UNIVERSITY OF CALGARY

Cognitive mechanisms in gambling: The temporal relationship between cognitive distortions and gambling involvement

by

Igor Yakovenko

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE

Department of Clinical Psychology

CALGARY, ALBERTA

09 / 2012

Abstract

The sequence of the development of gambling problems is not well studied. The present study examined cognitive distortions and gambling behaviour in a population sample recruited in Alberta, Canada. Data from 1371 participants over four assessment waves (five years) were used to generate a two-factor latent structure using gambling fallacies and gambling involvement measurements. Confirmatory factor analysis showed that cognitive distortions predicting future gambling behavior was the better fitting relationship, using CFI, AIC, and RMSEA fit indices. Results suggested that cognitive distortions were more likely to predict future gambling involvement than the reverse relationship. In addition, cognitive distortions declined over time, whereas gambling involvement was more stable. The results of the study imply that focusing primarily on cognitive mechanisms in public health policy for gambling disorders may be a more effective strategy than focusing on behavioural solutions.

Keywords: pathological gambling, longitudinal, structural equation modeling

Acknowledgements

First and foremost, I would like to thank my supervisor, Dr. David C. Hodgins, for guiding me throughout this project and providing valuable advice in all aspects of my graduate training. His contributions have been instrumental in my present success. I will forever appreciate and value his mentorship. I would also like to thank my M.Sc. committee members: Dr. Shawn R. Currie, Dr. David Crockford, and Dr. Tak Fung. Their input was insightful and educational. Likewise, the project would not have been possible without Ashley McInnes, who greatly facilitated all aspects of my data access and analysis. Finally, I would like to thank Cameron Clark, Jennifer Ference, Melanie Khu and Leanne Quigley (TSF) for their friendships over the past two years; and my parents for going above and beyond to provide me with endless opportunities and unconditional support.

Table of Contents

List of Tables

List of Figures and Illustrations

List of Abbreviations

AIC – Akaike Information Criterion

CAIC – Consistent Akaike Information Criterion

CBT – Cognitive Behavioural Therapy

CFI – Comparative Fit Index

CPGI – Canadian Problem Gambling Index

EM – Expectation Maximization

GEE – Generalized Estimating Equations

GFS – Gambling Fallacies Scale

LLLP – Leisure, Lifestyle, and Lifecycle Project

RMSEA – Root Mean Square Error of Approximation

SEM – Structural Equation Modeling

SOGS – South Oaks Gambling Screen

Introduction

In 1989, Gadboury and Ladouceur (1989) showed a predominance of erroneous perceptions during gambling. They referred to factors other than chance and posited that this cognitive bias may play an important role in the development and maintenance of gambling behaviors. Since then, there have been many studies that explored the role of cognitive factors in pathological and problem gambling (Ladouceur, & Dubé, 1997; Toneatto, 1999; Miller, & Currie, 2008). For the purposes of this study, the terms cognitive bias, distortion, cognitive error, cognitive mechanism, cognitive beliefs and cognitive perception will be used interchangeably. Similarly, problem and pathological gambling are terms used in the gambling literature to differentiate the severity of a gambling problem with problem gambling denoting lower severity than pathological gambling, which may be diagnosed using clinical criteria. Research had established that there are cognitive characteristics that are unique to problem gamblers and that this psychopathology is different from social gamblers (Joukhador, Maccallum, & Blaszczynski, 2003). It appears that problem gamblers endorse more cognitive distortions than social gamblers across all domains except denial. Irrational cognitions appear to reflect two general areas: beliefs that gambling outcomes can be predicted and controlled (Letarte, Ladouceur, & Mayrand, 1986). The illusion of control and prediction extends even to random games, such as slot machines (Toneatto et al., 1997). A number of specific maladaptive beliefs have since been documented in pathological gambling.

Illusion of control refers to the belief that the probability of winning is more than simple chance (Toneatto, & Nguyen, 2007). This cognitive mechanism also leads one to believe that outcomes may be predicted or controlled. It is responsible for some gamblers devising betting strategies that revolve around streaks of good and bad luck (Gadboury, & Ladouceur, 1989; Rogers, 1998). Gadboury and Ladouceur (1989) used the thinking-aloud method, which involves participants verbalizing what they are doing, thinking, or feeling during a task, allowing one to gain insight into their cognitive processes. They found that when playing roulette or slot-machines, participants provided more inadequate verbalizations that referred to factors other than chance that could influence their gambling. In his 1998 review, Rogers examined similar processes. He pointed out that lottery gambling is susceptible to a number of irrational beliefs and cognitive biases, which included hot and cold numbers, lucky streaks, the influence of social factors on play, the framing of gambling outcomes (i.e. attribution), and unrealistic optimism.

Another category of cognitive distortions in gambling relates to illusory correlations and superstitious beliefs. Specifically, cognitive superstitions lead some players to believe that mental states can influence gambling outcomes. Toneatto and colleagues (1997) conducted a survey of 38 problem and social gamblers and found that on average, problem gamblers endorsed more active illusory control over outcomes. This category included lucky numbers, reliance on lucky objects, superstitious beliefs, and unrealistic self-efficacy. This particular class of cognitions represented the most salient difference between problem and social gamblers.

The problem gambler may also interpret gambling losses in a way that would encourage continued gambling. This bias may result in several types of cognitive errors. Attributional biases may be used to underestimate situational factors such as luck and to overestimate dispositional factors such as skill and ability (Gadboury, & Ladouceur, 1989). Similarly, outcomes that are just short of a win may be regarded as near misses/wins rather than losses (Parke, & Griffiths, 2004). In this scenario, operant conditioning acts to reinforce the near wins as signs of encouragement. Players, particularly in games of skill such as poker, see near misses as a way of validating their strategy and recognizing that the win is within their reach.

A reverse process known as hindsight bias leads players to attribute losses to bad luck, discounting individual factors. Gilovich and Douglas (1986) conducted a study where participants played a computerized form of bingo. During the task, some players were provided with random “flukes” where they were able to bend the rules of the game by filling extra spaces on their cards. Results showed that players who eventually lost blamed their losses on these flukes, whereas players who eventually won discounted the random events and attributed their wins to skill.

The gambler’s fallacy refers to a belief that a gambling outcome will occur if it had not occurred for a period of time (Toneatto, & Nguyen, 2007). This cognitive mechanism covers a wide array of beliefs including the belief that a series of outcomes will soon change, a series of outcomes will continue, losses will be followed by wins and vice versa, there is dependence between independent outcomes (e.g., coin tosses), as well as the belief that a random process may be expressed in an extremely brief sequence of outcomes (Ladouceur, & Dubé, 1997; Rogers, 1998). Keren and Lewis (1995) differentiated between Type I and Type II gambler's fallacy. In the Type I fallacy, they referred to the above process of failure to perceive the independence of random events. The Type II fallacy was defined as the tendency to underestimate the number of observations required to detect biased numbers. In other words, players tend to believe that a biased number (e.g., on a roulette wheel) produces favorable outcomes even over a short number of gaming rounds.

Finally, interpretive biases may refer to the concept of chasing, which describes the tendency for problem gamblers to continue gambling in the face of heavy losses in order to recover their money (e.g., Breen, & Zuckerman, 1999; Campbell-Meiklejohn et al., 2008). Breen and Zuckerman (1999) distinguished between within-session chasing and between-session chasing. The former referred to the tendency to prolong single gambling sessions in the efforts to recover losses. The between-session chasing described the notion that as soon as new money or stakes are acquired, the gambler will try again. In their study, the within-session gambling was best predicted by measurements of impulsivity. On the other hand, sensation seeking did not appear to account for much of the within-session chasing behavior.

The mechanisms for gambling fallacies fall in line with other addictive behaviour theories. Specifically, the alcohol use disorder literature emphasizes the work of social learning and expectancy theories in the maintenance of the addiction. The former highlights two main cognitive factors: self-efficacy and outcome expectancies. Self-efficacy with regard to abstinence goals has been found to be a predictor of treatment outcome in alcohol use (Ilgen, McKellar, & Tiet, 2005). Similarly, beliefs about the consequences of alcohol use or expectancies have been implicated in the maintenance of alcohol use disorders for over three decades (Brown et al., 1980). Both of these mechanisms can be observed in gambling fallacies. For example, superstitious beliefs and talismans, failure to recognize the independence of gambling events, as well as chasing are all cognitions that in one way or another enhance self-efficacy or the belief of the individual in his or her own ability to predict and control outcomes. Just as in alcohol disorders, expectancies act as maladaptive beliefs by reinforcing the positive effects of gambling, such as excitement, escape, and the potential financial rewards. Any information that reflects the reinforcement value of gambling acts to increase positive expectancies regarding gambling.

Treatment models for gambling appear to support the role of cognitive distortions in promoting and maintaining problem gambling (Toneatto, 2002). Furthermore, treatment outcomes point to their susceptibility to change during treatment and consequent reduction in gambling behavior (Petry et al., 2006). The majority of empirical evidence in treatment has been found in cognitive-behavioral therapy (CBT). CBT targets the interplay between cognition, behavior, and emotion. Treatment involves guiding the client to recognize the error of his or her cognitions, providing corrective information, and improving gambling behavior through cognitive restructuring (Ladouceur et al., 2003; Toneatto, 2002). For example, McConaghy and colleagues (1983) have extensively used and evaluated treatment with imaginal desensitization, which combines relaxation techniques and cognitive/emotional restructuring to reduce gambling involvement. Finally, data show that cognitive and cognitive-behavioral therapies specifically result in the adoption of more adaptive cognitions (Blaszczynski, & Silove, 1995; Toneatto, & Sobell, 1990). Therefore, new research on the link between cognitive errors and gambling behavior can directly result in improved treatment for pathological and problem gambling.

Longitudinal research represents the next step in establishing the relationship between gambling cognition and gambling behavior. For example, for some individuals gambling problems are transient, whereas others experience persistent, long-term problems (Slutske, 2006). The connotation is that there may be individual characteristics that differ in terms of stability and susceptibility to change. Similarly, there may be specific sequences in which gambling involvement develops. Disentangling the temporal relations between gambling behavior and its correlates is an important step in determining the typical developmental sequence of participating in different gambling activities.

So far, there has been limited longitudinal research examining the relationship between cognitions and behaviors in gambling (el-Guebaly et al., 2008). Longitudinal research had focused on establishing prevalence rates and examining personality variables that may influence problem gambling. For example, Vitaro and colleagues (1997) examined impulsivity and its ability to predict gambling behavior. They followed a sample of boys from early adolescence through late adolescence. They found that impulsivity increased as gambling status moved from non-gambler to problem gambler. The results of the study confirmed a deficit in impulse control as a means of classifying problem gambling. Similarly, Barnes and colleagues (2005) found a correlation between moral disengagement and deviant gambling behavior in youth. In a sample of males only, those who scored higher on moral disengagement were found to be more involved in gambling 18 months later. Interestingly, the same correlation was not found in females.

Slutske, Jackson and Sher (2003) conducted an 11 year longitudinal study to examine the stability of gambling through prevalence rates. They found that prevalence rates remained stable, but individual gambling was more variable over time. Although not a longitudinal design, Miller and Currie (2008) further demonstrated the link between cognition and gambling behavior from different points in time. They used prevalence data from five surveys conducted between 2000 and 2005 to study the relationship between cognition and gambling. They distinguished between gambling practices (how people gamble), gambling cognitions (how people think about gambling), and gambling intensity (how much people gamble) and found that irrational cognitions moderated the relationship between gambling intensity, tolerance to gambling, and risky gambling practices.

To date, no large-scale population study has examined the temporal etiological relationship between cognitive distortions and gambling involvement. Specifically, the directionality of the interaction between cognitive fallacies and gambling practices/intensity over time is not established. In other words, correlational data do not indicate whether changes in cognition precede changes in behavior or whether changes in behavior distort future cognition. Although both models involve similar constructs, they have profoundly different implications for public policy, prevention and treatment planning. The establishment of the stronger direction of effect between cognitive fallacies and gambling behavior is helpful for the development of appropriate prevention and intervention strategies, as it would dictate the primary target of preventative approaches in research and clinical practice.

The present study sought to examine the association between gambling fallacies and gambling involvement. The term *gambling fallacies* is used broadly to refer to all of the previously reviewed cognitive distortions. The data for this project came from a longitudinal study of gambling Leisure, Lifestyle and Lifecycle Project (LLLP) conducted at the University of Calgary, University of Lethbridge and University of Alberta (el-Guebaly et al., 2008). The current study focused on two goals: (1) to ascertain the stability of gambling fallacies and gambling behavior over time in a population sample; and (2) to establish the temporal relationship and sequential development of gambling cognitions and gambling involvement over a five year period. The latter was achieved by comparing several structural equation models (SEMs) that represent different theoretical relationships between the two chosen variables. Specifically, the models fell into two categories: those that assume that cognitive changes precede changes in gambling behavior and those that assume gambling involvement precedes changes in gambling cognition. The fit of the models to the data dictated a potential progressive relationship between these gambling correlates.

The study was exploratory and no specific a priori hypotheses with regard to the better model were formulated. This decision was influenced by two factors. First, research regarding the stability of gambling correlates over time is inconclusive (Ladouceur, Sylvain, & Gosselin, 2007; Slutske, Jackson, & Sher, 2003; Slutske et al., 2005). General prevalence rates appear to be stable, but individual gambling tends to fluctuate over time. Second, little is known about the typical sequence of development of dispositional characteristics of problem gamblers. Consequently, any a priori hypotheses would be based on little substantiated evidence. Instead, the goal was to test several competing models without any prior expectations in an attempt to delineate dispositional processes in problem gambling.

Methods

Participants

Participants were recruited using random digit dialing. Initial telephone surveys were followed up by face-to-face interviews and self-report questionnaires. Five age cohorts were examined in a five year longitudinal study in the province of Alberta, Canada (el-Guebaly et al., 2008). A general population sample was used with a portion of the participants being oversampled as “at-risk” gamblers based on age and gender specific cut-offs for the 70th percentile for gambling expenditure and frequency. Initial recruitment did not yield equal representation across age cohorts. Within the adult cohorts, 43-45 year old participants were overrepresented and 23-25 and 63-65 year old participants were underrepresented. Additionally, the original intent was to equally sample Calgary, Edmonton, and several outlying communities. Recruitment yielded an over sampling of participants from Calgary (41.7%) and an under sampling from Edmonton (29.6%) and the surrounding communities (28.7%). Similarly, the number of at-risk gamblers was under sampled at 524 participants.

The present study used all four waves of the LLLP. However, only the data from the adult age groups were analyzed (ages 18-20, 23-25, 43-45, and 63-65). Retention for the four adult cohorts was as follows: time 1 = 1372, time 2 = 1145 (83%), time 3 = 1001 (73%), and time 4 = 1029 (75%). Time 4’s increase in retention may be attributed to more rigorous follow-up conducted by the LLLP team. Following the drop in retention at Time 3, several phone calls were made to the participants in order to remind them of the final wave of data collection. Additionally, the increased follow-up rate may be a result of improving economic conditions, as Time 4 coincided with the end of the economic recession in Canada.

Instruments

Participants provided detailed responses on a number of variables of interest in the LLLP, including personality, gambling involvement, gambling practices, and co-morbid substance use. The present study employed two of these constructs. Gambling involvement and gambling cognition represented the latent variables in the structural equation models. Gambling involvement consisted of three indicators – gambling range (how many types of gambling people are involved in), frequency of gambling (how often people gamble), and gambling expenditure (how much money people spend on gambling). Gambling cognition had eight indicators – items from the Gambling Fallacies Scale (GFS; Williams, 2003, Williams et al., 2006). Frequency of gambling and gambling expenditure have been demonstrated to reliably correlate with gambling status and gambling involvement (Williams et al., 2011). Range was chosen as an appropriate indicator based on research that suggests that gamblers tend to prefer and stick to a specific gambling activity based on their individual characteristics (Petry, 2003).

The measurements for range, frequency, and expenditure consisted of three variables based on questions from the Canadian Problem Gambling Index (CPGI; Ferris, & Wynne, 2001). The range variable was a total of all types of gambling that the participant said he/she had participated in during the last 12 months (total score 0 to12). The specific question asked was: "In the past 12 months, have you bet or spent money on [specific gambling activity]?" See *Appendix A* for a list of the included types of gambling. The frequency variable was based on the question: "In the past 12 months, how often did you bet or spend money on [specific gambling activity]?" A total frequency number was derived for all gambling activities. The variable was coded on a seven point frequency scale, ranging from "Daily" to "Between 1-5 times per year". The expenditure variable was the total amount of money spent on all types of gambling. It was based on the question: "In the past 12 months, how much money did you spend on [specific gambling activity] in a typical month?" The values for all endorsed types of gambling were added to produce a total dollar amount.

Previous research has questioned the validity of self-reported gambling expenditure since it did not usually match actual gambling revenue (Wood, & Williams, 2007). The specific wording of the expenditure question was chosen as it had demonstrated the most robust evidence of validity. It appeared to better elicit responses that matched actual gambling revenues and amounts obtained from prospective diaries. The CPGI was used as the basis for the range and frequency variables (Ferris & Wynne, 2001; see

Appendix B for the questions from the CPGI scale on which the gambling involvement variables were based).

The 10-item Gambling Fallacies Scale was designed to assess all facets of gambling-related cognitive errors (Williams, 2003). In previous research, the summed GFS total correct score (0-10) demonstrated significant correlation with problem gambling status, problem gambling category on the CPGI and the South Oaks Gambling Screen (SOGS; Lesieur, & Blume, 1987), the CPGI total, gambling frequency and number of gambling activities engaged in, as well as with paranormal beliefs. Normative data suggested a Cronbach's alpha of .51 and a one month test-retest reliability of .70. For the purpose of the study, the scores were reverse coded, with 0 indicating the correct response in order to facilitate the final interpretation of the analysis (higher score was now equal to more gambling fallacies instead of less). See *Appendix C* for the full Gambling Fallacies Scale.

A principal component analysis through SPSS Version 19 was conducted on the baseline assessment wave data from the LLLP to confirm the psychometric properties of the GFS. Data were initially available from 1372 adult participants with no missing values. The correlation matrix revealed no correlations in excess of 0.30, with the largest one being 0.26 (see Table 1 for the full correlation matrix at Time 1). Most correlations fell in the range of 0.1 to 0.2. Kaiser's measure of sampling adequacy was acceptable with a value of 0.69.

Principal components extraction with varimax rotation was used to estimate the likely number of factors from eigenvalues. Table 2 shows three eigenvalues larger than 1, suggesting a three factor structure. The scree plot visually confirmed a break between 3 and 4 factors. The decision to use each item on the GFS as a separate indicator of the latent variable was influenced by several factors. First, treating each item as an indicator did not require a priori error term specification as would be the case if a single indicator (i.e. total score) was used and it allowed to maintain the integrity of the SEM models in spite of the poor reliability of the GFS. Second, all of the items except two loaded substantively on the first component of the unrotated matrix pointing to the fact that they measure a higher order single factor (in this case the cognition latent variable), while allowing for two additional lower-order factors. Cronbach's Alpha for the original 10 items, scored dichotomously was found to be 0.49. Due to the fact that they did not load substantively on the first unrotated component and in order to improve the internal consistency of the measure, items 6 and 7 were removed to produce a revised 8-item GFS with an alpha coefficient of 0.55. Also, these were the only items that were consistently answered incorrectly by the majority of the participants. This was likely due to the complex wording of the questions rather than the difficulty of the underlying concept. Thus, after eliminating the two items, all of the remaining indicators loaded on a single latent cognition variable. For the remainder of the study, the revised 8-item GFS was used.

Analysis

The postulated structural equation model is presented in *Figure 1*. In this model, a two-factor structure was hypothesized: a Gambling Involvement factor (with Range, Frequency, and Expenditure serving as indicators) and a Gambling Cognition factor (with items on the GFS serving as the indicators). Two main questions were of interest: (1) does the two-factor model adequately fit the data? (2) Which direction of effect between cognition and behavior better fits the data? Gambling involvement was represented as the independent variable and gambling cognition as the dependent variable in one set of models. The opposite direction was also tested, where gambling involvement was the dependent variable and cognition was the independent variable. Latent variables were paired two at a time with each factor representing a different time point.

Since there were four total time points in the longitudinal design, three models were tested for each direction of effect. To test the hypothesis of cognition predicting behavior, the following models were used: Time 1 cognition with Time 2 involvement, Time 2 cognition with Time 3 involvement, and Time 3 cognition with Time 4 involvement. To test the opposite sequence of development, the following models were employed: Time 1 involvement with Time 2 cognition, Time 2 involvement with Time 3 cognition, and Time 3 involvement with Time 4 cognition. In each case, either cognition or behavior was used to predict the opposite factor at the next time point. See *Appendix D* for a visual diagram of the hypothesized longitudinal models. The goal was to compare the fit of the models to the data, which would indicate a possible sequential development of problem gambling. In other words, if the cognition → involvement model produced a better fit, then it is likely that cognitive changes precede and predict changes in gambling behaviour. If the involvement → cognition model produced a better fit, then one can posit that being more involved in gambling precedes and predicts changes in gambling cognition.

A sample size of N > 1000 was deemed sufficient for the analyses. Multivariate normality was assessed using AMOS 19. Mardia's coefficients of multivariate skewness and kurtosis were used as indicators of non-normality (Jupp, & Mardia, 1980). Using the most complete data from Time 1, all of the coefficients supported non-normal distributions across the variables. West and colleagues (1995) summarized the main consequences of non-normality on SEM analyses. First, it may lead to unnecessary modification of the models in an effort to reduce spuriously high χ^2 values. Second, this inflation is more pronounced in small samples. Finally, fit indices based on non-normal data tend to be underestimated. Based on these observations, non-normality in the present study was dismissed as an important influence for several reasons: 1) the sample size was large enough to minimize any χ^2 inflations. 2) Modification indices were not employed as they did not make theoretical sense and the SEM models were already well-fitting according to the most conservative criteria. 3) Since the fit indices for all models were above the cut-off points for what constitutes a good fit, any underestimation effects due to non-normality would not affect the final interpretation of the results.

The conventional method of SEM model comparison is the chi-square difference test. However, given that the models used different data and parameters they could not be considered nested. As such, a statistical test of an improvement was not available and other fit indices were examined. Ullman (2007) suggests using the model Akaike Information Criterion (AIC) and the consistent Akaike Information Criterion (CAIC; Akaike, 1987; Bozdogan, 1987). These methods assess the fit of the model and also include a parsimony adjustment. Smaller values indicated a good-fitting, parsimonious model. Since these indices are not normed to a 0 - 1 scale, there is no clear cut-off for what constitutes a better model. The term "small enough" can only be used as compared to other competing models in this case.

To insure the adequacy of the generated models, two additional indices were examined. Bentler (1990) and Ullman (2007) recommend reporting the Comparative Fit Index (CFI). The CFI was used to evaluate the estimated model by comparing it to the independence model (i.e. one that corresponds to completely unrelated variables). Values of 0.95 or greater were considered indicative of good fit. Cheung and Rensvold (2002) have found that a CFI difference of .01 indicated variance between two models and constituted a meaningful difference. Consequently, this criterion was used to evaluate model differences in the study. Finally, the root mean square error of approximation (RMSEA) was interpreted to ensure that the error of the residuals in the models was sufficiently small (Steiger, & Lind, 1980). Values of 0.06 or less were desired for this index (Hu, & Bentler, 1999). Good-fitting models produce consistent results on many different indices in most cases. As such, the issue of which indices to report is not critical given appropriate model consistency.

For all analyses, the expenditure variable was transformed using a natural logarithm function in order to normalize the distribution of this variable since most participants tended to spend either very little or very large amounts of money gambling. Additionally, extreme outliers were detected using box-and-whisker-plots and converted to the highest typical value seen in the distribution ($20,000). The decision to down-convert these outliers was made after it was determined that their inclusion did not significantly change the results of the analyses. The conversion provided a way to include the more severe gamblers' data in the models while simultaneously addressing extreme outliers. Full descriptive statistics for this variable are provided in Table 3.

Using expectation maximization (EM), estimates were computed for all missing data, treating individuals who did not follow-up as missing data. Consequently, the missing data analysis resulted in four waves of 1372 data points since the first wave had the most participants and zero missing values. An alternative listwise deletion approach was also performed, including data from only those participants who completed all four data collection waves. A comparison of the effects of these two approaches on the final interpretation is reported in the results section.

Attrition bias was assessed by coding the sample based on whether or not they completed all four waves of the assessment. The categorical membership variable was used to compare those who stayed and those who dropped out on the following demographic variables: age, gender, marital status, problem gambling status as measured by the DSM-IV criteria, location, education level, current employment status, current school status and ethnicity.

In order to test the stability of gambling cognition and gambling involvement, the data were analyzed using Generalized Estimating Equations (GEE), which models repeated measures over time, and controls for the effects of autocorrelation and participant ID. In order to effectively represent gambling involvement in GEE, a custom variable was created using all three gambling behavior indicators from the SEM models. Each of the three indicator variables was converted into Z-scores at each wave and weighted proportionally to their loadings on the latent behaviour variable from the SEM models. An average of the loadings from the first two waves was taken for each behaviour variable. For example, the range variable is included twice in the SEM models for waves 1-2, one for cognition predicting behavior and one for behavior predicting cognition. The average of these two scores was used as the weight for the range Z-score in GEE. The average scores for each of the three variables were then added together to produce a composite variable termed “behavior” which represented gambling involvement for Time 1. This process was repeated for each wave of assessment to generate four composite “behavior” variables, which were subsequently converted into long form. A time variable consisting of the four time points was dummy coded in order to examine any interaction effects at each individual time point rather than just the main effect of time. Thus, the GEE procedure modeled the change over time of the gambling cognitions, gambling behavior, and their interaction at each assessment wave.

Results

The hypothesized model

A confirmatory factor analysis was performed through AMOS 19 on the 13-variable models presented in *Figure 1*, where circles represent latent variables and rectangles represent measured variables. Absence of a line connecting variables implies no hypothesized direct effect. Maximum likelihood estimation was used to estimate all six models. The independence model that tests the hypothesis that all variables are uncorrelated was rejected in every estimation. All six of the hypothesized models were supported and considered to have good fit, as indicated by CFI, AIC, and RMSEA values (CFI = .95 and RMSEA < .06 were used as criteria for good fit; Byrne, 2010). Thus, primarily, the SEM analysis reinforced the idea that both behavior and cognition are important constructs in gambling and form a bi-directional relationship. See Table 4 for the full list of fit indices.

Since the models tested in this study were not nested, a χ^2 difference test was not possible. Instead, Byrne (2010) suggests a CFI difference test for non-nested models or large samples where the χ^2 test is likely to almost always be significant regardless of any actual disparities between the models. All CFI differences between the cognition→behaviour and behaviour→cognition model pairs met the .01 cut-off, suggesting that each model was meaningfully different. In other words, a difference this large in CFI values was unlikely to be by chance alone and likely represented a real difference in fit between these models. Standardized regression weights for the GFS items ranged from .32 to .50 across the four time points and all values were statistically significant ($p < .001$). Standardized regression weights for the gambling involvement indicators ranged from .76 to .92 and were statistically significant ($p < .001$). Refer to Tables 5a and 5b for the complete list of the standardized regression weights.

Change over time

The GEE analysis showed a significant main effect of time with total score on the GFS as the dependent variable (i.e. GFS scores changed over time), Wald χ^2 (3) = 473.93, $p < .001$. This main effect of time was controlled for the main effect of behavior and time x behavior interaction. There was a significant main effect of behavior (i.e. as behavior changed, so did GFS scores), Wald χ^2 (1) = 56.56, $p < .001$. The overall interaction between time and behaviour was not significant when GFS was the dependent variable, Wald χ^2 (4) = 4.74, p = .19 (i.e. in general, the nature of the dependence of GFS on behaviour did not change at each time point). However, the individual parameter estimate for this interaction at Time 3 was significant, Wald χ^2 (1) = 4.70, $p < .03$. There was no significant main effect of time when behaviour was the dependent variable (Wald χ^2 (3) = 2.02, p = .57) nor was the interaction between GFS scores and time significant (Wald χ^2 (3) = 3.69, p = .30), which suggests that behaviour did not change over time. Overall, the results of the GEE analysis suggested that over time, the number of cognitive distortions endorsed by the participants, as indicated by total score on the GFS declined (see Table 6 for estimated marginal means at each time point). Additionally, gambling involvement did not significantly vary over time. Finally, the relationship between gambling cognition and gambling involvement did not significantly change at each time point. A summary of the χ^2 values from the GEE analysis is presented in *Appendix E*.

Attrition bias and missing data

The attrition bias analysis showed that the participants who completed all four waves of the assessment were: more likely to be married, χ^2 (4) = 34.10, $p < .001$; less likely to be a pathological or problem gambler, χ^2 (2) = 14.45, $p < .001$; more likely to be 43-65 years old, χ^2 (3) = 40.79, $p < .001$; more likely to be female, χ^2 (1) = 16.05, $p < .001$; more likely to be from an urban area such as Calgary or Edmonton, χ^2 (3) = 13.51, $p < .01$; more likely to have a bachelor's degree or higher, χ^2 (7) = 48.50, $p < .001$; and less likely to be aboriginal, χ^2 (7) = 18.47, $p < .05$. See Table 7 for a summary of attrition bias analysis for those who completed all four waves of assessment.

A second, identical set of analyses was conducted on the data using listwise deletion as the method for handling missing data instead of expectation maximization (EM). The analyses were conducted with the intention of identifying whether the chosen approach to missing data significantly affected the results of the study. The results of the listwise dataset were identical in terms of direction of relationship and significance within the SEM models and thus, are not reported here. The only observed change was in the magnitude of difference between the paired models at each time point. Using listwise deletion for missing data produced larger differences in fit indices.

Likewise, the GEE results using a listwise sample were identical, except the individual time 3 parameter that was significant in the EM analysis. In the listwise analysis, this parameter was no longer significant. There are several possible explanations for the change in this parameter. First, it may have been an artifact of the chosen missing data method rather than a real interaction at time 3. Second, the interaction may have been a real phenomenon in the sample resulting from attrition bias. The analysis above showed that at wave 3, there were fewer single, male, problem, aboriginal gamblers with lower education. The change in the characteristics of the sample due to dropout may have created a difference in the interaction between behaviour and cognition at time 3. Finally, it is important to acknowledge that a population sample is always influenced by real world phenomena. In this case, the data collection at time 3 occurred in 2009 – 2010, which coincided with the end of the Canadian recession. The large-scale economic influences of this event may have affected gambling behaviour in Alberta, which created a change in the dynamic of the constructs measured at this wave.

Discussion

The goal of the current study was to explore the temporal relationship between cognitive distortions in gambling and gambling involvement. Confirmatory factor analysis confirmed the hypothesized two-latent factor relationship. Results supported the idea that changes in cognitive distortions better predict future changes in gambling behaviour than the reverse relationship, as indicated by higher CFI values and lower AIC and RMSEA values of the cognition → behaviour models at times 1-2 and 3-4. Furthermore, all of the tested models met the criteria for a good fit, highlighting the fact that both cognitive and behavioural variables play a role in gambling. In other words, the results of the study comment on the relative importance of each construct rather than single out behaviour as an unimportant variable in the development of gambling disorders.

At times 2-3 the better fitting relationship was behaviour predicting cognition. However, this result only appeared at this time point and nowhere else. This may have been due to a larger amount of missing data at this time or the nature of the missing data. For example, attrition bias and the type of responses endorsed by participants as a result of this bias may have reversed the dominant relationship for one assessment wave. This hypothesis is partially supported by the significant parameter estimate of the time x behaviour interaction at time 3. This significance suggests that compared to time 1 which was used as the reference point in the dummy coding, there may have been something slightly different in the relationship between cognition and behaviour at time 3 despite the fact that over all the time periods together, this interaction was not significant (refer to the *Analysis* section for the possible reasons for this interaction).

The attrition bias analysis showed that those who dropped out of the study were more likely to be problem or pathological gamblers, aboriginal, single young males, from a rural area, with lower education. The analysis points to a potential problem with the generalizability of the results. First, the present study faces the problem of using a population sample. Although oversampling for high frequency and at risk gamblers was attempted, it could not replicate the advantages of a clinical sample. Therefore, any conclusions that are drawn from the study may not necessarily apply to clinical populations. This is problematic since clinical populations are where intervention is needed most. Additionally, the characteristics of those who dropped out of the study were those of the most high-risk populations for problem gambling. Specifically, aboriginal males with low education are underrepresented in research, yet maintain some of the highest rates of pathological gambling (Williams et al., 2011). Thus, some high-risk participants may have been lost over the course of the study.

Cognitive distortions declined over time, as indicated by significant GEE time effect for GFS. Behaviour was more stable and did not change over time nor was there any significant interaction between the variables, indicating that the relationship between cognitive distortions and gambling involvement remained fairly stable over the five-year period. Taken together, the GEE analysis showed that gambling fallacies are more likely than behaviour to naturally vary (specifically decline) over time. Regression to the mean is not likely to explain this phenomenon as the sample for the study was a general population sample, not a clinical one. As such, there was no unusual representation of extreme gamblers in the sample that could have resulted in regression to the mean. Similarly, practice effects were not likely as each data collection wave was one year apart. One possible explanation may be that since those who completed all four waves were more likely to be educated than those who dropped out, the decline in GFS scores was a result of greater awareness of the rules of probability and independence of random events due to the higher education level of the retained sample. Alternatively, the distribution of the education levels of the recruited sample may have changed over the duration of the study, as some participants may have obtained bachelor's degrees during the five-year period. More broadly, people may have learned from experience or media attention to gambling, which may represent a form of adaptation or a mediator of adaptation in gamblers.

The present study explored a significantly understudied area of gambling. Longitudinal studies are only beginning to discover the causal and temporal relations between gambling behaviour and its correlates. One of the ways of establishing these relations is by ruling out alternative theoretical models and hypotheses. The longitudinal design allows to not only test competing theories of the nature of gambling disorders, but also to provide insight into the typical developmental sequence of problem gambling. One goal is to specify whether there is a "gateway" to problems, much like marijuana is widely cited as the "gateway" to other illicit drugs (Kandel, 1975).

The longitudinal work that has been done in this area has focused on patterns of gambling activity involvement and symptomatology (Toce-Gerstein, Gerstein, & Volberg, 2003). Researchers have identified the potential sequences of development of sets of symptoms based on increasing levels of severity of gambling pathology. However, the same cannot be said for the development and the change in dispositional characteristics of gambling individuals. Is it environmental or personal/individual factors that effect change from social to pathological gambling? When does this change occur? Can it be prevented or reversed? The present study may contribute to the answers to some of these questions by showing that cognitive constructs may be the first to change in the movement from social to pathological gambling, thus providing a potential target for prevention.

The longitudinal design of the LLLP afforded several methodological advantages. First, a sample size of this magnitude allowed observation of subtle changes in individual and population trends over time. Similarly, it provided an optimal data pool for conducting statistical analyses such as structural equation modeling and principal component analysis – methods that often require very large samples to be valid. The current study also had the advantage of standardized sampling procedures and a carefully outlined recruitment plan. The sampling plan reflected both the urban and the rural populations in Alberta, Canada. This is important as these two populations may substantially vary on gambling dimensions. For example, accessibility to certain forms of gambling may influence gambling involvement differently in rural areas.

The sample represented a full adult life span divided between four age groups: 18-20, 23-25, 43-45, and 63-65. Using an accelerated longitudinal design, this sampling procedure allowed to cover all adult age ranges since the participants aged by five years at time 4 of data collection. Few studies manage to employ a scope of this magnitude. Furthermore, there is an apparent lack of research in certain age cohorts. For example, individuals over 40 and young females are rarely adequately sampled. The present methodology contributes to the knowledge gaps in these areas.

The combination of several different tools in the LLLP constituted a rigorous data gathering procedure. First, it increased participant engagement as people may respond differently to various survey methods. For example, face-to-face interviewing may have facilitated honest responding by building rapport. Second, the wide array of survey instruments measured a large number of constructs that have been associated with gambling behaviour. This significantly improved content validity for the study, as well as the scope of the chosen indicators for the SEM models. For example, the selected gambling involvement questions were based off of a widely used gambling tool (i.e. CPGI).

Finally, the stability or change of gambling behaviour over time is not well understood. The results of the present study suggest several important implications for both research and clinical practice in the area of gambling disorders. Most importantly, the way people think and interpret gambling consequences and probability of outcomes may be more predictive of their future gambling behaviour than the reverse relationship. The connotation is that the traditional behavioural methods such as credit or debit card limits and gambling cue avoidance (e.g., taking a route to work that avoids the gambling venue), although easier to administer, may not be as effective as cognitive restructuring with clients. However, it is important to recognize that the results of the study do not rule out gambling involvement and behavioural constructs as important concepts in the treatment of gambling disorders. After all, every hypothesized model, even those that predicted future cognition based on current behaviour met the most conservative cutoffs for a good-fitting structural equation model (e.g., .95 for CFI; Byrne, 2010). Thus, there is a clearly outlined, supported relationship between gambling fallacies and gambling involvement. Furthermore, the GEE analysis showed that this relationship is fairly consistent as the interaction did not change over time. Despite this, the results distinctly point to the greater susceptibility to change in cognitive distortions, as well as their greater potential to predict future changes in gambling behaviour and habits. Broadly, the findings suggest that cognitive restructuring should be a primary target for public policy, prevention and intervention efforts.

It is important to acknowledge that the present study faces a number of disadvantages from using the structural equation modeling procedure. First, causality cannot be inferred from this method. As such, the final accepted model does not dictate a causal relationship between gambling cognition and gambling involvement – merely a more probable relationship in the population. Second, SEM modeling with the goal of examining longitudinal trends presents a challenge when comparing models. Since they were not nested in this case, a statistical difference test was not possible. The final comparisons were made qualitatively on the basis of different indices of fit. Consequently, any interpretations of the results may be questioned on the basis of subjectivity and lack of statistical inference.

Finally, the Gambling Fallacies Scale also presents a limitation. Although it adequately samples a wide range of cognitive errors in gambling, it produces poor reliability estimates by psychology's standards (Cronbach's alpha coefficients in the range of 0.50 - 0.60). However, given the significant results of the study, improvement in the psychometrics of the cognition instrument would likely only further improve the fit of the models. In addition, the GFS has previously demonstrated good content validity. It covers all the cognitive distortions typically seen in gambling: independence of random events, belief that one is luckier than others, illusion of control, believing in superstitious conditioning, ignoring statistical probabilities, insensitivity to the law of large numbers, and stereotypic notions of randomness (Williams, 2003).

It is worth noting that structural equation modeling represents a special case, where "bad" indicators may not always affect the integrity of the final results. Little and colleagues (1999) conducted a simulation to examine the effects of indicator selection on the fidelity of construct representations and the relative ability of analyses to recover construct information. They addressed the question of whether indicators with low internal consistency can still be valid. Their conclusion was that instruments with low reliabilities are likely to still produce accurate estimates of the relationships among constructs provided that:

1) They are wide enough in scope to sufficiently capture the construct domain. In this case, the GFS provided more than adequate sampling of cognitive errors in gambling. The principal component analysis confirmed that most questions measured somewhat different knowledge of gambling cognition and comprised at least two viable lower-order factors while representing a single latent cognition construct.
2) They yield sufficient variability on the construct. This criteria was generally met as scores on every construct spanned the entire ranged of possible scores, although data were not normality distributed in most cases (refer to *Methods* for a discussion of normality analyses). This may have been an artifact of the underrepresentation of more severe gamblers since lower scores on the GFS reflected fewer cognitive errors.
3) They are analyzed by confirmatory analysis. The design of the present study used confirmatory factor analysis to assess a limited number of models specified a priori. In addition, exploratory model modification was not conducted.

Evidently, constructs can be represented validly even if their estimates (i.e. indicators) have poor reliability. It is therefore probable that including the Gambling Fallacies Scale did not affect the final fit of the models given that the other components of the SEM models were properly specified and identified.

Conclusion

The current study has implications for public health. Results from this and other similar studies may be used to inform the public about the dangers of gambling fallacies. Furthermore, many treatment approaches for problem gambling focus on correcting cognitive distortions. Cognitive-behavioral therapy (CBT) is just one example of a treatment method that targets gambling fallacies (Sylvain, Ladouceur. & Boisvert, 1997). Research has demonstrated that CBT produces positive results in adolescent and adult treatment (Takushi et al., 2004). Disentangling the relationship between cognition and behaviour in gambling will contribute to the improvement of CBT and other similar treatment methods. Given that cognitive fallacies appear to better predict changes in gambling involvement, secondary prevention would be most successful by attempting cognitive restructuring in clients. Limiting the amount of gambling behaviour should thus become a secondary parallel goal to treatment.

Although it may be difficult to generalize the results of this study to clinical populations, applying the findings to the general public also has merit. Public health initiatives begin with the social gambler. Results from studies similar to this may be used to inform the public of the concept of gambling fallacies and the dangers associated with them. Furthermore, they may provide guidelines for the typical way in which problem gambling develops at the individual level. Subsequently, prevention may be self-administered by teaching individual gamblers to recognize and address early warning signs such as increased chasing habits in gambling or increased time spent gambling.

Currently, targeted treatment is difficult to implement. It is clear that both cognitive distortions and gambling involvement contribute to the development of pathological and problem gambling, but the sequence, timeline and the “gateway” for this are not apparent. This is the first study to investigate these relationships longitudinally using a large population-based sample with four age cohorts, sampling from both rural and urban areas.

References

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, *52*, 317-332.

Barnes, G. M., Welte, J. W., Hoffman, J. H., & Dintcheff, B. A. (2005). Shared Predictors of Youthful Gambling, Substance Use, and Delinquency. *Psychology of Addictive Behaviors*, *19*(2), 165-174. doi: 10.1037/0893-164X.19.2.165

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588-606. doi: 10.1037//0033-2909.88.3.588

Blaszczynski, A., & Silove, D. (1995). Cognitive and behavioral therapies for pathological gambling. *Journal of Gambling Studies*, *11*(2), 195-220. doi: 10.1007/BF02107115

Bozdogan, H. (1987). Model selection and Akaike's information criteria (AIC): The general theory and its analytical extensions. *Psychometrika*, *52*, 345-370.

Breen, R., & Zuckerman, M. (1999). Chasing in gambling behavior: personality and cognitive determinants. *Personality and Individual Differences*, *27*(6), 1097-1111. doi: 10.1016/S0191-8869(99)00052-5

Brown, S. A., Goldman, M. S., Inn, A., & Anderson, L. R. (1980). Expectations of reinforcement from alcohol: Their domain and relation to drinking problems. *Journal of Consulting and Clinical Psychology, 48*, 419-426.

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). New York, NY: Routledge.

Campbell-Meiklejohn, D., Woolrich, M., Passingham, R., & Rogers, R. (2008). Knowing When to Stop: The Brain Mechanisms of Chasing Losses. *Biological Psychiatry*, *63*(3), 293-300. doi: 10.1016/j.biopsych.2007.05.014

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 9*, 233-255.

el-Guebaly, N., Casey, D. M., Hodgins, D. C., Smith, G. J., Williams, R. J., Schopflocher, D. P., & Wood, R. T. (2008). Designing a Longitudinal Cohort Study of Gambling in Alberta: Rationale, Methods, and Challenges. Journal of Gambling Studies, 24(4), 479-504. doi: 10.1007/s10899-008-9108-6

Ferris, J., & Wynne, H. (2001). *The Canadian Problem Gambling Index final report*. Phase II final report to the Canadian Inter-Provincial Task Force on Problem Gambling.

Gadboury, A., & Ladouceur, R. (1989). Erroneous perceptions and gambling. Journal of Social Behavior and Personality, 4, 411-420.

Gilovich, T., & Douglas, C. (1986). Biased evaluations of randomly determined gambling outcomes. *Journal of Experimental Social Psychology*, *22*(3), 228-241. doi: 10.1016/0022-1031(86)90026-0

Hu, L., & Bentler, P. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1-55.

Ilgen, M., McKellar, J., & Tiet, Q. (2005). Abstinence self-efficacy and abstinence 1 year after substance use disorder treatment. *Journal of Consulting and Clinical Psychology, 73*, 1175-1180.

Joukhador, J., Maccallum, F., & Blaszczynski, A. (2003). Differences in Cognitive Distortions Between Problem And Social Gamblers. *Psychological Reports*, *92*(4), 1203-1214. doi: 10.2466/PR0.92.4.1203-1214

Jupp, P. E., & Mardia, K. V. (1980). A general coefficient for directional data and related regression problems. *Biometrika, 67*, 163-173.

Kandel, D. (1975). Stages in adolescent involvement in drug use. *Science*, *190*(4217), 912-914. doi: 10.1126/science.1188374

Keren, G., & Lewis, C. (1995). The two fallacies of gamblers: Type I and Type II. *Organizational Behavior and Human Decision Processes*, *60*, 75-89.

Ladouceur, R., & Dube, D. (1997). Erroneous perceptions in generating random sequences: Identification and strength of a basic misconception in gambling behavior. *Swiss Journal of Psychology*, *56*, 256-259.

Ladouceur, R., Sylvain, C., & Gosselin, P. (2007). Self-Exclusion Program: A Longitudinal Evaluation Study. *Journal of Gambling Studies*, *23*(1), 85-94. doi: 10.1007/s10899-006-9032-6

Ladouceur, R., Sylvain, C., Boutin, C., Lachance, S., Doucet, C., & Leblond, J. (2003). Group therapy for pathological gamblers: a cognitive approach. *Behaviour Research and Therapy*, *41*(5), 587-596. doi: 10.1016/S0005-7967(02)00036-0

Letarte, H., Ladouceur, R., & Mayrand, M. (1986). Primary and secondary illusory control and risk-taking in gambling (roulette). *Psychological Reports*, *58*, 299-302.

Little, T. D., Lindenberger, U., & Nesselroade, J. R. (1999). On selecting indicators for multivariate measurement and modeling with latent variables: When "good" indicators are bad and "bad" indicators are good. *Psychological Methods*, *4*(2), 192-211. doi: 10.1037//1082-989X.4.2.192

McConaghy, N., Armstrong, M. S., Blaszczynski, A., & Allcock, C. (1983). Controlled comparison of aversive therapy and imaginal desensitization in compulsive gambling. *The British Journal of Psychiatry*, *142*(4), 366-372. doi: 10.1192/bjp.142.4.366

Miller, N. V., & Currie, S. R. (2008). A Canadian Population Level Analysis of the Roles of Irrational Gambling Cognitions and Risky Gambling Practices as Correlates of Gambling Intensity and Pathological Gambling. *Journal of Gambling Studies*, *24*(3), 257-274. doi: 10.1007/s10899-008-9089-5

Parke, J., & Griffiths, M. (2004). Gambling addiction and the evolution of the "near miss" *Addiction Theory and Research*, *12*, 407-411.

Petry, N. M. (2003). A comparison of treatment-seeking pathological gamblers based on preferred gambling activity. *Addiction*, *98*(5), 645-655. doi: 10.1046/j.1360-0443.2003.00336.x

Petry, N. M., Ammerman, Y., Bohl, J., Doersch, A., Gay, H., Kadden, R., ... Steinberg, K. (2006). Cognitive-Behavioral Therapy for Pathological Gamblers. *Journal of Consulting and Clinical Psychology*, *74*(3), 555-567. doi: 10.1037/0022-006X.74.3.555

Rogers, P. (1998). The cognitive psychology of lottery gambling: a theoretical review. *Journal of Gambling Studies*, *14*, 111-134.

Shaffer, H. J., Hall, M. N., & Vander Bilt, J. (1999). Estimating the prevalence of disordered gambling behavior in the United States and Canada: a research synthesis. *American Journal of Public Health*, *89*(9), 1369-1376. doi: 10.2105/AJPH.89.9.1369

Slutske, W. S. (2006). Natural Recovery and Treatment-Seeking in Pathological Gambling: Results of Two U.S. National Surveys. *American Journal of Psychiatry*, *163*(2), 297-302. doi: 10.1176/appi.ajp.163.2.297

Slutske, W. S., Caspi, A., Moffitt, T., & Poulton, R. (2005). Personality and Problem Gambling: A Prospective Study of a Birth Cohort of Young Adults. *Archives of General Psychiatry*, *62*(7), 769-775. doi: 10.1001/archpsyc.62.7.769

Slutske, W. S., Jackson, K. M., & Sher, K. J. (2003). The natural history of problem gambling from age 18 to 29. *Journal of Abnormal Psychology*, *112*(2), 263-274. doi: 10.1037/0021-843X.112.2.263

Sylvain, C., Ladouceur, R., & Boisvert, J. (1997). Cognitive and behavioral treatment of pathological gambling: A controlled study. *Journal of Consulting and Clinical Psychology*, *65*(5), 727-732. doi: 10.1037//0022-006X.65.5.727

Takushi, R. Y., Neighbors, C., Larimer, M. E., Lostutter, T. W., Cronce, J. M., & Marlatt, G. A. (2004). Indicated Prevention of Problem Gambling Among College Students. *Journal of Gambling Studies*, *20*(1), 83-93. doi: 10.1023/B:JOGS.0000016705.58903.8f

Toce-Gerstein, M., Gerstein, D. R., & Volberg, R. A. (2003). A hierarchy of gambling disorders in the community. *Addiction*, *98*(12), 1661-1672. doi: 10.1111/j.1360-0443.2003.00545.x

Toneatto, T. (1999). Cognitive Psychopathology of Problem Gambling. *Substance Use & Misuse*, *34*(11), 1593-1604. doi: 10.3109/10826089909039417

Toneatto, T. (2002). Cognitive therapy for problem gambling. *Cognitive and Behavioral Practice*, *9*(3), 191-199. doi: 10.1016/S1077-7229(02)80049-9

Toneatto, T., & Nguyen, L. (2007). Individual Characteristics and Problem Gambling Behavior. In G. Smith, D. Hodgins, & R. J. Williams (Eds.), *Research and Measurement Issues in Gambling Studies* (pp. 280-295). Burlington, MA: Academic Press.

Toneatto, T., & Sobell, L. C. (1990). Pathological gambling treated with cognitive behavior therapy: a case report. *Addictive Behaviors*, *15*(5), 497-501. doi: 10.1016/0306-4603(90)90038-Y

Toneatto, T., Blitz-Miller, T., Calderwood, K., Dragonetti, R., & Tsanos, A. (1997). Cognitive distortions in heavy gambling. *Journal of Gambling Studies*, *13*, 253-266.

Ullman, J. B. (2007). Structural Equation Modeling. In B. G. Tabachnick & L. S. Fidell (Authors), *Using multivariate statistics* (pp. 676-781). Boston, MA: Pearson.

Vitaro, F., Arseneault, L., & Tremblay, R. (1997). Dispositional predictors of problem gambling in male adolescents. *American Journal of Psychiatry*, *154*, 1769-1770.

West, S. G., Finch, J. F., & Curran, P.J. (1995). Structural equation models with non-normal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp.56-75). Thousand Oaks, CA: Sage.

Williams, R. J. (2003). Reliability and validity of four scales to assess gambling attitudes, gambling knowledge, gambling fallacies and ability to calculate gambling odds. Unpublished technical report.

Williams, R. J., Belanger, Y. D., & Arthur, J. N. (2011). Gambling in Alberta: History, current status, and socioeconomic impacts. Final report to the Alberta Gaming Research Institute. Edmonton, Alberta. April 2, 2011.

Williams, R. J., Connolly, D., Wood, R. T., & Nowatzki, N. (2006). Gambling and problem gambling in a sample of university students. *Journal of Gambling Issues, 16* [online journal: http://www.camh.net/egambling/].

Winters, K. C., Stinchfield, R. D., Botzet, A., & Anderson, N. (2002). A prospective study of youth gambling behaviors. *Psychology of Addictive Behaviors*, *16*(1), 3-9. doi: 10.1037//0893-164X.16.1.3

Wood, R., & Williams, R. (2007). 'How Much Money Do You Spend on Gambling?' The Comparative Validity of Question Wordings Used to Assess Gambling Expenditure. *International Journal of Social Research Methodology*, *10*(1), 63-77. doi: 10.1080/13645570701211209

Table 1. *Correlations of measured variables for Time 1.*

		GFS Item 1	GFS Item 2	GFS Item 3	GFS Item 4	GFS Item 5	GFS Item 6	GFS Item 7	GFS Item 8	GFS Item 9	GFS Item 10	Range 1	Frequency 1	Expenditure 1
GFS Item 1	Pearson Correlation	1	.264	.103	.133	.134	.038	.046	.091	.170	.168	.012	.059	-.011
	Sig. (2-tailed)		.000	.000	.000	.000	.158	.089	.001	.000	.000	.659	.028	.684
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 2	Pearson Correlation	.264	1	.104	.157	.107	-.044	-.055	.127	.142	.137	.072	.052	.020
	Sig. (2-tailed)	.000		.000	.000	.000	.103	.041	.000	.000	.000	.008	.053	.457
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 3	Pearson Correlation	.103	.104	1	.103	.136	-.037	.025	.133	.143	.128	.094	.074	.039
	Sig. (2-tailed)	.000	.000		.000	.000	.168	.356	.000	.000	.000	.000	.006	.149
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 4	Pearson Correlation	.133	.157	.103	1	.128	-.019	-.008	.150	.119	.113	.073	.082	-.010
	Sig. (2-tailed)	.000	.000	.000		.000	.491	.777	.000	.000	.000	.007	.002	.704
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 5	Pearson Correlation	.134	.107	.136	.128	1	.027	.034	.142	.206	.123	.152	.109	.056
	Sig. (2-tailed)	.000	.000	.000	.000		.311	.206	.000	.000	.000	.000	.000	.038
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 6	Pearson Correlation	.038	-.044	-.037	-.019	.027	1	.235	-.044	.046	-.033	-.090	-.051	-.035
	Sig. (2-tailed)	.158	.103	.168	.491	.311		.000	.104	.088	.218	.001	.060	.201
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 7	Pearson Correlation	.046	-.055	.025	-.008	.034	.235	1	-.114	.016	.029	-.136	-.112	-.043
	Sig. (2-tailed)	.089	.041	.356	.777	.206	.000		.000	.542	.283	.000	.000	.114
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372

GFS Item 8	Pearson Correlation	.091	.127	.133	.150	.142	-.044	-.114	1	.252	.072	.108	.043	.028
	Sig. (2-tailed)	.001	.000	.000	.000	.000	.104	.000		.000	.007	.000	.111	.292
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 9	Pearson Correlation	.170	.142	.143	.119	.206	.046	.016	.252	1	.116	.043	.047	.019
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.088	.542	.000		.000	.109	.080	.474
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
GFS Item 10	Pearson Correlation	.168	.137	.128	.113	.123	-.033	.029	.072	.116	1	-.009	.019	.018
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.218	.283	.007	.000		.752	.489	.506
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
Range1	Pearson Correlation	.012	.072	.094	.073	.152	-.090	-.136	.108	.043	-.009	1	.692	.255
	Sig. (2-tailed)	.659	.008	.000	.007	.000	.001	.000	.000	.109	.752		.000	.000
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
Frequency1	Pearson Correlation	.059	.052	.074	.082	.109	-.051	-.112	.043	.047	.019	.692	1	.159
	Sig. (2-tailed)	.028	.053	.006	.002	.000	.060	.000	.111	.080	.489	.000		.000
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
Expenditure1	Pearson Correlation	-.011	.020	.039	-.010	.056	-.035	-.043	.028	.019	.018	.255	.159	1
	Sig. (2-tailed)	.684	.457	.149	.704	.038	.201	.114	.292	.474	.506	.000	.000	
	N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372

Table 2. *Results of the principal component analysis on the Gambling Fallacies Scale.*

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.985	19.852	19.852	1.985	19.852	19.852	1.562	15.618	15.618
2	1.291	12.906	32.757	1.291	12.906	32.757	1.468	14.679	30.297
3	1.045	10.445	43.202	1.045	10.445	43.202	1.291	12.905	43.202
4	.955	9.553	52.755						
5	.887	8.873	61.628						
6	.857	8.567	70.195						
7	.827	8.266	78.461						
8	.741	7.411	85.872						
9	.713	7.130	93.001						
10	.700	6.999	100.000						

Extraction Method: Principal Component Analysis.

Table 3. *Descriptive statistics of measured variables for Time 1.*

	Mean	Std. Deviation	N
GFS Item 1	.3054	.46074	1372
GFS Item 2	.2813	.44982	1372
GFS Item 3	.2303	.42119	1372
GFS Item 4	.0598	.23714	1372
GFS Item 5	.2172	.41249	1372
GFS Item 6	.7631	.42532	1372
GFS Item 7	.9111	.28473	1372
GFS Item 8	.1079	.31033	1372
GFS Item 9	.1327	.33932	1372
GFS Item 10	.2362	.42487	1372
Range1	2.0999	1.87838	1372
Frequency1	2.2303	1.96156	1372
Expenditure1	273.0939	1490.79159	1372

Table 4. *Fit indices for the hypothesized SEM models.*

Model	χ^2*	CFI	AIC	RMSEA
Cognition1→Behaviour2	105.42	.98	173.42	.03
Behaviour1→Cognition2	140.78	.97	186.78	.04
Cognition2→Behaviour3	129.60	.96	175.60	.04
Behaviour2→Cognition3	107.16	.98	153.16	.03
Cognition3→Behaviour4	94.23	.98	162.23	.03
Behaviour3→Cognition4	124.87	.97	192.87	.04

Note: All χ^2values used a sample size of 1372, 43 degrees of freedom, and were significant at the .001 level.

Table 5a. *Standardized regression weights for the six hypothesized models.*

			Estimate
Behaviour2	<---	Cognition1	.20
Expenditure2	<---	Behaviour2	.87
Frequency2	<---	Behaviour2	.76
Range2	<---	Behaviour2	.84
w1gfs_q10rv	<---	Cognition1	.32
w1gfs_q9rv	<---	Cognition1	.44
w1gfs_q8rv	<---	Cognition1	.38
w1gfs_q5rv	<---	Cognition1	.39
w1gfs_q4rv	<---	Cognition1	.33
w1gfs_q3rv	<---	Cognition1	.32
w1gfs_q2rv	<---	Cognition1	.40
w1gfs_q1rv	<---	Cognition1	.41
Cognition2	<---	Behaviour1	.15
Expenditure1	<---	Behaviour1	.92
Frequency1	<---	Behaviour1	.79
Range1	<---	Behaviour1	.87
w2gfs_q10rv	<---	Cognition2	.34
w2gfs_q9rv	<---	Cognition2	.46
w2gfs_q8rv	<---	Cognition2	.32
w2gfs_q5rv	<---	Cognition2	.43
w2gfs_q4rv	<---	Cognition2	.38
w2gfs_q3rv	<---	Cognition2	.36
w2gfs_q2rv	<---	Cognition2	.43
w2gfs_q1rv	<---	Cognition2	.47
Behaviour3	<---	Cognition2	.15
w2gfs_q10rv	<---	Cognition2	.34
w2gfs_q9rv	<---	Cognition2	.47
w2gfs_q8rv	<---	Cognition2	.32
w2gfs_q5rv	<---	Cognition2	.43
w2gfs_q4rv	<---	Cognition2	.38
w2gfs_q3rv	<---	Cognition2	.36
w2gfs_q2rv	<---	Cognition2	.43
w2gfs_q1rv	<---	Cognition2	.47
Expenditure3	<---	Behaviour3	.78
Frequency3	<---	Behaviour3	.78
Range3	<---	Behaviour3	.82

Table 6b. *Standardized regression weights for the six hypothesized models.*

			Estimate
Cognition3	<---	Behaviour2	.15
w3gfs_q10rv	<---	Cognition3	.37
w3gfs_q9rv	<---	Cognition3	.44
w3gfs_q8rv	<---	Cognition3	.38
w3gfs_q5rv	<---	Cognition3	.37
w3gfs_q4rv	<---	Cognition3	.47
w3gfs_q3rv	<---	Cognition3	.39
w3gfs_q2rv	<---	Cognition3	.48
w3gfs_q1rv	<---	Cognition3	.50
Expenditure2	<---	Behaviour2	.87
Frequency2	<---	Behaviour2	.77
Range2	<---	Behaviour2	.84
Behaviour4	<---	Cognition3	.02
w3gfs_q10rv	<---	Cognition3	.37
w3gfs_q9rv	<---	Cognition3	.44
w3gfs_q8rv	<---	Cognition3	.38
w3gfs_q5rv	<---	Cognition3	.36
w3gfs_q4rv	<---	Cognition3	.47
w3gfs_q3rv	<---	Cognition3	.38
w3gfs_q2rv	<---	Cognition3	.49
w3gfs_q1rv	<---	Cognition3	.50
Expenditure4	<---	Behaviour4	.80
Frequency4	<---	Behaviour4	.77
Range4	<---	Behaviour4	.85
Cognition4	<---	Behaviour3	.01
w4gfs_q10rv	<---	Cognition4	.34
w4gfs_q9rv	<---	Cognition4	.41
w4gfs_q8rv	<---	Cognition4	.45
w4gfs_q5rv	<---	Cognition4	.45
w4gfs_q4rv	<---	Cognition4	.47
w4gfs_q3rv	<---	Cognition4	.35
w4gfs_q2rv	<---	Cognition4	.47
w4gfs_q1rv	<---	Cognition4	.48
Expenditure3	<---	Behaviour3	.78
Frequency3	<---	Behaviour3	.78
Range3	<---	Behaviour3	.82

Note: wXgfs_qYrv = item on the GFS, where X = wave number and Y = question number

Table 7. *Estimated marginal means of the gambling fallacies variable in the GEE analysis.*

			95% Wald Confidence Interval	
time	Mean	Std. Error	Lower	Upper
4	.6952	.02707	.6421	.7482
3	.8981	.03040	.8385	.9577
2	1.1850	.03505	1.1163	1.2537
1	1.5707	.04092	1.4905	1.6509

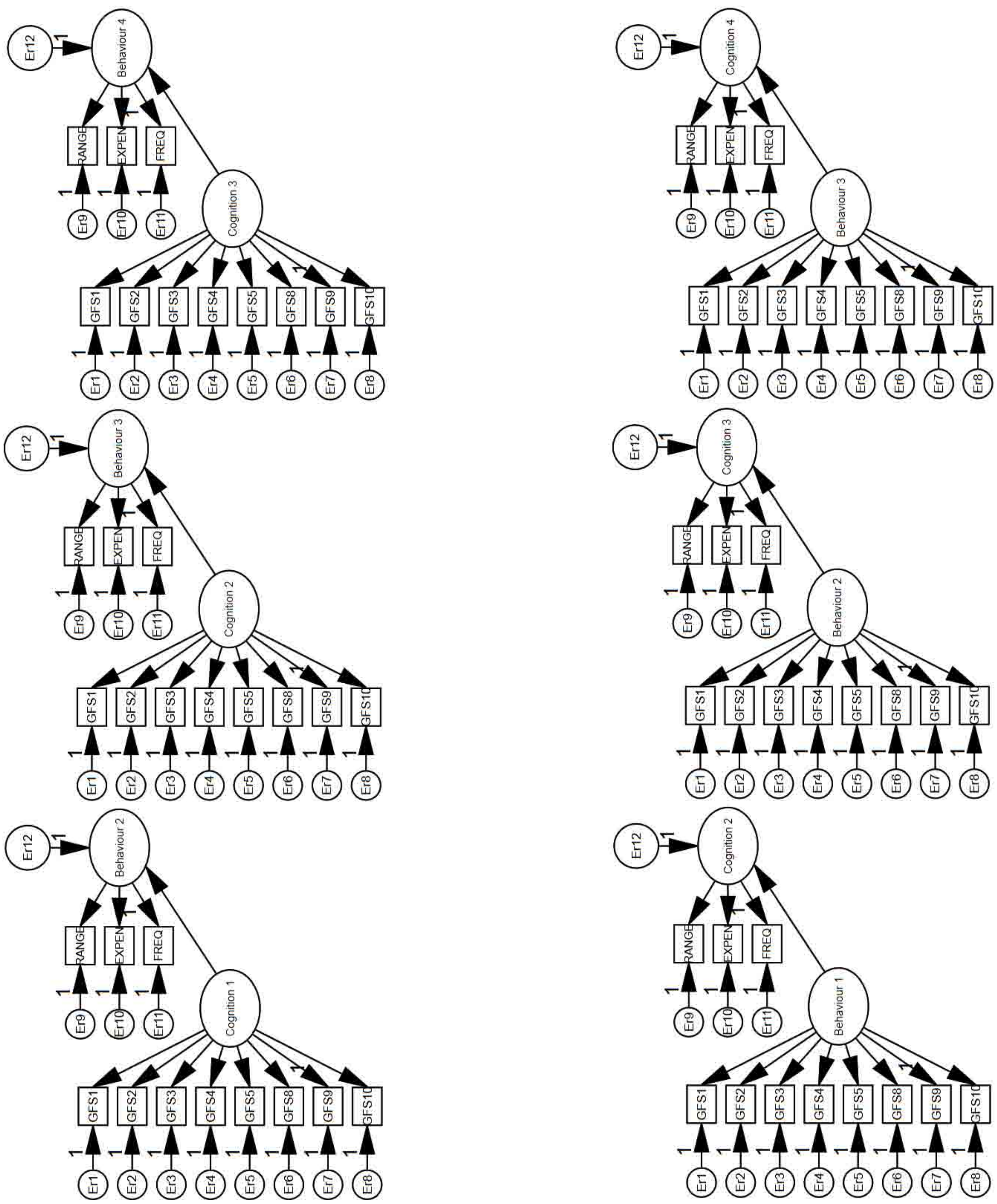
Covariates appearing in the model are fixed at the following values: behavior=.0000

Note: higher values indicate more endorsed gambling fallacies.

Table 8. *Summary of attrition bias analysis results for those who completed all four waves of assessment*.

Demographic variable	Attrition bias	χ^2	df	P-value
Marital status	More likely to be married	34.10	4	< .001
Gambling status	More likely to be a non-problem gambler	14.45	2	< .001
Age	More likely to be 43-65 years old	40.79	3	< .001
Gender	More likely to be female	16.05	1	< .001
Location	More likely to be from an urban area	13.51	3	< .01
Level of education	More likely to have a bachelor's degree or higher	48.50	7	< .001
Ethnicity	More likely to be non-aboriginal	18.47	7	< .05

Figure 1. Path models for the six hypothesized structural equation models.



Appendix A

Possible Gambling Activities

- ❑ Lottery (e.g. 649, Super 7)
- ❑ Daily lottery (e.g. Pick 3)
- ❑ Instant win or scratch tickets (e.g. break open, pull tab)
- ❑ Raffle or fundraising tickets
- ❑ Horse races (at the track and/or off-track)
- ❑ Bingo
- ❑ Casino, including illegal or charity casinos
- ❑ Coin slot machines or VLT's in a casino
- ❑ Cards, or board games with family or friends
- ❑ Gambling on the Internet
- ❑ Personally invest in stocks, options, or commodities markets (excludes mutual funds, RRSPs)
- ❑ Poker
- ❑ Blackjack
- ❑ Roulette
- ❑ Keno
- ❑ Craps
- ❑ VLT's other than at casino
- ❑ Sports lottery (e.g. Pro Line, Point Spread)
- ❑ Sports pools
- ❑ Games of skill such as pool, bowling, or darts
- ❑ Betting on sports with a bookie

Appendix B

Canadian Problem Gambling Index (Select Questions)

For each of the items in the CPGI questionnaire, respondents are asked to respond "in the past twelve (12) months." This past-year time frame does not apply to the following questions: 18, 19, 20, 21, 22, and 23. The response scales for each of the selected questionnaire items are as follows:

Question 1 - yes; no

Question 2 - daily; 2-6 times/week; about once/week; 2-3 times/month; about once/month; between 6-11 times/year; between 1-5 times/year; never in the past year

Questions 4 - record actual dollar amount

DOMAIN	VARIABLES	INDICATORS	ITEMS AND QUESTION NUMBERS
Gambling Involvement	Type	Gambling activities	1. Have you bet or spent money on (list of gambling activities)?
	Frequency	Frequency of play	2. How often did you bet or spend money on (list activity: daily, weekly, monthly, yearly)?
	Expenditure	Money wagered monthly	4. How much money, not including winnings, did you spend on (list activity) in a typical month?

Appendix C

The Gambling Fallacies Scale

1) Which of the following set of Lottery numbers has the greatest probability of being selected as the winning combination?

a. 1, 2, 3, 4, 5, 6

b. 14, 43, 5, 32, 17, 47

c. each of the above have an equal probability of being selected

1) Which gives you the best chance of winning the jackpot on a slot machine?

a. Playing a slot machine that has not had a jackpot in over a month.

b. Playing a slot machine that had a jackpot an hour ago.

c. Your chances of winning the jackpot are the same on both machines.

2) How lucky are you? If 10 people's names were put into a hat and one name drawn for a prize, how likely is it that <u>your name</u> would be chosen?

a. About the same likelihood as everyone else

b. Less likely than other people

c. More likely than other people

3) If you were to buy a lottery ticket, which would be the best place to buy it from?

a. a place that has sold many previous winning tickets

b. a place that has sold few previous winning tickets

c. one place is as good as another

5) A positive attitude increases your likelihood of winning money when playing bingo or slot machines.

a. Disagree

b. Agree

6) A gambler goes to the casino and comes out ahead 75% of the time. How many times has he or she likely gone to the casino?

a. 4 times

b. 100 times

c. It is just as likely that he has gone either 4 or 100 times

7) You go to a casino with $100 hoping to double your money. Which strategy gives you the best chance of doubling your money?

a. Betting all your money on a single bet

b. Betting small amounts of money on several different bets

c. Either strategy gives you an equal chance of doubling your money.

8) Which game can you consistently win money at if you use the right gambling strategy?

a. Slot machines

b. Roulette

c. Bingo

d. None of the above

9) Your chances of winning a lottery are better if you are able to choose your own numbers.

a. disagree

b. agree

10) You are on a betting hotstreak. You have flipped a coin and correctly guessed „heads' 5 times in a row. What are the odds that heads will come up on the next flip. Would you say…

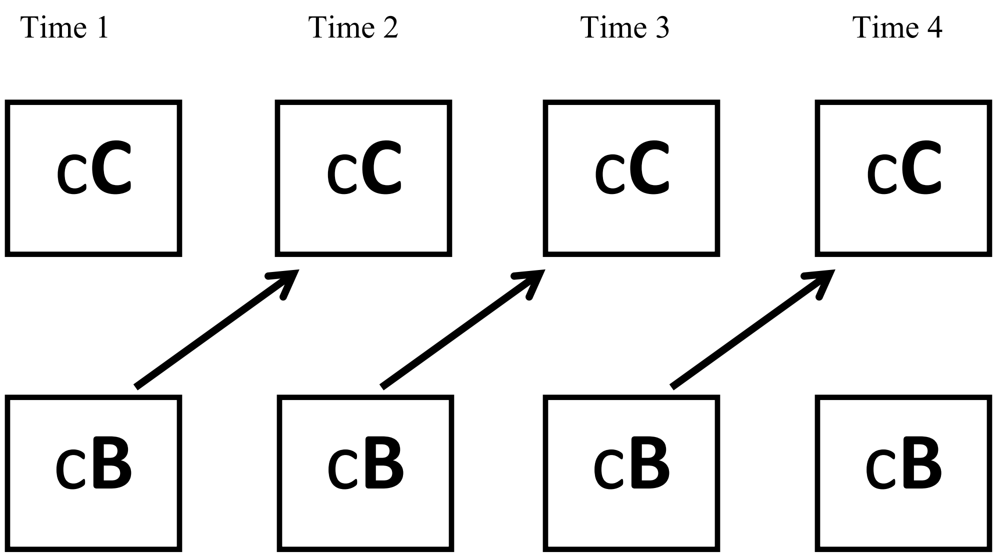
a. 50%

b. more than 50%

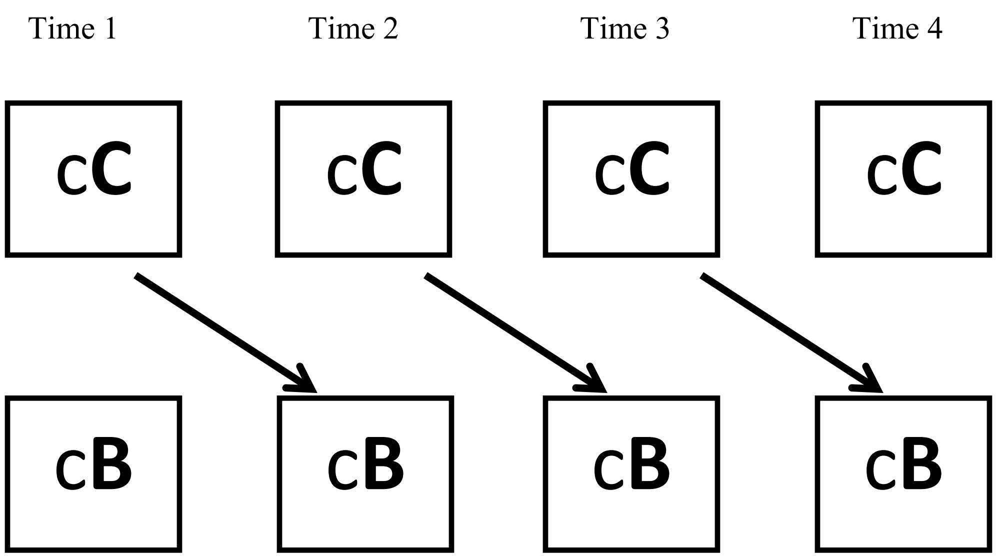
c. or less than 50%

Appendix D

Longitudinal Model 1



Longitudinal Model 2



C = Gambling cognition indicated by the items from the Gambling Fallacies Scale

B = Gambling involvement/behaviour indicated by the range, expenditure, and frequency variables

Appendix E

Tests of Model Effects			
	Type III		
	Wald Chi-Square	df	Sig.
Source			
(Intercept)	2023.025	1	.000
time	473.927	3	.000
behavior	56.555	1	.000
time * behavior	4.741	3	.192

Dependent Variable: gfs

Model: (Intercept), time, behavior, time*behavior

Tests of Model Effects			
	Type III		
	Wald Chi-Square	df	Sig.
Source			
(Intercept)	19.260	1	.000
time	2.020	3	.568
gfs	54.030	1	.000
time * gfs	3.687	3	.297

Dependent Variable: behavior

Model: (Intercept), time, gfs, time*gfs