that have captured gamblers engaging in a cluster of excitement heavy gambling games. For these gamblers, there are likely to be two motivations that overlap. The first is a desire for playing gambling games high in excitement, driven by a behavioural processes related to positive reinforcement (Jacobs, 1986). The second is thought to be the allure of the hastened latency between wagering and knowing the outcome of a bet (Gray et al., 2012).

It is worth emphasising differences between this group and Cluster 1 (disordered gamblers) again. Previous latent class modelling of internet gamblers (Lloyd et al., 2010) found a group of sports and casino gamblers who had an elevated risk of problem gambling, but a lower risk of prevalence than gamblers who gambled across many different types of game. Although sample sizes varied considerably in that analysis, the sports and casino gamblers were approximately half as likely than the multi activity gamblers to be classified as 'Problem Gamblers' (although it is not clear whether this refers to 3 or 5 DSM-IV criteria).

Behaviourally, it is predicted that these gamblers will seek bets that have a shorter latency between wager and outcome. This might emerge in the form of a 'late betting' effect, of the type that has been identified in high frequency bettors before (Dickerson, 1979), or in the selection of in-play bets in which the outcome will be known shortly. The other behavioural difference is that one would expect gamblers from this cluster to be more likely to play casino games, which is worthy of mention as many major UK bookmakers also include gaming functions, which are linked with betting accounts. It is also worth examining whether these gamblers have shorter latencies between when they gamble, both in betting and gaming environments.

A final contrast of interest is to examine their behaviour in the face of continued losses; a couple of studies have found that more impulsive gamblers persevere in the face of reducing or extinguished reinforcement relative to less impulsive gamblers in simulated gambling games (Breen & Zuckerman, 1999) and was also found in the experiment reported in Chapter 6. One might expect these gamblers to continue playing for longer in the face of a disadvantageous sequence of betting outcomes.

Cluster 4: Migratory Gamblers

In the general introduction multiple behavioural processes were highlighted that might explain why in-play betting may be more attractive. Data from European betting site data (LaBrie et al., 2007) identified that live action betting was associated with a lower net loss and a lower percentage of money wager lost, both on average across bettors and in the ratio between wager and loss summed across the entire sample. From this, it is possible that two different states of affair might emerge, both of which are expanded upon below.

The possibility this cluster rests upon relates to gamblers who have previously gambled at a relatively frequent rate, one would expect most likely from sports betting, either on mobile, online or at a bookmaker. The law of effect is related to the matching, a principle in behavioural psychology that predicts that people ought to distribute their responses according to the relative rates of reinforcement on concurrent schedules of reinforcement. The law of effect specifically predicts that organisms ought to increase their operant responding to a schedule if the rate of reinforcement increases. While in-play betting is a form of wagering that may or may not fit onto the law of effect (the typical environment for this type of work has been the simulated slot machine), the law of effect predicts that gamblers ought to a) show an increased preference for in-play over standard betting and b) increase the frequency of their wagering behaviours. In-play bettors at present do appear to gamble slightly more frequently than fixed odds bettors, and with less variability in the frequency of their wagering (LaBrie et al., 2007).

The distinguishing feature of this second group is likely to be their previous gambling history. It can be explicitly predicted that the distinguishing feature of this group, in addition to a relatively high frequency of in-play betting, is their previous engagement with fixed odds sports betting. The one caveat to consider with this group is that a behavioural analysis of betting is far less complete than of games of chance, particularly slot machines but also scratchcards and to a lesser extent table games such as blackjack. Although it cannot be conclusively argued that in-play betting has a higher rate of reinforcement, the extant data augurs well. LaBrie et al. (2007) reported that in-play bettors have a lower percentage of net loss despite equivalent levels of gambling.

The application of behavioural principles to the study of behavioural addiction

Introduction

The latest edition of the Diagnostic and Statistical Manual of Mental Disorders in 2013 (DSM-5) (American Psychiatric Association, 2013) saw the introduction of addictions as a discrete category within the manual, covering both substance and behavioural addictions. The use of the term addiction instead of dependence highlighted a rebalancing from the latter towards compulsive consumption of a substance or behaviour (O'Brien, Volkow, & Li, 2006). For the first time a behavioural addiction, Gambling Disorder, was included in this category, with Internet Gaming Disorder noted as worthy of further consideration. Future revisions may add further behavioural addictions, inclusions that might prove controversial as numerous critiques have queried the nature and appropriateness of an addictions analysis of activities such as frequently flying, tango dancing and fortune telling that have become increasingly common in the literature (Cohen, Higham, & Cavaliere, 2011; Grall-Bronnec, Bulteau, Victorri-Vigneau, Bouju, & Sauvaget, 2015; Higham, Cohen, & Cavaliere, 2014; Targhetta, Nalpas, & Perney, 2013). It has also been argued that aspects of this research programme may inappropriately categorize aspects of everyday life as addictive (Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015b; Young, Higham, & Reis, 2014). The literature and popular media has also identified further behaviours such as eating, work, sex, water consumption and exercise (e.g. cycling) as potential behavioural addictions.

This chapter explores the associative research on behavioural addictions, and its application to candidate behaviours. It has been previously noted that such a line of analysis is likely to prove most fruitful in expanding our understanding of behavioural addiction (Robbins & Clark, 2015). The first section surveys associative approaches to addiction, looking at their limited application to behavioural addictions and identifying similarities and distinctions between gambling and other addictions. The second section reviews the use of pathological gambling as a basis for behavioural addictions, focusing on the case of internet gaming disorder. The third section then outlines the areas where behavioural work would be useful in considering the use of an addictions analysis for excessive activities. Finally, this is then considered in the context of treating behavioural addictions. For behavioural addictions such as problem gambling, cognitive behavioural therapy (CBT) is often the first line of treatment offered to disordered gamblers. Many of the considerations outlined here might be of relevance when designing interventions treatments for people with difficulties or addictions to other candidate behaviours.

1.a Behavioural research in addiction

The standard account of addiction in the research literature focuses on the role of behavioural conditioning in reinforcing drug consumption and compulsive use (Everitt et al., 2008; Everitt & Robbins, 2005, 2016; Hogarth, Balleine, Corbit, & Killcross, 2013a; Koob, 2013; Koob & Volkow, 2009; Ostlund & Balleine, 2008; Wise & Koob, 2014). Different models emphasise various components of associative learning: some consider the relative importance of positive versus negative reinforcement (i.e. the effects of drug consumption versus withdrawal), some place greater emphasis on the instrumental (operant) or classical elements of conditioning. Some of these models instead consider the how behavioural control changes from being directed by the outcome to antecedent stimuli as addiction progresses. Others still attempt to model in animals the transition from primarily impulsive to compulsive behaviour that appears to be characteristic of drug addictions. Many are complementary but ultimately all identify learning processes as the central locus of addiction.

Associative learning processes have been modelled across the entire spectrum of addiction, from drug consumption to negative reinforcement during withdrawal, compulsive drug seeking and relapse during extinction (i.e. post-treatment). The prevailing accounts of substance use addictions place these at the heart of explaining how individuals transition from recreational to pathological use of substances (Everitt & Robbins, 2016; Hogarth et al., 2013a). A number of these theories emphasise an imbalance in behavioural control toward habitual processes, with dysfunction or failure of control.

1.b Associative Learning in Behavioural Addictions

While this is the standard account of drug addictions, this is not the case for behavioural addictions. As the following two sections will highlight, an individual differences approach to behavioural addiction tends to be the most common within the research literature. Gambling however does have a significant associative learning research base (Brown, 1987; Dickerson, 1979;

Ghezzi, Wilson, & Porter, 2006; Haw, 2008a), following Skinner's (1953) analysis of slot machines. Like drug addictions, these have attempted to model different aspects of gambling play. A significant research effort has been focused on how contextual stimuli drive preferences in equivalent concurrent slot machines (Nastally et al., 2010; Zlomke & Dixon, 2006). Others have focused on the effect of different types of stimulus, such as the near misses (Daly et al., 2014; Ghezzi et al., 2006; Reid, 1986), big wins (Kassinove & Schare, 2001), losses disguised as wins (Dixon et al., 2010), or the structural features of gambling games (Griffiths & Auer, 2013) and their effect on behaviour. Many of these studies have looked at different aspects of gambling, such as machine preference (Dymond et al., 2012), rate of gambling (Dixon et al., 2012), post reinforcement pauses (Delfabbro & Winefield, 1999), latencies between gambles (Chapters 6 and 7), fixed interval schedules in betting (Dickerson, 1979), the random ratio schedule of reinforcement (Crossman et al., 1987; Haw, 2008a; Hurlburt et al., 1980) and perseverance during extinction (Chapter 6). Similar to drug addictions, these have also looked at the role of different types of reinforcement in addictive gambling and changes in behavioural processes. The concept that different types of reinforcement drive distinct subtypes of gambler is central to models of problem gambling (Blaszczynski & Nower, 2002; Sharpe, 2002). Nonetheless, it has been argued that the predominant approach to gambling research focuses on individual differences between recreational ('normal') and 'problem' gamblers (Cassidy, 2014). The behavioural literature on gambling is still less developed than substance addictions. Animal models of gambling are still in their infancy (Winstanley & Clark, 2016), and new types of reinforcement are still being discovered (Dixon et al., 2010). There is also a lack of betting related analysis in this field, some notable instances excepted (Dickerson, 1979; McCrea & Hirt, 2009).

Although it is often assumed that gambling and other behavioural addictions share common, underlying features, research looking at behavioural and cognitive processes in gambling and substance use addictions suggest this might not be so. Gambling has many similarities to drug addictions (Leeman & Potenza, 2012), but the existing differences may seriously qualify whether indicators of behavioural addiction should directly translated from disordered gambling. The learning processes in gambling have a number of idiosyncrasies that distinguish it not only from drug addictions but also many of the candidate behavioural addictions identified in the literature.

One possible difference is in the respective schedules of reinforcement and the maintenance of drug consumption. Drug consumption is by and large continuously reinforced although the value/magnitude of reinforcement may alter as addiction progresses, either due to changes in the rewarding value of the drug (Robinson, Fischer, Ahuja, Lesser, & Maniates, 2016b) or reward processing (Koob & Le Moal, 2001). Additionally drug seeking is modelled on a second order schedule of reinforcement.

In gambling it is unclear which component of gambling behaviour translates to this concept, and there are multiple candidates in the literature. The primary candidate is physiological arousal produced by gambling behaviour that is subsequently associated with gambling cues and stimuli. It has been argued that arousal is one of the primary components in maintaining.

The other alternative is near-misses, where a similar component to drug seeking has been proposed (Ghezzi et al., 2006). It has been alternatively proposed that near-misses get their predictive value from winning outcomes i.e. near-misses on a slot machine must occur prior to a win (Daly et al., 2014), largely in the same manner as arousal. Additionally the two interact; studies have shown greater levels of autonomic arousal in recreational gamblers to losses disguised as wins (Dixon et al., 2010), and greater reactivity to near-misses in problem gamblers (Dymond et al., 2014; van Holst, Chase, & Clark, 2014).

Whereas in drug consumption associations are maintained by conditioned reinforcers, in gambling it is more complex. First, gambling's schedule of reinforcement independent of cues is thought to be associated with increased elicitation of behaviour (Crossman et al., 1987; Haw, 2008a; Hurlburt et al., 1980; Madden et al., 2007). Second, there may be two components to the role of conditioned stimuli and conditioned reinforcement in gambling. The first is the standard environmental cues that might trigger gambling associations in the same manner as drug behaviour. The second, which has been extensively studied in slot machine paradigms, is the role of conditioned reinforcement during gambling consumption in the absence of wins.

Other considerations focus on the role of extinction, where the contingencies between response and outcome are abolished, or shifting responses in the face of a reversal of contingencies. Studies of gambling addiction suggest that deficits in this domain are more common and consistent than other substance addictions (Leeman & Potenza, 2012). With gambling, the interesting question is whether this is due to exposure to gambling's schedule of reinforcement that, as explored above, drives perseverance through multiple aspects of conditioned reinforcement. Although the different components of compulsivity are less understood than impulsivity, it may be the case that both gambling and drug addictions transition from impulsive to compulsive behaviour, but behaviourally express the latter in different ways. If this is the case, these differences may be specific to gambling and not translate to other behaviours.

In contrast, there is evidence that numerous disorders on an impulsive-compulsive spectrum, including behavioural addictions, show similar deficits in impulsive choice and action as other addictions including gambling (Robbins & Clark, 2015). Studies have looked at the application of behavioural economic approaches to impulsive choice drawn from operant conditioning research (Bickel & Marsch, 2001), such as the application of the delay discounting paradigm in understanding behavioural addictions (Reed, Becirevic, Atchley, Kaplan, & Liese, 2016). A greater literature exists in the field of obesity, where parallels with eating/food addiction have been discussed (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016) in delay discounting performance in addictions (Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016; MacKillop et al., 2011). Other studies have found in binge eating that there is no difference in impulsive action against controls (Voon et al., 2014).

Other associative research has looked at different models of addiction in the context of eating. There have been several strands to this research. The first looks at the type of addiction model to apply to disordered eating behaviours; whether a substance or behaviour based addiction model is the most appropriate (De Jong, Vanderschuren, & Adan, 2016; Hebebrand et al., 2014). This kind of research has studied the question of whether the locus of addictive behaviour is in the food (i.e. the nutritional constituents of processed or sugary food) or in the actual act of eating. The second is the application of associative models of addiction to eating behaviours and disorders (Berridge, 2009; Robinson et al., 2016b; Smith & Robbins, 2013). Third is the comparison with other addictions such as tobacco as an example of an addiction where evidence for many of the prototypical markers of addiction are attenuated, but belie key similarities and public health outcomes (Schulte, Joyner, Potenza, Grilo, & Gearhardt, 2015). These are considered alongside the role of reinforcement and behaviour in the similarities with other addictions.

1.c Research approaches to behavioural addiction

The typical approach to behavioural addictions has been described in three steps (Billieux et al., 2015b). The first step to applying an addictions analysis begins with observations around the behaviour in question. Often in the same exercise, this then forms the justification for developing an assessment instrument for an addiction to that behaviour. This is typically developed by adapting the criteria from the DSM-IV conceptualisation of pathological gambling or drug dependence (American Psychiatric Association, 2000), general criteria for addiction, or by translating across from other behavioural addictions scales (e.g. internet, video gaming). This is conducted alongside, or spurs subsequent research, collecting additional psychometric data measuring a number of constructs related to addictions, primarily in the domains of risk taking and impulsivity. It has been argued that this is part of a confirmatory, atheoretical approach that lacks specificity and a theoretical model (Billieux et al., 2015b). The end result of this has been a series of candidate addictions where there appear to be a substantial number of addicts but rarely a clear reason for why the behaviour they engage in is addictive. In many cases these have the superficial markers of addiction; they, often showing associations with constructs more common among disordered gamblers or substance users. An associative approach is a useful heuristic model for capturing this, at least for behaviours that researchers may compare against gambling. Although these criticisms have been well stated in the literature, it is the contention of this commentary that without taking into account the role of behaviour and the wider environment a consensus about which behaviours may meet the definition of a psychiatric diagnosis, require public health attention or intervention is unlikely to emerge.

The previous sections highlight how the individual or trait determinants of addictive behaviour take precedence over behavioural research. Much of the work that considers reinforcement and conditioning in behavioural addictions does so in the form of vicarious reinforcement (Bandura, Ross, & Ross, 1963) or discusses operant conditioning in a very general sense, rather than identifying how specific aspects of a behaviour are reinforced, maintain or become habitual. The majority of attempts to apply learning based approaches have been in gambling and food/eating addictions. Many commentaries or research papers do mention there is a role for conditioning in the behaviours in question. However, as in behavioural addictions as a whole, there is a lack of specificity in this regard. There is little consideration of the reinforcers that drive perseverative behaviour. Like gambling, many of these behaviours will be conducted repeatedly in a short space of time. Even then, surveys of the gambling literature have noted that there is an overwhelming preponderance to focus on individual pathology and disorder (Cassidy, 2014; Reith, 2013). This has meant that the causal understanding of problem gambling has focused on why problem gamblers behave in a disordered fashion rather than why gambling is addictive. One of the concerns, as enunciated by Young et al. (2014) was the over application of the addiction model to behaviours where its relevance is at best tenuous (in this case frequent flying). It is highlighted how an addictions narrative can be highly powerful, but there were compelling reasons why it should not be applied. This reiterates the criticisms of a behavioural addictions approach from the social sciences that the predominant account of addiction is one that seeks to 'other-ize' inappropriate forms of consumption. This seats the locus of consequences and causality in the disordered consumer rather than the industries that propagate these behaviours. However, as noted by Reith (2013), a number of these critiques are less relevant to a behavioural approach to gambling and addictions, which focus on the role of the product in controlling behaviour.

While there have multiple commentaries on behavioural addictions over the past 2-3 years (Billieux et al., 2015b; Griffiths et al., 2016; Petry et al., 2016; Starcevic & Aboujaoude, 2016), the role of associative learning in behavioural addictions has not been explored in detail. It has been noted among these that the decision to include gambling in the DSM-5 as an addiction was made based on the convergence between substance addictions and pathological gambling across a range of different domains (Potenza, 2015). A behavioural approach is likely to be prominent among these, and is therefore helpful in considering the criteria under which a pathological, behavioural addictions model is appropriate for certain behaviours. The contention put forth is that an associative learning based conceptualisation of behavioural addictions is the most parsimonious model of the current state of behavioural addictions in the DSM, notwithstanding the trenchant criticisms the DSM also faces. The following section explores Internet Gaming Disorder in further detail, identifying behavioural similarities and how an increasing convergence between video gaming and gambling provides further evidence these originate from a similar model.

2. Behavioural Addictions in the DSM – the case of internet gaming disorder

2.a Addictions in the DSM

The conceptualisation of addiction in the DSM has changed over time, emerging from personality disorders before becoming a discrete type of disorder in the 1980's. In the first DSM (American Psychiatric Association, 1952), addictions (alcohol and drugs) were considered as a secondary diagnosis under the category of 'sociopathic personality disorder' alongside a range of other antisocial and deviant behaviours. In the DSM-II (American Psychiatric Association, 1968), both became primary diagnoses in the category of personality and non-psychotic disorders, the non-personality, non-psychotic disorders being addictions and sexual deviance. The present conceptualisation as a distinct category primarily emerged with the DSM-III (American Psychiatric Association, 1987). This separated addictions from personality disorders, with addictions being assessed on Axis I under 'psychoactive substance-induced organic mental disorders' whereas personality disorders were assessed on Axis II of the DSM's multiaxial system. The DSM-IV (American Psychiatric Association, 2000) retained this demarcation under 'Substance Related Disorders', identifying these as disorders of dependence. Pathological Gambling was introduced in the DSM-III as part of Disorders of Impulse Control Not Otherwise Specified, included alongside other disorders such as kleptomania, pyromania, intermittent and isolated explosive disorders. This approach has been maintained in the ICD-11 (Grant & Chamberlain, 2016). Gambling Disorder was included as the first behavioural addiction in the DSM-5 (American Psychiatric Association, 2013), which also included Internet Gaming Disorder as potentially suitable for future inclusion, given further research. In addition to the addiction's transitory history, models of addiction focus on a shift from impulsivity to compulsivity, highlighting how facets of the transition toward addictive behaviour touch on a range of other psychopathologies. This is not to mention that drug, alcohol and gambling addictions are typically highly comorbid with a range of other psychiatric conditions on both Axes I and II.

2.b Internet Gaming Disorder – the next behavioural addiction?

Internet Gaming Disorder considered in the DSM-5 refers to a highly restricted set of behaviours focusing around online video game usage. One of the controversies concerning whether this is included as a disorder in future revisions is whether it should include other forms of content consumed over the internet, as an internet use disorder or internet addiction (Kuss, Griffiths, & Pontes, 2016). Many aspects of online and mobile video gaming, particularly when free, have a similar behavioural profile to gambling. For many games, items are distributed on a VR or RR schedule designed to elicit copious behaviour, often utilising gambling or pseudo-gambling mechanisms in a ‘freemium’ model to monetise their platform. These mechanisms are used to nudge in-game spending in lieu of an up-front payment. Video gaming is an example where translating from problem gambling to a behavioural addiction is a reasonable first step. The typical profile of internet games (at least traditionally) has been different from other video games. Online games have traditionally been more ‘grind’ heavy, where random processes dominate the mechanisms for item drops within the game. These tend to use VR or RR schedules that, as has been shown in gambling, produce copious consumption.

While previous commentaries consider the role of game played, from a behavioural perspective both miss an important behavioural consideration: Griffiths et al. (2016) for instance raise the possibility that the type (i.e. goal-directed versus competitive) or genre of game as being worth consideration under separate addictions, whereas Petry et al. (2016) suggest that such a demarcation is unhelpful and unlikely to endear psychiatrists. The possibility that certain video games are designed towards maximising perseverance is not surprising, as developers have always attempted to maximise playtime. Ultimately however a behavioural perspective suggests that some games will be addictive and some will not, not that internet games or a specific genre are addictive as a whole.

2.c Does internet gaming follow a gambling model?

A fundamental consideration that has yet to be answered is whether the addictive nature of internet games is the same or distinct from gambling – is it due to a schedule of reinforcement that encourages extended play in the face of a frequently frustrated outcome? From a behavioural perspective, it follows that this is the case. Moreover, it suggests that internet gaming in of itself is not addictive, but that certain games are based on how they are designed. This echoes a similar distinct between gambling games that have a relatively negligible risk of harm (e.g. lotteries) versus those that are linked with an increase prevalence of problem gambling (e.g. electronic gaming machines or fixed odds betting terminals) based on their structural features (Griffiths & Auer, 2013). The DSM's tentative demarcation based on monetary loss is heuristically useful as it captures a number of the contextual differences that are observed between gambling and game. However, there is increasing evidence that this demarcation is becoming obsolete.

Innovations in the gaming market have increasingly involved the adoption of gambling-like processes into games. The literature has previously studied both simulated gambling (e.g. (Griffiths, King, & Delfabbro, 2012)) and of social casino games (e.g. (Gainsbury et al., 2014)). These forms of simulated play allow the opportunity for some form of free engagement with a gambling mechanism. Increasingly games are expanding upon this by using gambling mechanics as a means of item distribution. These, like simulated or social games, typically allow some form of free engagement, usually using a form of secondary currency earned in-app. Extra plays can then be sought, typically by the player purchasing extra secondary currency using real money. The amount an individual can spend typically ranges from between $1 and $3.

The appearance of many of these mechanisms is not drawn from games of chance, but it is also worth noting that many of these games also explicitly use gambling themes, such as scratchcards or reels to present the outcomes to the player. Although the DSM distinguishes between internet gaming and gambling on these grounds, freemium games are nudging spending behaviour for some players that increasingly makes this distinction fuzzy. As mobile gaming continues to grow these mechanisms are likely to become more prevalent, but there is little data on how they affect players. Although only a minority of players spend money on social gambling apps (Parke et al., 2012), it is unclear whether a similar pattern exists for simulated gambling in video games, and whether these players overlap. It is also unclear if these subsequently transition to real-money gambling, or if there is a gradient between these activities.

There is cross-pollination between these activities; recent events have highlighted how potentially illicit betting takes place in e-sports, and how in-game currencies ('skins') have been used as currency for betting and gambling, including among adolescents. These are behaviourally interesting as it involves users gambling using a currency that can only be obtained via random outcomes (or trading). The illicit nature of these is due in part to legal restrictions in the USA over online betting, and a potential population of bettors gambling under the age of 18. A number of the most prominent websites in this area have recently been restricted by game distribution platforms for this reason. Some have sought gambling licenses to continue operations. A similar media focus has been raised over the convergence of video gaming and gambling in the form of betting on spectator video games (e-sports) in an analogous manner to sports spectatorship.

The other thing to consider is that distinct from many behavioural addictions is that the manner that a game, gambling or video, is designed is intrinsically related to its harmful and potentially addictive properties. Griffiths and Auer (2013), in critiquing the research on problem gambling prevalence in game type, note how behavioural characteristics have dramatic effects on behaviour, using the example of how the difference between lotteries and keno is primarily in the latency between plays. This has been highlighted both in the behavioural (General Introduction) and social sciences literatures (Schüll, 2012) to explore how slot machines are designed to be addictive. Whereas in drug addictions many of the cues and conditioned reinforcers are incidental in the environment with the salient exceptions of licensed drinking and smoking (e.g. shisha or hookah bars) establishments, in gambling and internet games these are directly under the control of the person designing them.

2.d Caveats

A behavioural analysis is unlikely to capture all of the features sufficient for a potential behavioural addiction, and there are important contextual differences between gambling and internet gaming. The games on which problem gamblers tend to most over-represented (machine gaming, online gambling) are generally solitary and isolating whereas the instances where random ratio schedules are most employed in internet gaming tend to be social and collaborative affairs (i.e. in MMORPG's). Moreover reinforcement schedules are not the only thing that makes gambling addictive, and there are individual and wider social determinants that must be kept in mind. Even RR heavy online games typically offer a wider array of options to the player than a typical game of chance. Similarly some forms of gambling (i.e. betting) do not fall as straightforwardly onto an RR schedule (Dickerson, 1979) but do appear to be addictive. While there is behavioural research in these domains it is less well explored than the slot machine.

The DSM-5's evidence base for Internet Gaming Disorder is primarily based on disordered gaming in Asia, where some of the games that might be characterised as especially addictive (i.e. *Starcraft* in South Korea) don't have these schedules of reinforcement. It is of considerable interest that some of these games are strategic and highly goal-directed. As many accounts of addiction model a transition from goal-directed to stimulus-directed behaviour, understanding the potential addiction to a goal-directed game might be informative in understanding addictive behaviour more generally.

Additionally, the accounts mentioned in this chapter are primarily derived from positive reinforcement. There is a voluble literature on the role of negative reinforcement in substance addictions, and models of problem gambling identify a subgroup of gamblers for whom gambling is driven by escape (Blaszczynski & Nower, 2002; Jacobs, 1986). Additionally, it is well known that some personality traits exert an influence on behaviour. Impulsivity for example effects components of response perseverance as identified by Leeman & Potenza (2012) and others (Breen & Zuckerman, 1999).

3. A framework for understanding behavioural addictions

The aim of this is to consider when it is appropriate to apply an addictions perspective to a behaviour that is harmful across the population when consumed in excess. Gambling and video gaming might be reinforced quite differently to substance addictions, and it is unlikely to be replicated across other potentially harmful behaviours. Most accounts of addiction and studies of behaviour note that these behaviours are positively reinforcing, making reference to operant conditioning and habit. References to operant conditioning in particular are common in the literature, but do not tend to expand too far on the reinforcing elements within a behaviour (Andreassen, 2015; Grall-Bronnec et al., 2015; Shepherd & Vacaru, 2016; Wallace, 1999; Wu, Cheung, Ku, & Hung, 2013) a greater specificity is required.

A number of factors are likely to affect the relationship between acquisition, reinforcement and extinction of addictive behaviours. Although in this section frequent reference is made to the critiques of correlating risk taking constructs with behavioural addictions, there is utility is examining how these constructs act in interactions between human behaviour and these addictive products. Moreover in the case of new technologies, some of these might mediate the relationship between addiction and behaviour; this case has previously been made for mobile gambling, as the introduction, Chapters 6 and 7 and parts of the first section of the discussion highlight. For other excessive behaviours, content downloaded onto phones might form an additional source of reinforcement or a cue (i.e. push notifications) that maintain or prompt behaviour. It is also important to consider where positive reinforcement is coming from; is it primarily from the activity itself (which is where most analyses of behavioural addictions stop), or is it more from generalised contextual cues, as an arousal based explanation of problem gambling predicts. It is also important to consider what cues and contextual stimuli are driving behaviour, particularly for technology-based addictions where these are under greater control of the designer.

The most important challenge is to model how a candidate behavioural addiction is maintained. The research thus far has focused on identifying indicators of addiction without considering how the potential addicts have reached that point. Aside from the concerns that these states appear transient (Konkolÿ Thege et al., 2015), what differentiates these from gambling and substance addictions is that the maintenance of these behaviours prior to habitual or compulsive seeking have been modelled extensively. Many behavioural addictions papers have noted that a potentially addictive behaviour is reinforcing, but have not explored which components of that behaviour are reinforcing.

These very rarely consider the manner in which the reinforcement is delivered, for example, if the behaviour is partially reinforced (such as gaming or gambling), what is the schedule of reinforcement? Reinforcement might be also delivered by the physiological consequents of the behaviour, such as arousal from gambling that subsequently generalises, or from the act of eating or the effects of sugar/fat/salt. Many of the activities classified as addictive are a composite of a number of behaviours. Take the use of Twitter for example, especially pertinent as social media use has been hypothesized to be a putative addiction (Wu et al., 2013). Which component or components drive persistent use? It might be the act of being followed by other people, posting and sharing information (and the uncertain, intermittent feedback and reinforcement from this), or the repeated, habitual checking given the live nature of the website. The analysis of gambling behaviour is notably more granular than other behavioural addictions.

Research studying candidate behavioural addictions ought to begin by considering whether there is a behavioural basis to translate from gambling (and potentially internet gaming) to the behaviour in question. Starting from the associative research in addictions might generate a wider array of potential approaches than currently exist in the literature. For many activities highlighted in the literature a direct application of disordered gambling is unlikely to be appropriate. Instead there is scope to translate from a range of other addictions, and the theories and paradigms of eliciting behaviour that are associated with them. Earlier on the commentary explored how the starting point for eating addiction came from substance addictions, with an interest comparison with nicotine addiction and is now starting to move towards a behavioural addiction model in some areas. These kinds of approach may prove more fruitful (and more interesting) than developing an instrument and measuring the prevalence of addiction-like indicators of recreational activities.

Another consideration is the drivers of persistent behaviour within engagement in an activity. Most behavioural addictions (gambling, social media, cycling) may involve a large number of reinforcements within a session. There may also be need for greater clarity concerning the changes in reinforcement that might occur as a behavioural addiction progresses. In gambling for example, near-misses appear to acquire an increased salience (or other outcomes lose theirs) over the course of a gambling addiction (Dymond et al., 2014). The key caveat here is that this requires a way of identifying individuals experience some sort of change in their interaction with an addictive behaviour. This may be an instrument (and thus form the latter part of a program of research), or a clinical sample.

Combining these processes together, there is a case to be made that behavioural addictions research ought to begin from a different starting point, and with different initial questions to ask. The present approach of identifying these addictions appears to miss a considerable amount of important groundwork before attempting to measure an addiction within a validation sample or the general population. It is worth making parallels with gambling here again. Prior to the classification of Pathological Gambling in the DSM-III in 1980 (American Psychiatric Association, 1987), there had been over two decades of intermittent research on the effects gambling had on behaviour. Post-classification, it was another seven years before the first major screen (the SOGS) (Lesieur & Blume, 1987) was developed for clinical screening and a further few years before gambling prevalence surveys became commonplace. While such latency is unlikely to be appropriate and in large part emerged from opposition to treating gambling as mental disorder, many explorations of behavioural addiction appear to skip a crucial step in this regard.

4. Concluding remarks on behavioural addictions

The behavioural addictions literature has focused on identifying people with behavioural addictions but has frequently failed to consider why certain behaviours might be addictive. One of the criticisms of gambling research has been an over-emphasis on individual dysfunction as the locus of gambling problems as well as preponderance upon the latter stages of addictive gambling. At present the behavioural addictions literature has translated markers across from gambling and other addictions to identify participants with an addiction. It remains unclear whether the participants identifying as displaying indicators of an addiction are doing so as the polymorphous and multi-faceted expression of a general addiction syndrome or psychopathology, or whether it is peculiar to a specific behaviour. In other words, while the literature successfully identifies 'addicts', whether this has any relation to an addictive behaviour or not, it has not explored addictive-ness. The aim of this exercise is to highlight how a behavioural approach can be used to look at the behaviour itself, and consider how these may ultimately drive pathological behaviour at least partially independent of individual psychopathology.

What emerges from the behavioural addictions literature at present is that there are a substantial number of people who appear to experience levels of distress (in many cases severe) from kinds of behaviour. Irrespective of whether a behaviour is addictive or not, more specific, behaviourally targeted research can still be beneficial to these people. Practically if the unit of addiction (or harm, or distress) can be behaviourally identified, this can be used to inform the targeting of cognitive and behavioural therapies to make them more efficacious. These are typically used at present as a treatment for people presenting with a behavioural addiction. At present CBT is one of the first lines of treatment for problem and disordered gamblers (Bowden-Jones & George, 2015). Some tenets of CBT (e.g. challenging irrational thinking) might be perceived as controversial in their extension to addictive consumption behaviours, but there are behavioural therapies (i.e. targeting processes such as extinction) that might be equally beneficial.

The search for candidate behavioural addictions is unlikely to be futile. Although disordered gambling is currently the prototypical behavioural addiction by default, developments in this field may eventually show that a constellation of other behaviours are more typical of a behavioural addiction. More likely than not is that disordered gambling will be the first behavioural addiction that comes to mind for most, but it is quite possible that it will be idiosyncratic among other behavioural addictions once those being to emerge.

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APPENDIX 1

Psychometric assessments used over the course of this thesis, included in order of use.

A. **Problem Gambling Severity Index (Ferris & Wynne, 2001).**

Used in Chapters 2, 3, 5, 7. Version on following page is the version administered to participants in Chapter 7, adapted from:

https://www.problemgambling.ca/EN/ResourcesForProfessionals/pages/problemgamblingseverityindexpgsi.aspx

Problem Gambling Severity Index (BGPS 2007, BGPS 2010, SHS & HSE 2012)

Responses (all items) – Never (0), sometimes (1), most of the time (2), almost always (3).

1. Have you bet more than you could really afford to lose?
2. Have you needed to gamble with larger amount of money to get the same feeling of excitement?
3. When you gambled, did you go back another day to try to win back the money you lost?
* - Presented in the BGPS series as: Have you gone back to try to win back the money you'd lost?
4. Have you borrowed money or sold anything to get money to gamble?
5. Have you felt you might have a problem with gambling?
6. Has gambling caused you any health problems, including stress or anxiety?
* Presented in the BGPS series as: Have you felt that gambling has caused you any health problems, including stress or anxiety?
7. Have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?
8. Has your gambling caused any financial problems for you or your household?
* Presented in the BGPS series as: Have you felt your gambling has caused financial problems for you or your household?
9. Have you felt guilty about the way you gamble or what happens when you gamble?

Please indicate the extent to which each question has applied to you in the previous 12 months.
Have you bet more than you could really afford to lose?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Have you needed to gamble with larger amounts of money to get the same feeling of excitement?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

When you gambled, did you go back another day to try to win back the money you lost?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Have you borrowed money or sold anything to get money to gamble?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Have you felt that you might have a problem with gambling?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Has gambling caused you any health problems, including stress or anxiety?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Has your gambling caused any financial problems for you or your household?

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

Have you felt guilty about the way you gamble or what happens when you gamble

0	1	2	3
NEVER	**SOMETIMES**	**MOST OF THE TIME**	**ALMOST ALWAYS**

B. DSM-IV Pathological Gambling Criteria (BGPS Version) (Fisher, 1996)

Used in Chapters 2, 3, 4, 5.

DSM-IV Pathological Gambling Criteria (BGPS series and HSE 2012)

Responses (BGPS): Item 1: Never (0), Some of the time (less than half the time I lost) (1), Most of the time I lost (2), Every time I lost (3)
Items 2 – 10: Never (0), Occasionally (1), Fairly Often (2), Very Often (3)

Classification: BGPS: Items 1-7: Present = score of 2 or 3; Items 8-10: present = Score of 1,2 or 3
Alternate (McBride et al., 2010) All items: Present = Score of 1, 2 or 3

1. When you gamble, how often do you go back another day to win back money you lost?
2. How often have you found yourself thinking about gambling (that is relieving past gambling experiences, planning the next time you will play, or thinking of ways to get money to gamble)?
3. Have you needed to gamble with more and more money to get the excitement you are looking for?
4. Have you felt restless or irritable when trying to cut down gambling?
5. Have you gambled to escape from problems or when you are feeling depressed, anxious or bad about yourself?
6. Have you lied to family, or others, to hide the extent of your gambling?
7. Have you made unsuccessful attempts to control, cut back or stop gambling?
8. Have you committed a crime in order to finance gambling or pay gambling debts?
9. Have you risked or lost an important relationship, job, educational or work opportunity because of gambling?
10. Have you asked others to provide money to help with a desperate financial situation caused by gambling?

C. DSM-IV Pathological Gambling Criteria (APMS Version) (APA, 2000).

Used in Chapter 3.

DSM-IV Pathological Gambling Criteria (APMS 2007)

Responses (all items): Yes/No

1. Are you preoccupied with gambling (e.g. preoccupied with reliving past gambling experiences or planning the next venture, or thinking of ways to get money with which to gamble)?
2. Do you need to gamble with increasing amounts of money in order to achieve the desired excitement?
3. Have you made repeated unsuccessful attempts to control, cut back or stop gambling?
4. Are you restless when attempting to cut down or stop gambling?
* Q4 only asked if answer to Q3 was 'YES'.
5. Do you gamble as a way of escaping from problems or relieving feelings of helplessness, guilt, anxiety or depression?
6. After losing money gambling, do you often return another day to get even?
7. Do you lie to family members, therapists, or to others to conceal the extent of involvement with gambling?
8. Have you committed illegal acts such as forgery, fraud, theft or embezzlement to finance gambling?
9. Have you jeopardised or lost a significant relationship, job, or educational or career opportunity because of gambling?
10. Do you rely on others to provide money to relieve a desperate financial situation caused by gambling?

D. South Oaks Gambling Screen (Lesieur & Blume, 1987).

Used in Chapter 3.

South Oaks Gambling Screen (BGPS 1999) – Unless stated, responses are yes/no. This only includes items that contribute to the calculated SOGS score. When responses that contribute to the SOGS score are not 'YES', they are highlighted in bold. Please note than several items are slightly different, either for purpose of brevity or adapted for a British population.

4. When you gamble, how often do you go back another day to win back money you have lost?
Responses: "Never", "Some of the time (less than half the time I lose)", "**Most of the times I lose", "Every time I lose"**
5. Have you ever claimed to be winning money gambling, but weren't really? In fact, you lost?
Presented as: Have you claimed to be winning money from gambling when in fact, you lost?
Responses: "Never", **"Yes, less than half the time I lost", "Yes, most of the time"**
7. Did you ever gamble more than you intended to?
Presented as: Do you spend more time or money gambling than you intended?
8. Have people criticized your betting or told you that you had a problem, regardless of whether or not you thought it was true?
Presented as: Have people criticized your gambling?
9. Have you ever felt guilty about the way you gamble, or what happens when you gamble?
10. Have you ever felt like you would like to stop betting money on gambling, but didn't think you could?
11. Have you ever hidden betting slips, lottery tickets, gambling money, IOU's, or other signs of betting or gambling from your spouse, children or other important people in your life?
13. (If answered "Yes" to 12: Have you ever argued with people you live with over how you handle money?) Have these arguments ever centred on your gambling?
14. Have you ever borrowed from someone and not paid them back as a result of your gambling?
15. Have you ever lost time from work (or school) due to betting money or gambling?
16. If you borrowed money to gamble or pay gambling debts, who or where did you borrow money from:
16a. From household money
16b. From your spouse
16c. From other relatives or in-laws
16d. From banks, loan companies or credit unions
Presented as: banks, building societies, loan companies, or credit companies
16e. From credit cards
16f. From loan sharks
16g. You cashed in stocks, bonds or other securities
16h. You sold personal or family property.
16i. You borrowed on your checking accounts (passed bad cheques).
6. Do you feel you have ever had a problem with betting or money gambling?
Responses: "No", **"Yes", "Yes, in the past, but not now"**
* Presented as Yes/No in the BGPS 1999, as adapted for past year prevalence.

E. Beck Depression Inventory (Beck et al., 1961).

Used in Chapters 6 and 7.

Instructions:

This is a questionnaire. On the questionnaire are groups of statements. Please read the entire group of statements in each category. Then pick out the one statement in the group which best describes the way you feel today, that is, *right now*. Circle the number beside the statement you have chosen. If several statements in the group seem to apply equally well, circle each one.

A.

0	I do not feel sad.
1	I feel blue or sad.
2a	I am blue or sad all the time and I can't snap out of it.
2b	I am so sad or unhappy that it is very painful.
3	I am so sad or unhappy that I can't stand it.

B.

0	I am not particularly pessimistic or discouraged about the future.
1	I feel discouraged about the future.
2a	I feel I have nothing to look forward to.
2b	I feel that I won't ever get over my troubles.
3	I feel that the future is hopeless and that things cannot improve.

C.

0	I do not feel like a failure.
1	I feel I have failed more than the average person.
2a	I feel I have accomplished very little that is worthwhile or that means anything.
2b	As I look back on my life all I can see is a lot of failures.
3	I feel I am a complete failure as a person (parent, husband, wife).

D.

0	I am not particularly dissatisfied.
1a	I feel bored most of the time.
1b	I don't enjoy things the way I used to.
2	I don't get satisfaction out of anything any more.
3	I am dissatisfied with everything.

E.

0	I don't feel particularly guilty.
1	I feel bad or unworthy a good part of the time.
2a	I feel quite guilty.
2b	I feel bad or unworthy practically all of the time.
3	I feel as though I am very bad or worthless.

F.

0 I don't feel I am being punished.
1 I have a feeling that something bad may happen to me.
2 I feel I am being punished or will be punished.
3a I feel I deserve to be punished.
3b I want to be punished.

G.

0 I don't feel disappointed in myself.
1a I am disappointed in myself.
1b I don't like myself.
2 I am disgusted with myself.
3 I hate myself.

H.

0 I don't feel I am worse than anybody else.
1 I am very critical of myself for my weaknesses or mistakes.
2a I blame myself for everything that goes wrong.
2b I feel that I have many bad faults.

I.

0 I don't have any thoughts of harming myself.
1 I have thoughts of harming myself but I would not carry them out.
2a I feel I would be better off dead.
2b I have definite plans about committing suicide.
2c I feel my family would be better off if I were dead.
3 I would kill myself if I could.

J.

0 I don't cry any more than usual.
1 I cry more now than I used to.
2 I cry all the time now. I can't stop it.
3 I used to be able to cry but now I can't cry at all even though I want to.

K.

0 I am no more irritated now than I ever am.
1 I get annoyed or irritated more easily than I used to.
2 I feel irritated all the time.
3 I don't get irritated at all at the things that used to irritate me.

L.

0 I have not lost interest in other people.
1 I am less interested in other people now than I used to be.
2 I have lost of my interest in other people and have little feeling for them.
3 I have lost all my interest in other people and don't care about them at all.

M.

0 I make decisions about as well as ever.
1 I am less sure of myself now and try to put off making decisions.
2 I can't make decisions any more without help.
3 I can't make any decisions at all any more.

N.

0 I don't feel I look any worse than I used to.
1 I am worried that I am looking old or unattractive.
2 I feel that there are permanent changes in my appearance and they make me look unattractive.
3 I feel that I am ugly or repulsive looking.

O.

0 I can work about as well as before.
1a It takes extra effort to get started at doing something.
1b I don't work as well as I used to.
2 I have to push myself very hard to do anything.
3 I can't do any work at all.

P.

0 I can sleep as well as usual.
1 I wake up more tired in the morning than I used to.
2 I wake up 1-2 hours earlier than usual and find it hard to get back to sleep.
3 I wake up early every day and can't get more than 5 hours sleep.

Q.

0 I don't get any more tired than usual.
1 I get tired more easily than I used to.
2 I get tired from doing anything.
3 I get too tired to do anything.

R.

0 My appetite is no worse than usual.
1 My appetite is not as good as it used to be.
2 My appetite is much worse now.
3 I have no appetite at all any more.

S.

0 I haven't lost much weight, if any, lately.
1 I have lost more than 5 pounds.
2 I have lost more than 10 pounds.
3 I have lost more than 15 pounds.

T.

0 I am no more concerned about my health than usual.
1 I am concerned about aches and pains *or* upset stomach *or* constipation *or* other unpleasant feelings in my body.
2 I am so concerned with how I feel or what I feel that it's hard to think of much else.
3 I am completely absorbed in what I feel.

U.

0 I have not noticed any recent change in my interest in sex.
1 I am less interested in sex than I used to be.
2 I am much less interested in sex now.
3 I have lost interest in sex completely.

F. Barratt Impulsiveness Scale 11 (BIS-11) (Patton et al., 1995).

Used in Chapters 6 and 7.

N.B. The version administered to participants is available to download from http://www.impulsivity.org/pdf/BIS11English.pdf

DIRECTIONS: People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Read each statement and put an X on the appropriate circle on the right side of this page. Do not spend too much time on any statement. Answer quickly and honestly.

All items are scored from 1 to 4. 1 = Rarely/Never, 2 = Occasionally, 3 = Often, 4 = Almost Always/Always. Items 1-15 left column, 16-30 right.	
I plan tasks carefully	I change jobs
I do things without thinking	I act "on impulse"
I make-up my mind quickly	I get easily bored when solving thought problems
I am happy-go-lucky	I act on the spur of the moment
I don't "pay attention"	I am a steady thinker
I have "racing" thoughts	I change residences
I plan trips well ahead of time	I buy things on impulse
I am self controlled	I can only think about one thing at a time
I concentrate easily.	I change hobbies
I save regularly	I spend or charge more than I earn
I "squirm" at plays or lectures	I often have extraneous thoughts when thinking
I am a careful thinker	I am more interested in the present than the future
I plan for job security	I am restless at the theatre or lectures
I say things without thinking	I like puzzles
I like to think about complex problems	I am future oriented

G. Gambling Related Cognitions Scale (Raylu & Oei, 2004).

Used in Chapter 7.

Please indicate the extent to which you agree with the value expressed in each statement. Scoring: 1 = strongly disagree; 2 = moderately disagree; 3 = mildly disagree; 4 = neither agree or disagree; 5 = mildly agree; 6 = moderately agree; 7 = strongly agree

1 Gambling makes me happier.

2 I can’t function without gambling.

3 Praying helps me win.

4 Losses when gambling, are bound to be followed by a series of wins.

5 Relating my winnings to my skill and ability makes me continue gambling.

6 Gambling makes things seem better.

7 It is difficult to stop gambling as I am so out of control.

8 Specific numbers and colours can help increase my chances of winning.

9 A series of losses will provide me with a learning experience that will help me win later.

10 Relating my losses to bad luck and bad circumstances makes me continue gambling.

11 Gambling makes the future brighter.

12 My desire to gamble is so overpowering.

13 I collect specific objects that help increase my chances of winning.

14 When I have a win once, I will definitely win again.

15 Relating my losses to probability makes me continue gambling.

16 Having a gamble helps reduce tension and stress.

17 I’m not strong enough to stop gambling.

18 I have specific rituals and behaviours that increase my chances of winning.

19 There are times that I feel lucky and thus, gamble those times only.

20 Remembering how much money I won last time makes me continue gambling.

21 I will never be able to stop gambling.

22 I have some control over predicting my gambling wins.

23 If I keep changing my numbers, I have less chances of winning than if I keep the same numbers every time.

H. Positive and Negative Affect Scale (Watson, Clark & Tellegen, 1988).

Used in Chapter 7.

This scale consists of a number of words that describe different feelings and emotions. Read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you feel this way right now, that is, at the present moment. Use the following scale to record your answers.

1	2	3	4	5
very slightly or not at all	a little	moderately	quite a bit	extremely

______Interested	______Irritable
______Distressed	______Alert
______Excited	______Ashamed
______Upset	______Inspired
______Strong	______Nervous
______Guilty	______Determined
______Scared	______Attentive
______Hostile	______Jittery
______Enthusiastic	______Active
______Proud	______Afraid

I. Sensation Seeking Scale, Form V (Zuckerman, Eysenck & Eysenck, 1976).

Used in Chapter 7.

Each of the items below contains two choices, A and B. Please indicate (circle) on your answer sheet which of the choices most describes your likes or the way you feel. In some cases you may find items in which both choices describe your likes or feelings. Please choose the one which better describes your likes or feelings.

1A. I like `wild' uninhibited parties.
1B I prefer quiet parties with good conversation.

2A. There are some movies I enjoy seeing a second or even third time.
2B. I can't stand watching a movie that I've seen before.

3A. I often wish I could be a mountain climber.
3B. I can't understand people who risk their necks climbing mountains.

4A. I dislike all body odours.
4B. I like some of the earthy body smells.

5A. I get bored seeing the same old faces.
5B. I like the comfortable familiarity of everyday friends.

6A. I like to explore a strange city or section of town by myself, even if it means getting lost.
6B. I prefer a guide when I am in a place I don't know well.

7A. I dislike people who do or say things just to shock or upset others.
7B. When you can predict almost everything a person will do or say he or she must be a bore.

8A. I usually don't enjoy a movie or play where I can predict what will happen in advance.
8B. I don't mind watching a movie or play where I can predict what will happen in advance.

9A. I have tried marijuana or would like to.

9B. I would never smoke marijuana.

10A. I would not like to try any drug which might produce strange and dangerous effects on me.

10B. I would like to try some of the new drugs that produce hallucinations.

11A. A sensible person avoids activities that are dangerous.

11B. I sometimes like to do things that are a little frightening.

12A. I dislike `swingers' (people who are uninhibited and free about sex).

12B. I enjoy the company of real `swingers'.

13A. I find that stimulants make me uncomfortable.

13B. I often like to get high (drinking liquor or smoking marijuana).

14A. I like to try new foods that I have never tasted before.

14B. I order the dishes with which I am familiar, so as to avoid disappointment and unpleasantness.

15A. I enjoy looking at home movies or travel slides.

15B. Looking at someone's home movies or travel slides bores me tremendously.

16A. I would like to take up the sport of water skiing.

16B. I would not like to take up the sport of water skiing.

17A. I would like to try surf board riding.

17B. I would not like to try surf board riding.

18A. I would like to take off on a trip with no preplanned or definite routes, or timetable.

18B. When I go on a trip I like to plan my route and timetable fairly carefully.

19A. I prefer the `down to earth' kinds of people as friends.

19B. I would like to make friends in some of the `far out' groups like artists or `punks'.

20A. I would not like to learn to fly an aeroplane.

20B. I would like to learn to fly an aeroplane.

21A. I prefer the surface of the water to the depths.

21B. I would like to go scuba diving.

22A. I would like to meet some persons who are homosexual (men or women).

22B. I stay away from anyone I suspect of being `gay or lesbian'.

23A. I would like to try parachute jumping.

23B. I would never want to try jumping out of a plane with or without a parachute.

24A. I prefer friends who are excitingly unpredictable.

24B. I prefer friends who are reliable and predictable.

25A. I am not interested in experience for its own sake.

25B. I like to have new and exciting experiences and sensations even if they are a little frightening, unconventional or illegal.

26A. The essence of good art is in its clarity, symmetry of form and harmony of colours.

26B. I often find beauty in the `clashing' of colours and irregular forms of modern paintings.

27A. I enjoy spending time in the familiar surroundings of home.

27B. I get restless if I have to stay around home for any length of time.

28A. I like to dive off the high board.

28B. I don't like the feeling I get standing on the high board (or I don't go near it at all).

29A. I like to date members of the opposite sex who are physically exciting.

29B. I like to date members of the opposite sex who share my values.

30A. Heavy drinking usually ruins a party because some people get loud and boisterous.

30B. Keeping the drinks full is the key to a good party.

31A. The worst social sin is to be rude.
31B. The worst social sin is to be a bore.

32A. A person should have considerable sexual experience before marriage.
32B. It's better if two married persons begin their sexual experience with each other.

33A. Even if I had the money I would not care to associate with flighty rich persons like those in the `jet set'.
33B. I could conceive of myself seeking pleasures around the world with the `jet set'.

34A. I like people who are sharp and witty even if they do sometimes insult others.
34B. I dislike people who have their fun at the expense of hurting the feelings of others.

35A. There is altogether too much portrayal of sex in movies.
35B. I enjoy watching many of the `sexy' scenes in movies.

36A. I feel best after taking a couple of drinks.
36B. Something is wrong with people who need liquor to feel good.

37A. People should dress according to some standard of taste, neatness and style.
37B. People should dress in individual ways even if the effects are sometimes strange.

38A. Sailing long distances in small sailing crafts is foolhardy.
38B. I would like to sail a long distance in a small but seaworthy sailing craft.

39A. I have no patience with dull or boring persons.
39B. I find something interesting in almost every person I talk to.

40A. Skiing down a high mountain slope is a good way to end up on crutches.
40B. I think I would enjoy the sensations of skiing very fast down a high mountain slope

APPENDIX 2

Supplementary tables from Chapter 3

Table A2.1

Indices of model fit for weighted LCA's conducted on the modified version of the DSM-IV Pathological Gambling Criteria used in the BGPS, scored using the cutoffs used in the BGPS reports (symptoms classified as present – items 1 – 7 > 1, items 8 – 10 – > 0).

Classes	Log-likelihood	AIC	BIC	SSABIC	Entropy	LMR-LRT *p*	VLMR-LRT *p*
BGPS 1999							
1-class	-2472.021	4964.042	5029.715	4997.939	-	-	-
2-class	-1849.968	3741.935	3879.849	3813.118	0.99	<.0001	<.0001
3-class	-1798.731	3661.463	**3871.617**	**3769.931**	0.967	.0104	.0099
4-class	-1773.361	**3632.722**	3915.116	3778.476	0.97	**.0327**	**.0343**
5-class	-1762.833	3633.667	3988.302	3816.708	0.972	.4925	.4879
6-class	-1753.605	3637.21	4064.085	3857.536	0.973	.5103	.5072
BGPS 2007							
1-class	-3272.314	6564.627	6630.758	6598.981	-	-	-
2-class	-2557.443	5156.886	5295.76	5229.029	**0.994**	**<.0001**	**<.0001**
3-class	-2508.816	5081.632	**5293.249**	**5191.563**	0.974	0.1013	0.0989
4-class	-2490.336	**5066.671**	5351.032	5214.392	0.984	0.2883	0.2846
5-class	-2484.135	5076.271	5433.375	5261.78	0.993	0.5255	0.5246
6-class	-2472.895	**5075.79**	5505.638	5299.088	0.852	0.4904	0.4899
BGPS 2010							
1-class	-3748.56	7517.121	7583.601	7551.824	-	-	-
2-class	-2831.913	5705.827	5845.435	5778.704	0.984	**<.0001**	**<.0001**
3-class	-2771.551	5607.102	**5819.839**	**5718.153**	0.958	0.1708	0.1676
4-class	-2745.868	5577.736	5863.602	5726.961	0.972	0.5028	0.5007
5-class	-2727.647	5563.294	5922.289	5750.693	0.969	0.1712	0.1703
6-class	-2715.692	**5561.385**	5993.508	5786.957	0.912	0.4336	0.4325
HSE 2012 & SHS 2012							
1-class	-2885.033	5790.066	5858.472	5826.694	-	-	-
2-class	-2233.364	4508.728	4652.381	4585.648	0.992	**<.0001**	**<.0001**
3-class	-2179.977	4423.954	**4642.852**	**4541.165**	0.984	0.2627	0.2581
4-class	-2159.378	**4404.755**	4698.9	4562.256	0.988	0.502	0.4999
5-class	-2143.427	4394.855	4764.246	4592.647	0.982	0.5484	0.5474
6-class	-2122.869	4375.738	4820.376	4613.821	0.983	0.3493	0.3486

Table A2.2

Response probabilities for two-latent class models based on an assessment derived from the DSM-IV Pathological Gambling Criteria used in the BGPS series, scored using the cutoff's from the BGPS series (scores 0-3, 1-7 > 1, 8-10 > 0). Classes are ordered by severity/size of group membership, and standard errors are reported in brackets.

	BGPS 1999		BGPS 2007		BGPS 2010		HSE 2012	
	L1 (98.65%)	L2 (1.35%)	L1 (98.75%)	L2 (1.25%)	L1 (98.05%)	L2 (1.95%)	L1 (98.9%)	L2 (1.1%)
1	0.019 (.002)	0.416 (.071)	0.052 (.004)	0.49 (.073)	0.019 (.002)	0.518 (.063)	0.024 (.003)	0.387 (.082)
2	0.012 (.002)	0.601 (.072)	0.011 (.002)	0.635 (.07)	0.021 (.003)	0.633 (.061)	0.007 (.001)	0.499 (.087)
3	0.001 (.001)	0.355 (.073)	0.001 (0)	0.444 (.07)	0.003 (.001)	0.458 (.066)	0.001 (.001)	0.363 (.09)
4	0 (0)	0.315 (.073)	0 (0)	0.468 (.078)	0.001 (.001)	0.457 (.081)	0 (0)	0.252 (.067)
5	0.001 (.001)	0.504 (.089)	0.002 (.001)	0.522 (.091)	0.001 (0)	0.364 (.075)	0.001 (0)	0.296 (.073)
6	0 (0)	0.321 (.072)	0 (0)	0.465 (.081)	0.000 (0)	0.267 (.066)	0.001 (.001)	0.448 (.096)
7	0.001 (.001)	0.396 (.086)	0.002 (.001)	0.32 (.071)	0.003 (.001)	0.281 (.057)	0.002 (.001)	0.355 (.081)
8	0 (0)	0.185 (.056)	0 (0)	0.101 (.043)	0 (0)	0.147 (.044)	0 (0)	0.261 (.08)
9	0 (0)	0.239 (.06)	0 (0)	0.28 (.073)	0.001 (0)	0.244 (.057)	0.001 (0)	0.304 (.086)
10	0.001 (0)	0.346 (.078)	0.002 (.001)	0.465 (.081)	0.002 (.001)	0.354 (.067)	0.001 (0)	0.393 (.094)

Table A2.3

Response probabilities for three latent class model for the adapted version of the DSM-IV Pathological Gambling Criteria used in the BGPS series, scored using the cutoff's recommended in the BGPS series (scores 0-3, 1-7 > 1, 8-10 > 0). Latent classes are ordered by severity/group membership, and standard errors are reported in brackets.

		1	2	3	4	5	6	7	8	9	10
BGPS 1999	1 (97.59%)	0.017 (.002)	0.007 (.003)	0.001 (.001)	0 (0)	0.001 (.001)	0 (0)	0.001 (.001)	0 (0)	0 (0)	0.001 (0)
	2 (1.85%)	0.3 (.087)	0.585 (.107)	0.106 (.054)	0.107 (.052)	0.184 (.067)	0.05 (.037)	0.092 (.046)	0 (0)	0.014 (.015)	0.049 (.031)
	3 (0.56%)	0.451 (.109)	0.452 (.109)	0.565 (.111)	0.446 (.1)	0.727 (.096)	0.626 (.1)	0.698 (.104)	0.441 (.121)	0.53 (.115)	0.692 (.108)
BGPS 2007	1 (97.88%)	0.049 (.004)	0.007 (.002)	0 (0)	0.001 (0)	0.001 (.001)	0 (0)	0.002 (.001)	0 (0)	0 (0)	0.002 (.001)
	2 (1.58%)	0.426 (.071)	0.55 (.094)	0.177 (.056)	0.126 (.047)	0.08 (.068)	0.106 (.066)	0.045 (.028)	0.028 (.02)	0.101 (.049)	0.179 (.064)
	3 (0.53%)	0.587 (.112)	0.637 (.097)	0.61 (.125)	0.761 (.136)	1 (0)	0.788 (.082)	0.648 (.128)	0.154 (.081)	0.407 (.116)	0.625 (.131)
BGPS 2010	1 (96.57%)	0.015 (.002)	0.016 (.002)	0.002 (.001)	0.001 (.001)	0 (0)	0 (0)	0.003 (.001)	0 (0)	0 (0)	0.002 (.001)
	2 (2.83%)	0.373 (.082)	0.466 (.093)	0.214 (.07)	0.188 (.068)	0.137 (.07)	0.07 (.042)	0.102 (.044)	0.036 (.023)	0.091 (.05)	0.145 (.057)
	3 (0.6%)	0.684 (.126)	0.808 (.116)	0.81 (.111)	0.847 (.118)	0.712 (.102)	0.642 (.153)	0.594 (.146)	0.362 (.137)	0.482 (.142)	0.657 (.132)
HSE & SHS 2012	1 (98.51%)	0.023 (.003)	0.005 (.001)	0 (.001)	0 (0)	0.001 (0)	0.001 (.001)	0.002 (.001)	0 (0)	0 (0)	0 (0)
	2 (1.25%)	0.335 (.086)	0.423 (.097)	0.172 (.062)	0.166 (.062)	0.208 (.066)	0.279 (.086)	0.273 (.084)	0.048 (.032)	0.08 (.053)	0.166 (.066)
	3 (0.23%)	0.479 (.166)	0.578 (.186)	0.837 (.088)	0.355 (.15)	0.379 (.155)	0.727 (.176)	0.401 (.164)	0.961 (.031)	1 (0)	1 (0)

Table A2.4

Frequency distributions for each score compared against each latent class on the assessment derived from the DSM-IV Pathological Gambling criteria, scored using the same method as the BGPS reports (items rated from 0-3 by respondent, scored as present on items 1 – 7 if > 1, on items 8 – 10 if > 0).

	BGPS 1999			BGPS 2007			BGPS 2010			SHS/HSE 2012		
DSM Score	1	2	3	1	2	3	1	2	3	1	2	3
0	5005	0	0	5065	0	0	5310	0	0	6592	0	0
1	168	9	0	346	5	0	239	18	0	238	1	0
2	0	35	0	2	33	0	0	60	0	0	36	0
3	0	8	2	0	17	2	0	24	0	0	14	1
4	0	5	6	0	2	4	0	13	1	0	6	3
5	0	0	2	0	2	7	0	2	7	0	0	0
6	0	0	12	0	0	6	0	0	7	0	3	4
7	0	0	2	0	0	1	0	0	8	0	2	1
8	0	0	2	0	0	7	0	0	6	0	0	1
9	0	0	1	0	0	1	0	0	2	0	0	3
10	0	0	1	0	0	2	0	0	2	0	0	2

Table A2.5

Indices of model fit for weighted LCA's conducted on the modified version of the DSM-IV Pathological Gambling Criteria used in the BGPS, classifying respondents who gave a response other than 'Never' (0) to any of the items as displaying a symptom present.

Classes	Log-likelihood	AIC	BIC	SSABIC	Entropy	LMR-LRT *p*	VLMR-LRT *p*
BGPS 1999							
1-class	-7401.198	14102.395	14168.068	14136.291	-	-	-
2-class	-5706.346	11454.692	11592.606	11525.875	**0.96**	<.001	<.001
3-class	-5527.124	11118.248	**11328.402**	11226.717	0.93	**<.001**	**<.001**
4-class	-5487.991	11061.982	11344.377	**11207.737**	0.92	0.145	0.142
5-class	-5473.252	11054.503	11409.138	11237.544	0.93	**0.031**	**0.030**
6-class	**-5458.301**	**11046.602**	11473.748	11266.929	0.87	0.095	0.093
BGPS 2007							
1-class	-8013.933	16047.865	16113.996	16082.219	-	-	-
2-class	-6553.48	13148.96	13287.834	13221.102	**0.94**	<.001	<.001
3-class	-6339.104	12742.208	**12953.825**	12852.139	0.89	**<.001**	**<.001**
4-class	-6300.403	12686.807	12971.168	**12834.527**	0.86	0.087	0.085
5-class	-6271.074	12650.149	13007.253	12835.658	0.90	0.380	0.377
6-class	-6250.972	**12631.944**	13061.792	12855.242	0.92	0.355	0.353
BGPS 2010							
1-class	-9670.177	19360.354	19426.835	19395.058	-	-	-
2-class	-7689.533	15421.067	15560.675	15493.944	0.93	<.001	<.001
3-class	-7404.648	14873.296	**15086.033**	14984.347	0.89	**<.001**	**<.001**
4-class	-7361.663	14809.325	15095.191	**14958.55**	0.89	0.104	0.102
5-class	-7342.02	**14792.039**	15151.034	14979.438	0.90	0.553	0.551
6-class	-7332.073	14794.146	15226.269	15019.718	0.90	0.683	0.682
HSE 2012 & SHS 2012							
1-class	-8702.537	17425.074	17493.48	17461.703	-	-	-
2-class	-7016.133	14074.266	14217.918	14151.185	0.95	0.011	0.010
3-class	-6738.368	13540.736	13759.639	13657.946	0.91	**0.030**	**0.029**
4-class	-6655.985	13397.969	**13692.114**	**13555.47**	0.90	0.078	0.076
5-class	-6630.339	13368.678	13738.07	13566.47	0.92	0.258	0.256
6-class	-6610.379	**13350.758**	13795.396	13588.841	0.93	0.423	0.421

Table A2.6

Response probabilities for the adapted version of the DSM-IV Pathological Gambling Criteria, with cutoff's of any behaviour endorsed more than 'never'. Three (and four in the case of the SHS & HSE 2012 data) class solutions. Latent classes are ordered by severity/group membership, and standard errors are reported in brackets.

	Class	1	2	3	4	5	6	7	8	9	10
BGPS	1 (92.31%)	0.046 (.004)	0.09 (.006)	0.004 (.001)	0 (0)	0.013 (.002)	0 (0)	0.001 (.001)	0 (0)	0 (0)	0 (0)
1999	2 (6.69%)	0.625 (.043)	0.796 (.036)	0.265 (.035)	0.096 (.022)	0.274 (.031)	0.067 (.02)	0.128 (.025)	0 (0)	0.009 (.005)	0.013 (.007)
	3 (1.00%)	0.855 (.055)	0.892 (.049)	0.778 (.066)	0.789 (.071)	0.867 (.064)	0.914 (.053)	0.912 (.054)	0.246 (.076)	0.296 (.076)	0.467 (.102)
BGPS	1 (88.95%)	0.068 (.006)	0.052 (.006)	0.005 (.002)	0 (.001)	0.007 (.002)	0.002 (.001)	0.002 (.001)	0 (0)	0 (0)	0 (0)
2007	2 (9.62%)	0.621 (.038)	0.675 (.045)	0.251 (.036)	0.079 (.022)	0.17 (.024)	0.074 (.022)	0.07 (.024)	0.004 (.003)	0.002 (.002)	0.022 (.010)
	3 (1.44%)	0.8 (.066)	0.868 (.068)	0.864 (.066)	0.754 (.064)	0.769 (.095)	0.847 (.082)	0.809 (.065)	0.058 (.032)	0.241 (.08)	0.377 (.092)
BGPS	1 (86.69%)	0.033 (.004)	0.112 (.007)	0.005 (.002)	0 (0)	0.005 (.001)	0.001 (.001)	0 (0)	0 (0)	0 (0)	0 (0)
2010	2 (11.44%)	0.544 (.038)	0.776 (.034)	0.293 (.032)	0.099 (.022)	0.158 (.022)	0.085 (.017)	0.117 (.02)	0.001 (.001)	0.01 (.005)	0.023 (.008)
	3 (1.87%)	0.899 (.068)	0.975 (.021)	0.858 (.06)	0.858 (.051)	0.807 (.065)	0.813 (.063)	0.67 (.076)	0.158 (.049)	0.243 (.062)	0.365 (.071)
HSE &	1 (90.49%)	0.057 (.006)	0.058 (.008)	0.001 (.001)	0 (0)	0.002 (.001)	0.001 (.001)	0.001 (.001)	0 (0)	0 (0)	0 (0)
SHS	2 (8.15%)	0.618 (.064)	0.775 (.06)	0.184 (.041)	0.035 (.027)	0.103 (.03)	0.051 (.024)	0.066 (.031)	0.004 (.004)	0.005 (.011)	0 (0)
2012	3 (1.36%)	0.795 (.104)	0.928 (.086)	0.716 (.109)	0.798 (.132)	0.662 (.108)	0.683 (.123)	0.794 (.106)	0.187 (.084)	0.25 (.085)	0.339 (.117)
HSE &	1 (88.95%)	0.053 (.007)	0.051 (.009)	0.001 (.001)	0 (0)	0.002 (.001)	0.001 (.001)	0.001 (.001)	0 (0)	0 (0)	0 (0)
SHS	2 (9.14%)	0.558 (.064)	0.723 (.074)	0.143 (.033)	0.007 (.009)	0.07 (.016)	0.033 (.015)	0.038 (.016)	0.03 (.004)	0 (0)	0 (0)
2012	3 (1.65%)	0.754 (.076)	0.883 (.058)	0.574 (.075)	0.631 (.089)	0.529 (.076)	0.474 (.08)	0.613 (.085)	0.004 (.004)	0.089 (.039)	0.118 (.05)
	4 (0.026%)	0.775 (.15)	1 (0)	1 (0)	1 (0)	0.993 (.068)	1 (0)	1 (0)	0.935 (.051)	0.889 (.107)	1 (0)

Table A2.7

Frequency distributions for each score compared against each latent class on the assessment derived from the DSM-IV Pathological Gambling criteria, scored as a symptom being present if any response other than 'Never' was given.

	BGPS 1999			BGPS 2007			BGPS 2010			SHS/HSE 2012		
DSM Score	1	2	3	1	2	3	1	2	3	1	2	3
0	4151	0	0	4286	0	0	4222	0	0	5554	0	0
1	738	0	0	744	5	0	861	10	0	854	14	0
2	0	198	0	0	246	0	0	308	0	0	286	0
3	0	68	0	0	107	0	0	118	0	0	85	5
4	0	34	0	0	33	5	0	64	0	0	23	11
5	0	17	7	0	4	18	0	8	30	0	0	27
6	0	0	12	0	0	19	0	0	26	0	0	20
7	0	0	15	0	0	15	0	0	26	0	0	13
8	0	0	5	0	0	9	0	0	11	0	0	3
9	0	0	8	0	0	7	0	0	5	0	0	6
10	0	0	4	0	0	3	0	0	10	0	0	11

Table A2.9

Indices of model fit for weighted LCA's conducted on the modified version of the DSM-IV Pathological Gambling Criteria used in the BGPS series, in the polytomous format the assessments was administered in.

Classes	Log-likelihood	AIC	BIC	SSABIC	Entropy	LMR-LRT *p*	VLMR-LRT *p*
BGPS 1999							
1-class	-8264.801	16589.601	16786.621	16691.291	-	-	-
2-class	-6857.508	13837.015	14237.622	14043.784	**0.969**	<.0001	<.0001
3-class	-6634.07	13452.141	**14056.334**	**13763.988**	0.927	**.0038**	**.0037**
4-class	-6575.468	13396.935	14204.715	13813.861	0.926	.7766	.7766
5-class	-6530.489	13368.978	14380.345	13890.983	0.937	.7856	.7856
6-class	-6500.12	**13370.239**	14585.192	13997.323	0.937	.7603	.7603
BGPS 2007							
1-class	-9643.828	19347.655	19546.047	19450.716	-	-	-
2-class	-8099.425	16320.849	16724.245	16530.406	**0.957**	<.0001	<.0001
3-class	-7785.486	15754.972	**16363.372**	16071.025	0.915	**.0278**	**.0272**
4-class	-7687.598	15621.196	16434.601	**16043.745**	0.901	.762	.762
5-class	-7642.304	15592.609	16611.018	16121.654	0.914	.8478	.8478
6-class	-7609.158	**15588.317**	16811.731	16223.858	0.899	.7619	.7619
BGPS 2010							
1-class	-11590.23	23240.456	23439.897	23344.566	-	-	-
2-class	-9536.282	19194.564	19600.095	19406.255	0.946	<.0001	<.0001
3-class	-9164.643	18513.285	**19124.905**	18832.557	0.914	**.0026**	**.0025**
4-class	-9059.587	18365.174	19182.884	**18792.026**	0.894	.7866	.7866
5-class	-9019.424	18346.849	19370.648	18881.281	0.905	.7889	.7889
6-class	-8986.905	**18343.81**	19573.699	18985.824	0.898	.7626	.7626
HSE 2012 & SHS 2012							
1-class	-10099.83	20259.66	20464.877	20369.544	-	-	-
2-class	-8353.352	16828.703	17245.979	17052.135	0.965	**<.001**	**<.001**
3-class	-8033.812	16251.624	**16880.958**	16588.603	0.912	0.7259	0.7255
4-class	-7915.787	16077.575	16918.966	**16528.101**	0.917	0.7699	0.7698
5-class	-7838.602	15985.204	17038.653	16549.278	0.927	0.7608	0.7608
6-class	-7788.164	**15946.327**	17211.835	16623.948	0.939	0.769	0.769

Frequency distributions for this type of scoring are not reported, as it is unclear whether this approach can be meaningfully represented in a continuous fashion (i.e. present/absent criteria, PGSI).

Table A2.10 (part 1 of 2)

Response probabilities from polytomous LCAs for the DSM-IV Pathological Gambling criteria derived assessment. Groups are ordered by severity/group membership, and standard errors are reported in brackets.

Item		1999			2007			2010			2012		
		L1 (92.10%)	L2 (6.73%)	L3 (1.17%)	L1 (90.15%)	L2 (8.77%)	L3 (1.08%)	L1 (88.19%)	L2 (10.43%)	L3 (1.38%)	L1 (90.78%)	L2 (7.95%)	L3 (1.27%)
1	0	0.954 (.004)	0.401 (.042)	0.126 (.048)	0.928 (.006)	0.344 (.034)	0.153 (.049)	.963 (.005)	.412 (.04)	.021 (.025)	.942 (.006)	.373 (.059)	.182 (.073)
	1	0.034 (.004)	0.466 (.042)	0.497 (.079)	0.031 (.003)	0.483 (.034)	0.373 (.081)	.028 (.004)	.464 (.034)	.427 (.082)	.041 (.005)	.523 (.056)	.497 (.085)
	2	0.007 (.001)	0.085 (.019)	0.259 (.07)	0.029 (.003)	0.148 (.019)	0.248 (.062)	.006 (.001)	.095 (.019)	.328 (.068)	.009 (.002)	.096 (.023)	.29 (.071)
	3	0.005 (.001)	0.047 (.015)	0.118 (.039)	0.013 (.002)	0.025 (.011)	0.226 (.076)	.003 (.001)	.029 (.008)	.224 (.071)	.008 (.002)	.008 (.007)	.031 (.023)
2	0	0.911 (.006)	0.21 (.04)	0.109 (.045)	0.942 (.005)	0.3 (.038)	0.07 (.035)	.881 (.007)	.182 (.032)	.014 (.014)	.94 (.008)	.224 (.065)	.043 (.044)
	1	0.086 (.006)	0.625 (.035)	0.388 (.08)	0.055 (.005)	0.589 (.034)	0.279 (.069)	.11 (.007)	.667 (.031)	.279 (.092)	.059 (.007)	.715 (.054)	.522 (.081)
	2	0.002 (.001)	0.135 (.026)	0.299 (.072)	0.003 (.001)	0.086 (.019)	0.293 (.079)	.007 (.001)	.12 (.019)	.46 (.073)	.001 (.001)	.043 (.02)	.275 (.066)
	3	0.001 (.001)	0.03 (.013)	0.204 (.057)	0 (0)	0.024 (.011)	0.358 (.09)	.002 (.001)	.031 (.009)	.248 (.069)	.001 (.001)	.019 (.009)	.16 (.061)
3	0	0.996 (.001)	0.757 (.034)	0.212 (.064)	0.994 (.002)	0.704 (.033)	0.069 (.044)	.994 (.002)	.66 (.039)	.061 (.037)	.999 (.001)	.814 (.041)	.23 (.81)
	1	0.004 (.001)	0.22 (.031)	0.423 (.078)	0.006 (.002)	0.28 (.031)	0.482 (.076)	.005 (.001)	.293 (.033)	.411 (.089)	.001 (.001)	.173 (.039)	.495 (.75)
	2	0 (0)	0.019 (.009)	0.259 (.066)	0 (0)	0.011 (.007)	0.296 (.066)	.001 (.001)	.042 (.011)	.341 (.071)	0 (0)	.011 (.009)	.187 (.74)
	3	0 (0)	0.003 (.004)	0.106 (.042)	0 (0)	0.004 (.003)	0.153 (.07)	0 (0)	.006 (.003)	.187 (.064)	0 (0)	.002 (.002)	.088 (.44)
4	0	1 (0)	0.92 (.019)	0.233 (.07)	0.999 (.001)	0.892 (.023)	0.182 (.064)	.999 (0)	.851 (.037)	.163 (.057)	1 (0)	.962 (.03)	.158 (.083)
	1	0 (0)	0.074 (.018)	0.42 (.085)	0.001 (.001)	0.098 (.02)	0.285 (.084)	0 (0)	.115 (.028)	.327 (.092)	0 (0)	.035 (.029)	.63 (.088)
	2	0 (0)	0.006 (.004)	0.207 (.068)	0 (0)	0.01 (.006)	0.344 (.066)	0 (0)	.033 (.015)	.282 (.062)	0 (0)	(0)	.133 (.049)
	3	0 (0)	0 (0)	0.14 (.048)	0 (0)	0 (0)	0.189 (.056)	.001 (0)	0 (0)	.228 (.075)	0 (0)	.003 (.003)	.08 (.039)
5	0	0.987 (.002)	0.731 (.033)	0.204 (.066)	0.992 (.002)	0.802 (.026)	0.148 (.073)	.995 (.001)	.798 (.035)	.166 (.06)	.998 (.001)	.893 (.027)	.302 (.097)
	1	0.012 (.002)	0.246 (.031)	0.259 (.076)	0.008 (.002)	0.178 (.024)	0.303 (.077)	.005 (.001)	.188 (.033)	.327 (.089)	.002 (.001)	.098 (.024)	.415 (.072)
	2	0 (0)	0.017 (.009)	0.4 (.068)	0 (0)	0.011 (.005)	0.265 (.063)	0 (0)	.011 (.005)	.247 (.063)	0 (0)	.005 (.004)	.23 (.065)
	3	0 (0)	0.006 (.004)	0.137 (.046)	0 (0)	0.01 (.005)	0.284 (.083)	0 (0)	.003 (.003)	.26 (.08)	0 (0)	.004 (.003)	.052 (.032)

Table A2.10 (part 2 of 2)

Item			1999			2007			2010			2012	
		L1 (92.10%)	L2 (6.73%)	L3 (1.17%)	L1 (90.15%)	L2 (8.77%)	L3 (1.08%)	L1 (88.19%)	L2 (10.43%)	L3 (1.38%)	L1 (90.78%)	L2 (7.95%)	L3 (1.27%)
6	0	1 (0)	0.937 (.019)	0.191 (.061)	0.998 (.001)	0.885 (.023)	0.143 (.06)	.999 (.001)	.871 (.03)	.176 (.07)	0.999 (.001)	0.938 (.022)	0.331 (.129)
	1	0 (0)	0.063 (.019)	0.427 (.075)	0.001 (.001)	0.109 (.022)	0.371 (.078)	.001 (.001)	.12 (.028)	.467 (.079)	0.001 (.001)	0.044 (.016)	0.329 (.07)
	2	0 (0)	0 (0)	0.246 (.064)	0 (0)	0.006 (.004)	0.231 (.048)	0 (0)	.009 (.005)	.187 (.061)	0 (0)	0.013 (.012)	0.252 (.089)
	3	0 (0)	0 (0)	0.136 (.043)	0 (0)	0 (0)	0.256 (.085)	0 (0)	0 (0)	.171 (.059)	0 (0)	0.005 (.005)	0.088 (.044)
7	0	0.999 (.001)	0.886 (.023)	0.145 (.061)	0.998 (.001)	0.894 (.022)	0.164 (.064)	.999 (0)	.855 (.026)	.238 (.073)	0.999 (.001)	0.922 (.031)	0.214 (.098)
	1	0.001 (.001)	0.093 (.02)	0.405 (.081)	0 (0)	0.095 (.021)	0.452 (.086)	.001 (0)	.104 (.022)	.407 (.07)	0 (.001)	0.06 (.023)	0.428 (.084)
	2	0 (0)	0.011 (.007)	0.245 (.063)	0 (0)	0.002 (.002)	0.249 (.073)	0 (0)	.016 (.007)	.233 (.06)	0 (0)	0.015 (.013)	0.189 (.057)
	3	0 (0)	0.009 (.006)	0.205 (.057)	0.001 (0)	0.009 (.006)	0.135 (.051)	0 (0)	.025 (.007)	.122 (.047)	0 (0)	0.003 (.004)	0.169 (.066)
8	0	1 (0)	1 (0)	0.789 (.063)	1 (0)	0.995 (.004)	0.924 (.041)	1 (0)	.998 (.002)	.789 (.072)	1 (0)	0.996 (.004)	0.8 (.084)
	1	0 (0)	0 (0)	0.089 (.041)	0 (0)	0.002 (.002)	0 (0)	0 (0)	.002 (.002)	.108 (.044)	0 (0)	0 (0)	0.086 (.046)
	2	0 (0)	0 (0)	0.085 (.042)	0 (0)	0 (0)	0.044 (.032)	0 (0)	0 (0)	.072 (.037)	0 (0)	0 (0)	0.075 (.044)
	3	0 (0)	0 (0)	0.037 (.026)	0 (0)	0.003 (.003)	0.032 (.024)	0 (0)	0 (0)	.031 (.023)	0 (0)	0.004 (.004)	0.038 (.029)
9	0	1 (0)	0.992 (.005)	0.745 (.063)	1 (0)	0.997 (.003)	0.692 (.084)	1 (0)	.992 (.004)	.67 (.094)	1 (0)	0.99 (.011)	0.765 (.088)
	1	0 (0)	0.008 (.005)	0.166 (.053)	0 (0)	0.002 (.002)	0.17 (.054)	0 (0)	.008 (.004)	.187 (.063)	0 (0)	0.01 (.011)	0.143 (.067)
	2	0 (0)	0 (0)	0.055 (.032)	0 (0)	0 (0)	0.037 (.026)	0 (0)	0 (0)	.075 (.036)	0 (0)	0 (0)	0.047 (.026)
	3	0 (0)	0 (0)	0.035 (.025)	0 (0)	0.002 (.002)	0.101 (.047)	0 (0)	0 (0)	.068 (.035)	0 (0)	0 (0)	0.045 (.031)
10	0	1 (0)	0.986 (.007)	0.603 (.082)	1 (0)	0.971 (.011)	0.53 (.094)	.999 (0)	.965 (.013)	.601 (.096)	1 (0)	0.998 (.002)	0.651 (.109)
	1	0 (0)	0.014 (.007)	0.229 (.061)	0 (0)	0.027 (.01)	0.252 (.06)	0 (0)	.032 (.013)	.243 (.061)	0 (0)	0.002 (.002)	0.226 (.082)
	2	0 (0)	0 (0)	0.13 (.051)	0 (0)	0 (0)	0.126 (.053)	0 (0)	.004 (.002)	.098 (.045)	0 (0)	0 (0)	0.069 (.031)
	3	0 (0)	0 (0)	0.038 (.027)	0 (0)	0.002 (.002)	0.091 (.044)	0 (0)	0 (0)	.057 (.033)	0 (0)	0 (0)	0.053 (.034)

Table A2.11

Mean items scores for each of the adapted DSM-IV Pathological Gambling criteria assessment items, for each of the three latent classes from each of the surveys that the PGSI was administered in (BGPS 1999, BGPS 2007, BGPS 2010, SHS & HSE 2012).

		1	2	3	4	5	6	7	8	9	10
BGPS	1	0.0971	0.0048	0	0.0111	0.0010	0.0593	0.0004	0.0004	0	0
1999	2	1.0574	0.3100	0.0959	0.3648	0.1653	0.9493	0.0707	0	0.0099	0.0151
	3	1.6031	1.2587	1.2725	1.4886	1.5060	1.3704	1.3304	0.3717	0.3796	0.6084
BGPS	1	0.1271	0.0633	0.0065	0.0010	0.0075	0.0022	0.0025	0	0.0009	0.0009
2007	2	0.9833	0.9599	0.3682	0.1369	0.2821	0.1415	0.1645	0.0124	0.0080	0.0372
	3	1.5890	1.9459	1.5509	1.5849	1.7206	1.6390	1.3898	0.1893	0.5646	0.8043
BGPS	1	0.0460	0.1352	0.0075	0.0017	0.0047	0.0017	0.0012	0.0002	0.0009	0.0013
2010	2	0.8715	1.0656	0.4439	0.2131	0.2498	0.1504	0.2361	0.0015	0.0095	0.0432
	3	1.7750	1.9580	1.6653	1.5859	1.6560	1.4124	1.2564	0.3594	0.5610	0.6331
SHS/HSE	1	0.0861	0.0736	0.0021	0	0.0024	0.0017	0.0008	0	0	0.0002
2012	2	0.9367	0.9833	0.2639	0.0628	0.1679	0.1130	0.1468	0.0162	0.0164	0.0036
	3	1.1834	1.5587	1.1855	1.1705	1.0489	1.1363	1.3398	0.3667	0.3788	0.5447

Table A2.12

Response probabilities for the LCA conducted on a DSM-IV Pathological Gambling criteria derived assessment administered in the APMS 2007. Classes are ordered by severity/group membership, and standard errors are reported in brackets.

Item	L1 – 97.58%	L2 – 2.02%	L3 - 0.41%
1	0.004 (.002)	0.374 (.067)	0.975 (.038)
2	0.001 (.001)	0.188 (.051)	0.947 (.07)
3	0.009 (.002)	0.285 (.066)	1 (0)
4	0 (0)	0.071 (.032)	1 (0)
5	0.003 (.001)	0.274 (.068)	1 (0)
6	0.006 (.002)	0.437 (.075)	1 (0)
7	0.001 (.001)	0.086 (.042)	0.922 (.072)
8	0 (0)	0.035 (.018)	0.379 (.168)
9	0.001 (.001)	0.051 (.023)	0.616 (.16)
10	0 (0)	0.04 (.026)	0.613 (.17)

Note: The order in which these were presented to respondents differed from the other DSM measure (see Table S1). The order used in the graphs to compare these is as follows: 6, 1, 2, 4, 5, 7, 3, 8, 9, 10.

Table A2.13

Frequency distributions compared for each scored against each latent class for the DSM-IV Pathological Gambling criteria-derived assessment used in the APMS 2007.

DSM Score	1	2	3
0	3362	0	0
1	120	1	0
2	0	43	0
3	0	22	0
4	0	1	0
5	0	5	0
6	0	0	1
7	0	0	5
8	0	0	0
9	0	0	3
10	0	0	5

Table A2.14

Indices of model fit for weighted polytomous LCA's conducted on Problem Gambling Severity Index data from the BGPS 2007, 2010 and SHS & HSE 2012.

Classes	Log-likelihood	AIC	BIC	SSABIC	Entropy	LMR-LRT *p*	VLMR-LRT *p*
BGPS 2007							
1-class	-6446.533	12947.067	13125.98	13040.182	-	-	-
2-class	-4751.487	9612.975	9977.427	9802.654	**0.981**	**.0032**	**.0031**
3-class	-4481.076	9128.152	**9678.144**	9414.395	0.967	.1543	.1551
4-class	-4362.823	8947.646	9683.177	**9330.453**	0.957	.828	.828
5-class	-4324.576	8927.152	9848.222	9406.523	0.965	.7723	.7723
6-class	-4293.064	**8920.128**	10026.063	9496.063	0.968	.7606	.7606
BGPS 2010							
1-class	-7425.183	14904.366	15083.892	14998.094	-	-	-
2-class	-5431.798	10973.596	11339.296	11164.523	0.976	<.0001	<.0001
3-class	-5135.229	10436.458	10988.334	10724.584	0.95	**.0222**	**.0217**
4-class	-5013.377	10248.755	**10986.805**	**10634.079**	0.945	.7769	.7768
5-class	-4955.385	10188.771	11112.996	10671.295	0.964	.7603	.7603
6-class	-4908.076	**10150.153**	11260.552	10729.876	0.941	.7659	.7659
HSE 2012 & SHS 2012							
1-class	-5938.988	11931.977	12116.836	12031.037	-	-	-
2-class	-4255.934	8621.869	8998.434	8823.657	0.986	**<.0001**	**<.0001**
3-class	-4051.545	8269.091	**8837.362**	8573.607	0.984	.0662	.0652
4-class	-3967.105	8156.211	8916.199	**8563.456**	0.986	.2875	.2865
5-class	-3932.543	8143.086	9094.769	8653.059	0.97	.8062	.8062
6-class	-3896.419	**8126.839**	9270.228	8739.541	0.971	.7611	.7611

Table A2.15

Means item scores for each of the Problem Gambling Severity Index items, for each of the three latent classes from each of the surveys that the PGSI was administered in (BGPS 2007, BGPS 2010, SHS & HSE 2012).

		1	2	3	4	5	6	7	8	9
BGPS 2007	1	0.013	0.003	0.045	0.001	0.001	0.0003	0.006	0	0.004
	2	0.697	0.298	0.804	0.118	0.169	0.079	0.355	0.142	0.334
	3	1.565	1.203	1.634	0.882	1.644	1.224	1.463	1.508	1.738
BGPS 2010	1	0.015	0.002	0.028	0.001	0.001	0.001	0.006	0.001	0.008
	2	0.616	0.266	0.711	0.103	0.156	0.127	0.392	0.084	0.446
	3	1.474	0.844	1.416	0.903	1.443	1.129	1.176	1.261	1.324
SHS/HSE 2012	1	0.010	0.002	0.029	0.0004	0	0.001	0.003	0	0.002
	2	0.555	0.248	0.715	0.082	0.405	0.264	0.421	0.161	0.552
	3	1.734	1.234	1.426	1.132	1.870	1.831	1.772	1.702	1.824

Table A2.16

Frequency distributions for each score compared against each latent class for the Problem Gambling Severity Index.

	BGPS 2007			BGPS 2010			SHS/HSE 2012		
PGSI Score	1	2	3	1	2	3	1	2	3
0	4984	0	0	5075	0	0	6453	0	0
1	312	1	0	300	124	0	254	4	0
2	15	99	0	9	47	0	18	77	0
3	15	47	0	9	28	0	8	45	0
4	0	23	0	0	30	1	0	19	0
5	0	17	0	0	5	0	0	19	0
6	0	7	0	0	0	7	0	19	0
7	0	5	6	0	0	12	0	4	0
8	0	0	7	0	0	14	0	4	0
9	0	0	13	0	0	15	0	2	3
10	0	0	2	0	0	4	0	0	2
11	0	0	1	0	0	3	0	0	6
12	0	0	2	0	0	1	0	0	3
13	0	0	1	0	0	4	0	0	2
14	0	0	1	0	0	0	0	0	3
15	0	0	1	0	0	0	0	0	4
16	0	0	4	0	0	1	0	0	0
17	0	0	1	0	0	4	0	0	0
18	0	0	0	0	0	1	0	0	1
19	0	0	3	0	0	3	0	0	0
20	0	0	1	0	0	0	0	0	0
21	0	0	1	0	0	2	0	0	0
22	0	0	0	0	0	0	0	0	1
23	0	0	2	0	0	1	0	0	0
24	0	0	0	0	0	1	0	0	0
25	0	0	0	0	0	1	0	0	0
26	0	0	0	0	0	1	0	0	0
27	0	0	4	0	0	1	0	0	4

Table A2.17

Indices of model fit for weighted LCA's conducted on the South Oaks Gambling Screen from BGPS 1999 data, and an assessment derived from the DSM-IV Pathological Gambling criteria, administered in a Yes/No format in the APMS 2007.

Classes	Log-likelihood	AIC	BIC	SSABIC	Entropy	LMR-LRT *p*	VLMR-LRT *p*
BGPS 1999 - SOGS							
1-class	-6564.075	13168.15	13298.53	13234.977	-	-	-
2-class	-5235.222	10552.445	10819.723	10689.44	**0.966**	<.0001	<.0001
3-class	-5100.393	10324.786	**10728.964**	**10531.949**	0.94	**.0031**	**.0028**
4-class	-5049.3	10264.601	10805.677	10541.932	0.942	.4121	.4095
5-class	-5011.744	10231.487	10909.462	10578.986	0.958	.1983	.1964
6-class	-4984.704	**10219.409**	11034.283	10637.076	0.956	.5296	.5278
APMS 2007 – DSM (Y/N)							
1-class	-2214.985	4449.969	4511.767	4479.992	-	-	-
2-class	-1620.285	3282.569	3412.344	3345.617	**0.983**	<.0001	<.0001
3-class	-1527.795	3119.591	**3317.343**	**3215.663**	0.959	**.0013**	**.0012**
4-class	-1508.86	3103.719	3369.449	3232.817	0.962	.1862	.1812
5-class	-1489.371	3086.742	3420.449	3248.865	0.981	.3126	.2934
6-class	-1476.972	**3083.091**	3485.627	3279.091	0.986	.2013	.1996

Table A2.18

Response probabilities for the LCA conducted on the South Oaks Gambling Screen Data collected as part of the BGPS 1999 questionnaire. Groups are ordered by severity/group membership, and standard errors are reported in brackets.

	L1 – 93.72%	L2 – 5.39%	L3 – 0.9%
4	0.015 (.002)	0.124 (.026)	0.52 (.099)
5	0.011 (.002)	0.224 (.045)	0.601 (.081)
7	0.019 (.003)	0.412 (.058)	0.736 (.08)
8	0.014 (.003)	0.475 (.059)	0.704 (.075)
9	0.006 (.002)	0.297 (.052)	0.76 (.074)
10	0.005 (.001)	0.093 (.024)	0.684 (.099)
11	0.004 (.001)	0.104 (.02)	0.482 (.098)
13	0 (0)	0.079 (.025)	0.462 (.089)
15	0 (0)	0.025 (.013)	0.149 (.057)
14	0 (0)	0.033 (.015)	0.358 (.089)
16a	0.001 (.001)	0.089 (.03)	0.442 (.09)
16b	0.003 (.001)	0.147 (.025)	0.303 (.077)
16c	0 (0)	0.072 (.028)	0.328 (.079)
16d	0 (0)	0.011 (.007)	0.2 (.072)
16e	0.002 (.001)	0.066 (.019)	0.467 (.108)
16f	0 (0)	0 (0)	0.083 (.045)
16g	0 (0)	0.007 (.005)	0.061 (.038)
16h	0 (0)	0 (0)	0.169 (.075)
16i	0 (0)	0 (0)	0.229 (.074)
6	0 (0)	0.016 (.012)	0.386 (.087)

Note: The order in which the SOGS questions were administered was slightly different to the screen as reported in the SOGS (Lesieur & Blume, 1987). The order in this table represents the order respondents in the BGPS were given the questions.

Table A2.19

Frequency distributions compared for each score against each latent class for the South Oaks Gambling Screen data from the BGPS 1999.

SOGS Score	1	2	3
0	4345	0	0
1	408	1	0
2	5	102	0
3	0	60	0
4	0	27	0
5	0	12	3
6	0	6	6
7	0	0	9
8	0	0	13
9	0	0	3
10	0	0	2
11	0	0	0
12	0	0	2
13	0	0	1
14	0	0	1
15	0	0	0
16	0	0	0
17	0	0	1
18	0	0	1
19	0	0	0
20	0	0	0

APPENDIX 3

Supplementary tables from Chapter 5

Table A3.1

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for MAMBAC taxonic data.

MAMBAC	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	0.002	1								
br(input)	0.250***	0.083***	1							
N	-0.114***	-0.022	0.015	1						
K	0.331***	0.242***	0.004	-0.005	1					
D	0.195***	-0.162***	0.014	0.016	0.009	1				
G	-0.027	-0.390***	0.024	0.001	-0.033*	-0.006	1			
H	-0.059***	0.013	0.006	0.002	0.002	-0.217***	-0.009	1		
Tax.*r*	0.012	0.058***	0.011	-0.001	-0.008	0.132***	0.010	0.001	1	
Comp.*r*	0.010	-0.125***	-0.005	0.003	-0.017	0.195***	0.020	0.001	0.027	1

Note: *** <. .001,

Significance values are corrected for multiple comparisons.

Table A3.2

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for MAXCOV taxonic data.

MAXCOV	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	-0.372***	1								
br(input)	-0.31***	0.912***	1							
N	0.034*	-0.040*	0.006	1						
K	0.427***	0.019	0.004	-0.005	1					
D	0.286***	-0.144***	0.015	0.013	-0.003	1				
G	-0.208***	-0.093***	0.022	-0.008	-0.029	-0.005	1			
H	-0.082***	0.038*	0.001	0.000	0.009	-0.221***	-0.014	1		
Tax.*r*	0.063***	0.021	0.016	0.004	0.005	0.136***	0.009	0.000	1	
Comp.*r*	0.033*	-0.053***	-0.007	0.004	-0.004	0.201***	0.022	0.000	0.018	1

Table A3.3

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for MAXEIG taxonic data.

MAXEIG	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	-0.354***	1								
br(input)	-0.282***	0.914***	1							
n	0.056***	-0.034*	0.006	1						
k	0.407***	-0.001	0.004	-0.005	1					
d	0.318***	-0.119***	0.015	0.013	-0.003	1				
g	-0.208***	-0.119***	0.022	-0.008	-0.029	-0.005	1			
h	-0.086***	0.028	0.001	0.000	0.009	-0.221***	-0.014	1		
Tax.*r*	0.072***	0.033*	0.016	0.004	0.005	0.136***	0.009	0.000	1	
Comp.*r*	0.028	-0.053***	-0.007	0.004	-0.004	0.201***	0.022	0.000	0.018	1

Table A3.4

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for L-Mode Factor Analysis taxonic data.

L-Mode	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	0.395***	1								
br(input)	0.515***	0.036*	1							
N	0.017	-0.002	0.006	1						
K	0.406***	0.264***	0.004	-0.005	1					
D	0.237***	0.004	0.015	0.013	-0.003	1				
G	-0.194***	-0.193***	0.022	-0.008	-0.029	-0.005	1			
H	-0.045***	-0.038*	0.001	0.000	0.009	-0.221***	-0.014	1		
Tax.*r*	0.089***	0.064***	0.016	0.004	0.005	0.136***	0.009	0.000	1	
Comp.*r*	-0.008	-0.023	-0.007	0.003	-0.004	0.201***	0.022	0.000	0.018	1

Tables A3.5 – A3.8

Covariances between outcome and predictor variables – dimensional data

MAMBAC	CCFI	*br*	*n*	*k*	*g*	*h*	*r*
CCFI	1						
br	-0.045***	1					
n	-0.032*	-0.025	1				
k	0.277***	0.156***	-0.005	1			
g	-0.068***	-0.387***	0.001	-0.033*	1		
h	-0.063***	-0.046***	0.002	0.002	-0.009	1	
r	0.355***	-0.180***	-0.018	0.011	0.001	-0.004	1

MAXCOV	CCFI	*br*	*n*	*k*	*g*	*h*	*r*
CCFI	1						
br	-0.098***	1					
n	-0.076***	-0.055***	1				
k	0.098***	0.133***	-0.005	1			
g	-0.129***	-0.728***	-0.008	-0.029	1		
h	-0.042*	-0.070***	0.000	0.009	-0.014	1	
r	0.367***	-0.306***	-0.008	0.012	0.002	-0.007	1

MAXEIG	CCFI	*br*	*n*	*K*	*g*	*h*	*r*
CCFI	1						
br	-0.133***	1					
n	-0.070***	-0.061***	1				
k	0.094***	0.087***	-0.005	1			
g	-0.068***	-0.734***	-0.008	-0.029	1		
h	-0.034*	-0.069***	0.000	0.009	-0.013	1	
r	0.399***	-0.285***	-0.008	0.012	0.002	-0.007	1

L-Mode	CCFI	*br*	*n*	*K*	*g*	*h*	*r*
CCFI	1						
br	0.025	1					
n	-0.199***	-0.024	1				
k	-0.300***	0.042**	-0.005	1			
g	0.142***	-0.461***	-0.008	-0.029	1		
h	0.069***	-0.020	0.000	0.009	-0.014	1	
r	-0.039*	-0.159***	-0.008	0.012	0.002	-0.007	1

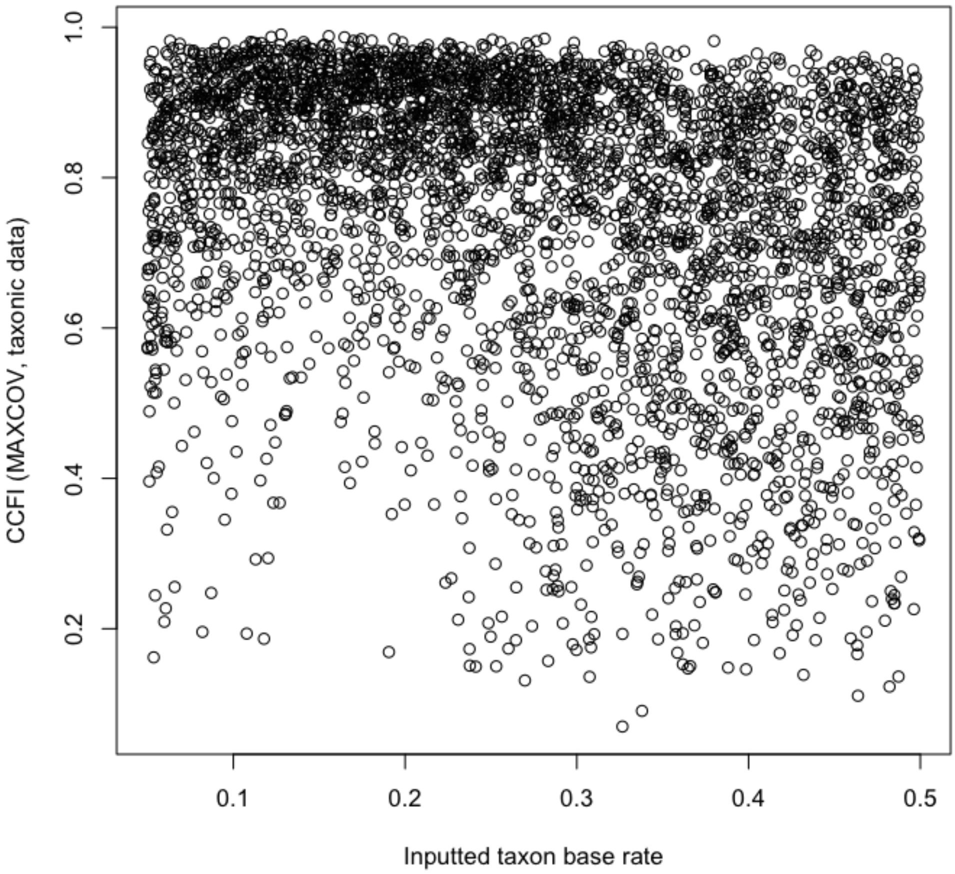

Figure A3.1

Scatterplot of the relationship between base rates and the CCFI for MAXCOV analyses for taxonic data

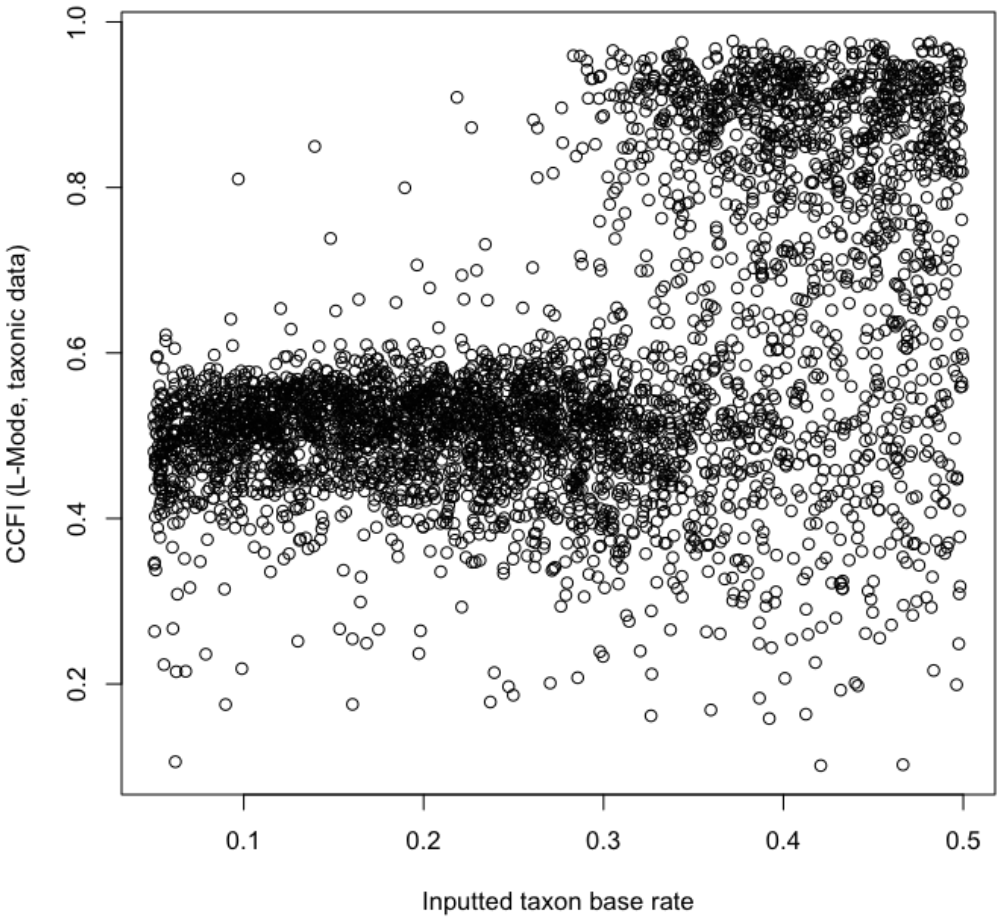

Figure A3.2

Scatterplot of the relationship between base rates and the CCFI for L-Mode factor analyses for taxonic data

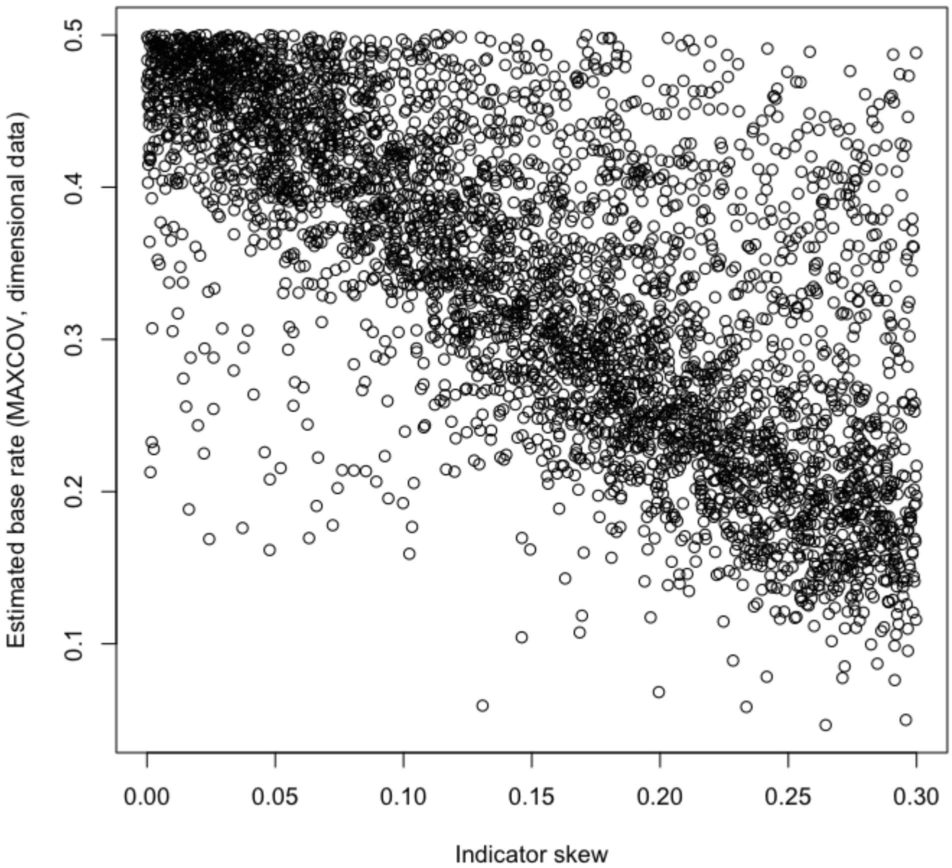

Figure A3.3

Relationship between indicator skew and the identification of spurious low base rate taxa in dimensional data, MAXCOV taxometric analyses

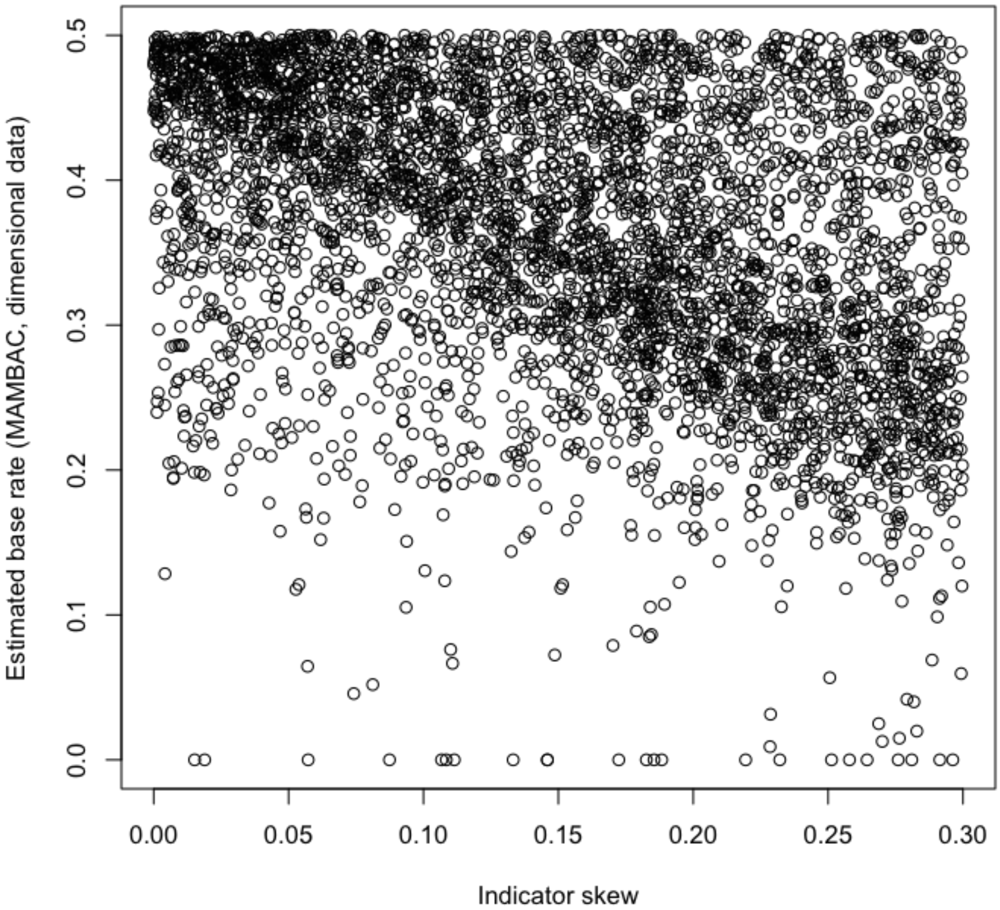

Figure A3.4

Relationship between indicator skew and the identification of spurious low base rate taxa in dimensional data, MAMBAC taxometric analyses

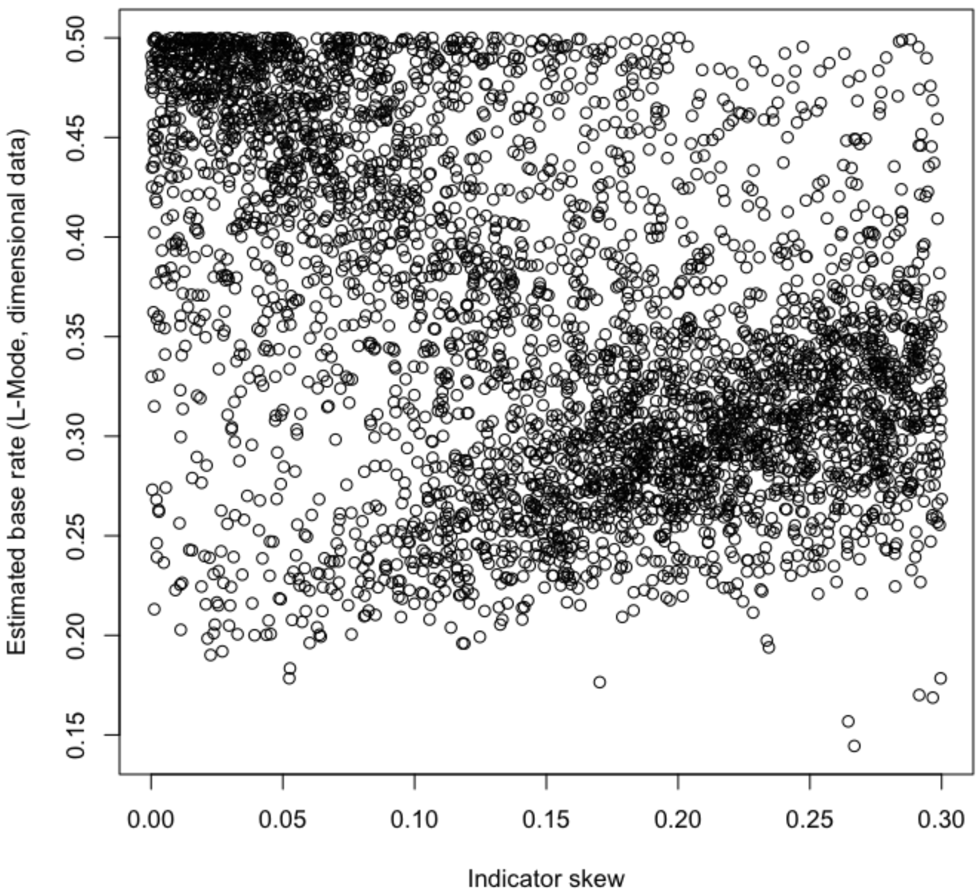

Figure A3.5

Relationship between indicator skew and the identification of spurious low base rate taxa, in L-Mode taxometric analyses on dimensional data

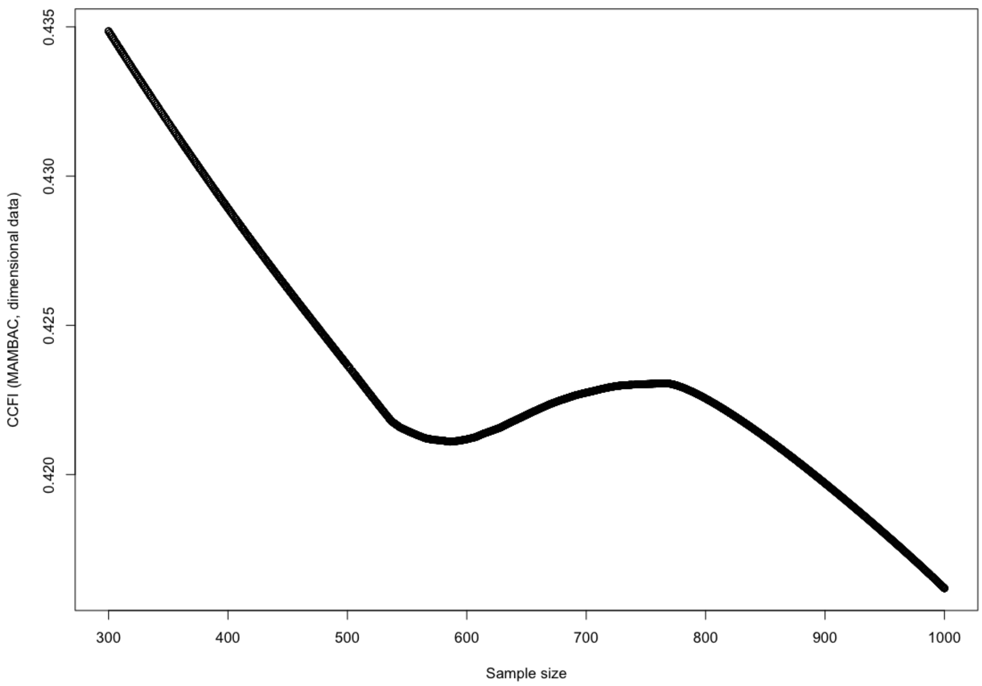

Figure A3.6

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for dimensional MAMBAC analyses.

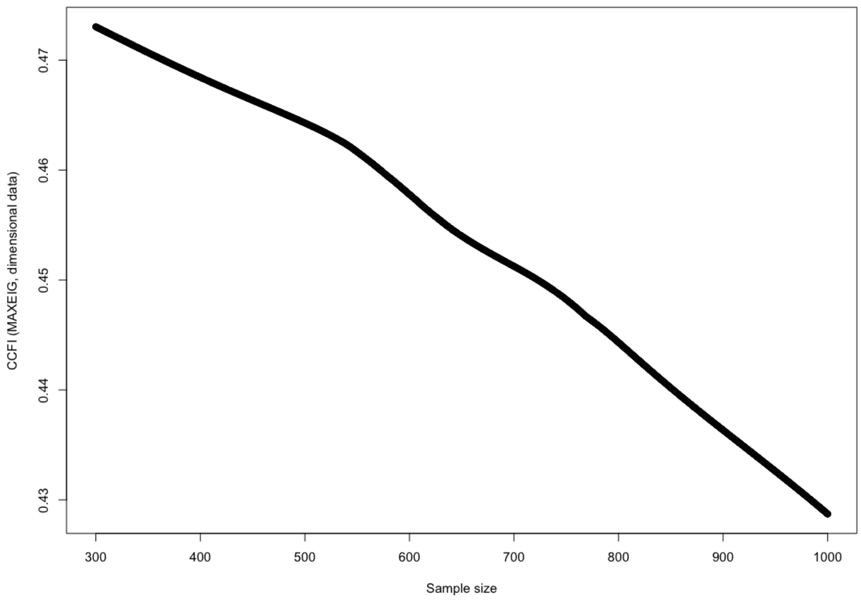

Figure A3.7

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for dimensional MAXEIG analyses. Please note unlike the taxonic data, we do not report the MAXCOV plot here, simply because it is identical to this one.

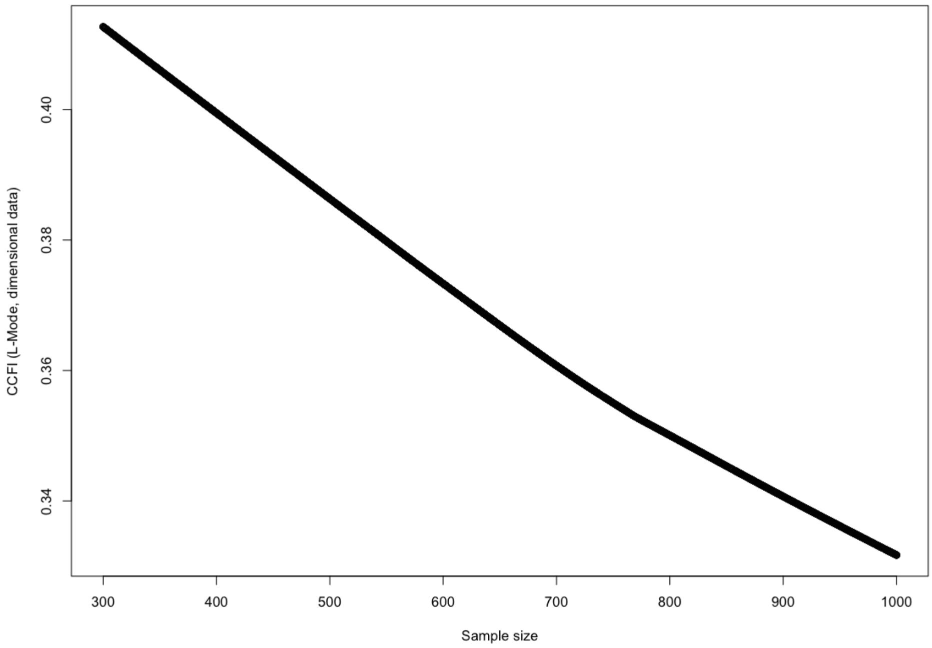

Figure A3.8

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for dimensional L-Mode Factor analyses.

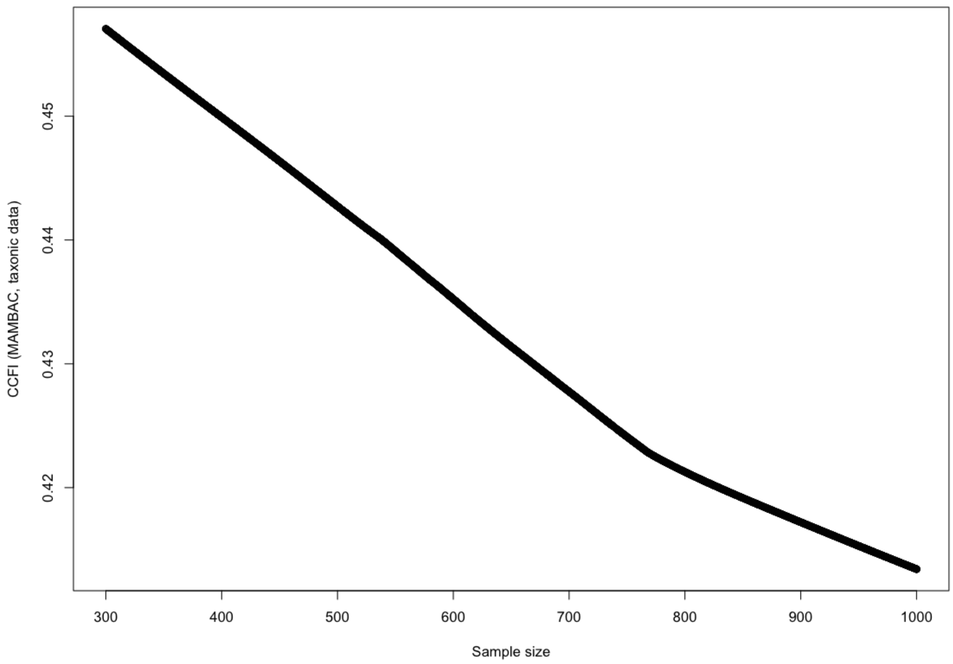

Figure A3.9

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for taxonic MAMBAC analyses.

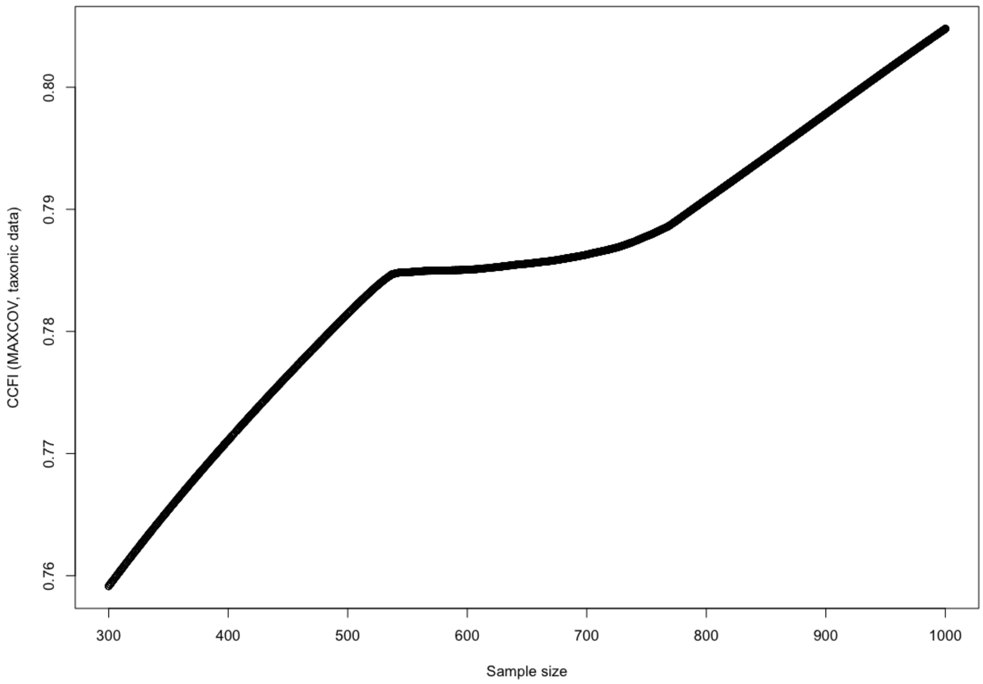

Figure A3.10

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for taxonic MAXCOV analyses.

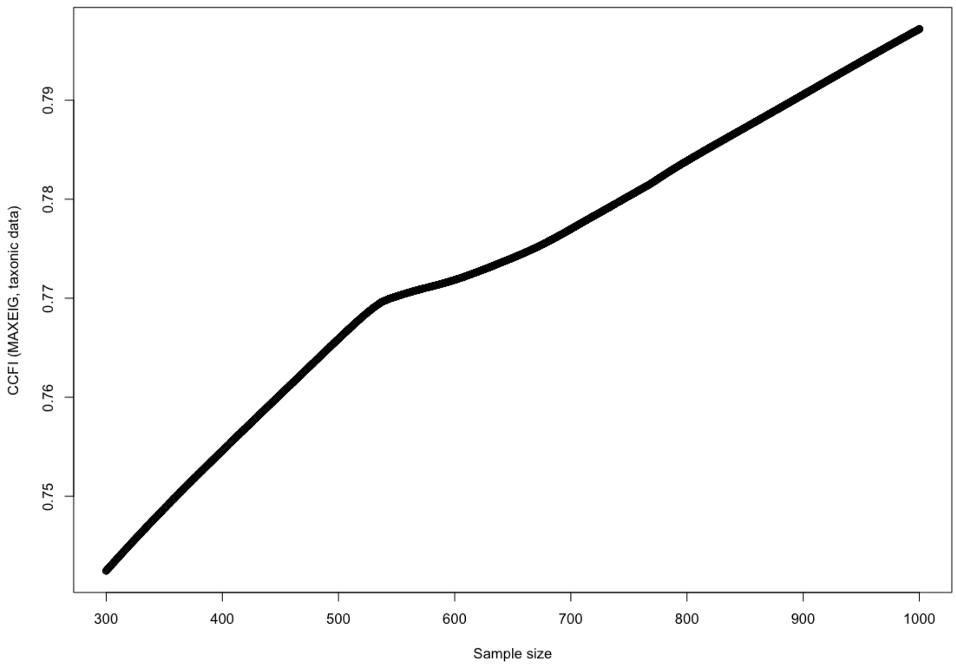

Figure A3.11

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for taxonic MAXEIG analyses.

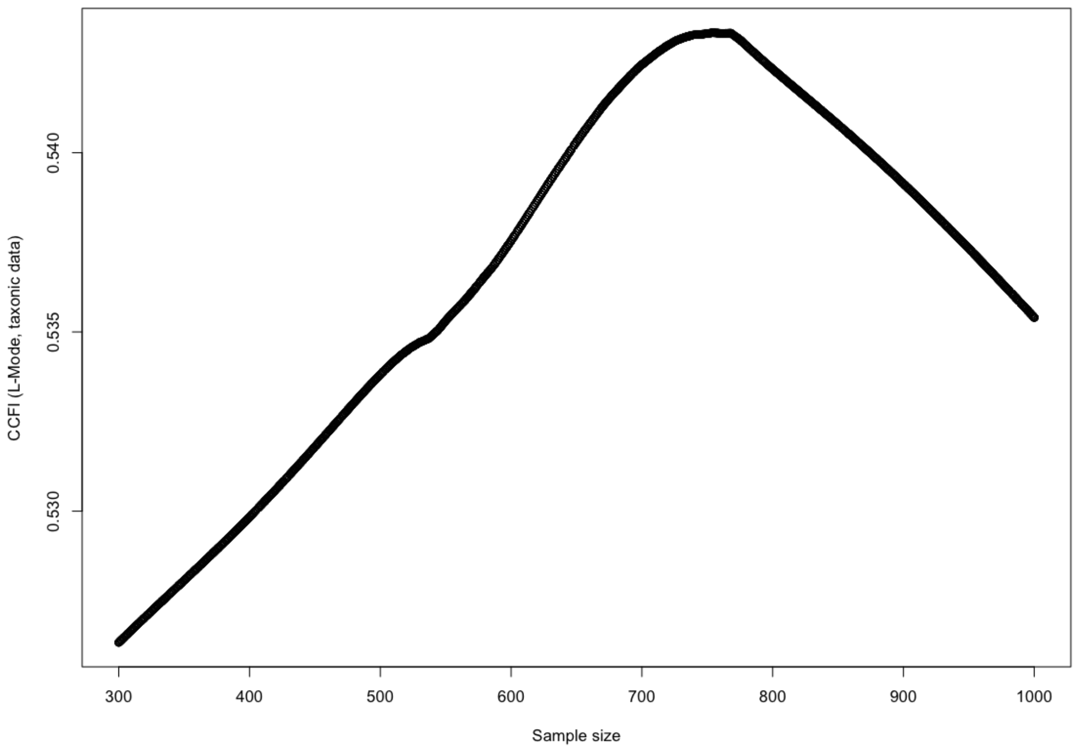

Figure A3.12

LOWESS curve plotting the relationship between sample size (x) and CCFI (y) for taxonic L-Mode factor analyses.

Table A3.9

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for MAMBAC summed input analysis on taxonic data.

MAMBAC	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	-0.156	1								
br(input)	-0.047***	0.766***	1							
N	-0.076***	-0.004	0.015	1						
K	0.660***	-0.099***	0.004	-0.005	1					
D	0.220***	-0.001	0.014	0.016	0.009	1				
G	-0.174***	-0.054***	0.024	0.001	-0.033***	-0.006	1			
H	-0.052***	0.004	0.006	0.002	0.002	-0.217***	-0.009	1		
Tax.*r*	0.063***	0.021	0.011	-0.001	-0.008	0.132	0.010	0.001	1	
Comp.*r*	0.003	-0.014	-0.005	0.003	-0.017	0.195	0.020	0.001	0.027	1

Table A3.10

Correlation coefficients for the CCFI, base rates and the parameters entered into the Monte Carlo analysis for MAXCOV summed input analysis on taxonic data.

MAXCOV	CCFI	*br*(actual)	*br*(input)	*n*	*k*	*d*	*G*	*h*	Tax.*r*	Comp.*r*
CCFI	1									
br(actual)	0.056***	1								
br(input)	0.107***	0.938***	1							
N	0.021	-0.026	0.006	1						
K	0.247***	-0.077***	0.004	-0.005	1					
D	0.335***	-0.068***	0.015	0.013	-0.003	1				
G	-0.136***	-0.016	0.022	-0.008	-0.029	-0.005	1			
H	-0.078***	0.022	0.001	0.000	0.009	-0.221***	-0.014	1		
Tax.*r*	0.060***	0.007	0.016	0.004	0.005	0.136***	0.009	0.000	1	
Comp.*r*	0.024	-0.023	-0.007	0.003	-0.004	0.201***	0.022	0.000	0.018	1

Tables A3.11 & A3.12

Covariances between outcome and predictor variables – dimensional data

MAMBAC	CCFI	*br*	*n*	*k*	*g*	*h*	*r*
CCFI	1						
br	-0.019	1					
n	-0.276***	-0.079***	1				
k	-0.024	0.172***	-0.005	1			
g	-0.019	-0.628***	0.001	-0.033*	1		
h	-0.007	-0.078***	0.002	0.002	-0.009	1	
r	0.106***	-0.011	-0.018	0.011	0.001	-0.004	1

MAXCOV	CCFI	*br*	*n*	*k*	*g*	*h*	*r*
CCFI	1						
Br	-0.050***	1					
n	-0.232***	-0.071***	1				
k	-0.187***	0.065***	-0.005	1			
g	0.003	-0.680***	-0.008	-0.029	1		
h	-0.005	-0.067***	0.000	0.009	-0.014	1	
r	-0.034*	-0.284***	-0.008	0.012	0.002	-0.007	1

Table A3.13

Between groups differences for each taxometric procedure on SOGS data, and measures of skew and kurtosis. Please consult Appendix 1.D for item content.

	MAMBAC	*MAXCOV*	*L-Mode*		
Item	*d*	*D*	*d*	Skew	Kurtosis
4	0.559	0.642	NA	1.496	0.239
5	0.781	1.018	0.815	1.448	0.096
7	NA	0.952	0.587	0.699	-1.517
8	NA	1.008	1.203	0.721	-1.484
9	1.326	1.566	1.441	1.436	0.062
10	1.186	1.728	1.150	2.364	3.599
11	1.357	0.961	0.951	2.621	4.886
13	1.842	1.719	NA	3.710	11.798
14	NA	NA	NA	6.772	43.993
15	1.128	1.329	0.784	4.846	21.552
16a	NA	NA	NA	3.252	8.605
16b	NA	NA	NA	2.539	4.459
16c	NA	NA	NA	4.109	14.931
16d	NA	NA	NA	7.066	48.075
16e	NA	NA	NA	3.297	8.897
16f	NA	NA	NA	12.48	154.2
16g	NA	NA	NA	11.14	122.4
16h	NA	NA	NA	9.366	85.985
16i	NA	NA	NA	7.778	58.689
6	1.461	1.957	NA	5.088	23.962
Merged	1.113	1.298	NA	1.322	-0.252

Table A.3.14

Levels of nuisance covariance from the L-Mode Factor Analysis procedure on DSM-IV Pathological Gambling Criteria data.

Item	1	2	3	4	5	6	7
1	-						
2	0.058	-					
3	0.014	0.028	-				
4	0.064	0.138	0.185	-			
5	0.090	0.102	0.075	0.257	-		
6	0.020	0.002	0.116	0.121	0.117	-	
7	0.036	0.015	0.111	0.118	0.085	0.134	-
Taxon	1	2	3	4	5	6	7
1	-						
2	0.204	-					
3	0.055	0.131	-				
4	-0.068	0.241	-0.043	-			
5	0.004	0.239	-0.174	0.208	-		
6	-0.125	-0.019	0.068	-0.072	-0.030	-	
7	-0.101	-0.112	-0.034	-0.051	-0.055	0.048	-
Comp	1	2	3	4	5	6	7
1	-						
2	-0.103	-					
3	-0.221	-0.148	-				
4	-0.140	-0.070	-0.047	-			
5	-0.093	-0.143	-0.124	-0.078	-		
6	-0.091	-0.140	-0.121	-0.077	-0.051	-	
7	-0.045	-0.014	0.018	0.035	-0.024	0.075	-

Table A3.15

Levels of nuisance covariance for the final summed-input MAXCOV taxometric procedure.

Item	1	2	3	4	5	6
1	-					
2	0.220	-				
3	0.202	0.409	-			
4	0.149	0.256	0.379	-		
5	0.215	0.315	0.432	0.368	-	
6	0.212	0.292	0.425	0.325	0.398	-
Taxon	1	2	3	4	5	6
1	-					
2	-0.076	-				
3	-0.066	0.162	-			
4	-0.090	-0.052	0.108	-		
5	0.320	0.216	-0.128	-0174	-	
6	-0.090	-0.052	-0.142	0.005	-0.174	-
Comp.	1	2	3	4	5	6
1	-					
2	0.134	-				
3	0.047	0.225	-			
4	0.029	0.090	0.110	-		
5	0.052	0.077	0.058	0.120	-	
6	0.079	0.088	0.102	0.063	0.057	-

Table A3.16

Levels of nuisance covariance for the final summed-input MAMBAC taxometric procedure.

Item	1	2	3	4	5
1	-				
2	0.409	-			
3	0.256	0.379	-		
4	0.315	0.432	0.368	-	
5	0.292	0.425	0.325	0.398	-
Taxon	1	2	3	4	5
1	-				
2	0.410	-			
3	0.025	-0.082	-		
4	0.225	-0.067	-0.02	-	
5	0.041	0.030	-0.105	-0.072	-
Comp	1	2	3	4	5
1	-				
2	0.155	-			
3	0.042	-0.001	-		
4	0.025	-0.031	-0.047	-	
5	0.073	-0.036	-0.054	-0.032	-

Table A3.17

Levels of nuisance covariance for the final L-Mode Factor Analysis taxometric procedure on SOGS data, within the entire sample

Item	1	2	3	4	5	6	7	8	9	10
1	-									
2	-0.316	-								
3	0.220	0.011	-							
4	0.202	0.066	0.409	-						
5	0.149	0.010	0.256	0.379	-					
6	0.215	0.050	0.315	0.432	0.368	-				
7	0.212	0.073	0.292	0.425	0.325	0.398	-			
8	0.121	0.027	0.171	0.268	0.201	0.308	0.273	-		
9	0.148	0.036	0.214	0.318	0.245	0.284	0.235	0.553	-	
10	0.158	0.000	0.226	0.273	0.251	0.378	0.265	0.418	0.440	-

Table A3.18

Levels of nuisance covariance for the final L-Mode Factor Analysis taxometric procedure, within the putative taxon

Item	1	2	3	4	5	6	7	8	9	10
1	-									
2	0.153	-								
3	0.094	0.229	-							
4	-0.035	0.036	0.227	-						
5	0.024	0.088	-0.055	0.193	-					
6	0.049	0.005	0.050	0.262	0.251	-				
7	0.047	0.069	-0.004	0.257	0.155	0.241	-			
8	0.082	-0.029	0.078	0.200	0.147	0.261	0.219	-		
9	0.092	-0.029	0.094	0.227	0.173	0.191	0.128	0.525	-	
10	0.052	-0.148	0.043	0.117	0.138	0.286	0.127	0.383	0.391	-

Table A3.19

Levels of nuisance covariance for the final L-Mode Factor Analysis taxometric procedure, within the complement

Item	1	2	3	4	5	6	7	8	9	10
1	-									
2	-0.507	-								
3	-0.087	-0.208	-							
4	-0.070	-0.090	-0.039	-						
5	-0.124	-0.156	-0.044	0.063	-					
6	-0.039	-0.090	-0.039	-0.017	-0.031	-				
7	-0.041	-0.062	-0.044	-0.019	-0.007	-0.019	-			
8	-0.001	-0.019	0.049	-0.046	0.029	0.010	0.012	-		
9	0.014	-0.006	0.051	0.018	-0.032	-0.003	-0.025	-0.023	-	
10	-0.028	-0.073	-0.013	-0.005	-0.010	-0.005	-0.006	0.039	-0.012	-

Table A3.20

Between groups separation, skew and kurtosis for items assigned to taxon and complement in the final taxometric analyses reported for DSM-IV Pathological Gambling criteria data from the British Gambling Prevalence Survey 2010. Item content is reported in Appendix 1.B

	MAXCOV	MAMBAC	L-Mode		
Item	*d*	*d*	*d*	Skew	Kurt.
1	1.229	N/A	1.146	0.374	-1.862
2	N/A	N/A	0.404	-1.369	-0.125
3	1.925	1.439	1.840	1.470	0.162
4	3.670	3.310	1.673	2.666	5.113
5	2.428	3.075	1.399	2.087	2.361
6	3.726	2.770	1.494	2.866	6.222
7	3.275	2.565	1.497	2.720	5.406
8	N/A	N/A	0.568	8.875	76.882
9	N/A	N/A	0.729	6.964	25.282
10	N/A	N/A	0.928	5.220	16.600