Assessment of Reliability and Validity of the Gambling Related Cognitions Scale (GRCS)

SUDHIR KALE[3] AND CHRIS DUBELAAR[4]

[1]Bond University, QLD, Australia. T: (07) 5595 2214
E-mail: skale@bond.edu.au
[2]Bond University, QLD, Australia. T: (07) 5595 1185
E-mail: cdubelaa@bond.edu.au

All correspondence should be addressed to the first author.

Abstract

This research sought to assess the reliability and validity of Raylu and Oei's (2004) widely used Gambling Related Cognitions Scale (GRCS). Two samples were used in this study. In the "teenage sample," 2,000 teenagers, aged 15-19, completed a web-based survey containing questions related to a host of gambling-related issues, including GRCS. The "university sample" comprised of 764 international students and 836 domestic students sampled from three universities in Australia. Our research used the same items as those utilized by Raylu and Oei (2004). After our exploratory factor analysis of the scale items yielded two factors for both samples, we tried to fit the five-factor model of GRCS to both datasets. Despite trying various approaches to achieve model fit, our data did not provide any evidence of the five factors underlying GRCS. However, the scale exhibited excellent concurrent validity and internal reliability across both samples. This research corroborates Taylor et al.'s (2013) suggestion that external independent validation of the GRCS is needed before it can be applied for diagnosis or treatment purposes, particularly among younger people.

Keywords: gambling cognitions, GRCS, validity, reliability.

Introduction

A variety of cognitive distortions and biases can lead gamblers to misperceive and often overestimate their chances of winning in gambling, with a number of studies suggesting that erroneous cognitions regarding gambling are more strongly observed in problem gamblers (Coulombe, et al., 1992; Ferland, et al., 2004; Michalczuk, et al., 2011; Sharpe &Terrier, 1992). Research into the role of cognitive factors in gambling has been undertaken for almost three decades (Coulombe et al., 1992; Gilovich, 1986; Miller &Currie, 2008; Joukhador, et al., 2003; Sharpe, 2002; Toneatto, 1999). However, despite the proliferation of research on gambling cognitions, there exist only a handful of instruments assessing gambling-related thoughts, and most remain untested across

diverse populations (cf. Moodie, 2008). Consequently, research linking problem gambling and gambling related cognitions remains subject to some qualifications (Taylor, et al., 2013).

One of the more recent scales to assess gambling cognitions is the Gambling Related Cognitions Scale (GRCS, Raylu & Oei, 2004). Based on five underlying dimensions, the domains tapped by GRCS are in line with previous research on gambling cognitions (Toneatto, et al., 1997) as well as cognitions linked to substance abuse (Beck, et al., 1993). Around 100 articles have thus far made reference to this scale, and there have been more than fifteen research studies that have actually utilized this scale for research into problem gambling (cf. Emond &Marmurek, 2010; Clark et al., 2009; Michalczuk et al., 2011; Young & Wohl, 2008). Until recently, however, the psychometric properties of the GRCS have not been independently validated (Grall-Bronnec, et al., 2012; Oei, Lin, & Raylu, 2009; Tang & Wu, 2012; Taylor et al., 2013). Moreover, Taylor, et al. (2013) call into question the psychometric properties of the scale, making a plea for further research to extend their findings, and to test the scale in younger and more diverse groups in order to further assess its generalizability. These researchers argue that the GRCS is unidimensional, not multidimensional when applied to a sample of young respondents. However, this argument has not yet been empirically tested.

We utilize data from two different samples to test the GRCS in an attempt to validate its underlying dimensions. The manuscript proceeds from here as follows. First, we provide a summary of the GRCS as developed and used. Second, we describe the methods and analysis weused to assess the GRCS. Third, we comment on the resulting factor structure and its implications for the generalizability of the GRCS. In light of the results obtained, we conclude with recommendations for future research to focus on the limitations of the applicability of the GRCS.

Summary of GRCS

According to Raylu and Oei (2004), the Gambling Related Cognitions Scale screens for five gambling-related cognition types as follows:

- Illusion of control: comprising of four items relating to an individual's belief in his/her ability to control the outcome of a game via skill, knowledge, or rituals (e.g., "I have specific rituals and behaviours that increase my chances of winning").
- Predictive Control: comprising of six items measuring the degree to which someone thinks he/she can predict wins (e.g., "Losses when gambling are bound to be followed by a series of wins").
- Interpretive Bias: comprising of four items measuring the degree to which an individual attributes successes to personal skill and losses to outside influences (e.g., "Relating my winnings to my skill and ability makes me continue gambling").
- Gambling Related Expectancies: comprising of four items regarding expectations of the outcome of gambling behaviour (e.g., "Having a gamble helps reduce tension and stress").
- Inability to Stop Gambling: comprising of five items measuring the lack of belief an individual has in his or her ability to resist gambling (e.g., "My desire to gamble is so overpowering").

Although the scale has been validated on French (Bronnec & Boutin, 2012) and Chinese (Oei, Lin, & Raylu, 2007) samples, neither study actually validated the multidimensionality of the scale. Recent work on the GRCS in the domain of adolescents (Taylor, et al., 2013) suggests that the GRCS

may not generalize well to younger gamblers and may not exhibit requisite multidimensionality as espoused by the scale's creators. Given Taylor et al.'s (2013) suspicion that the structure of the GRCS may not actually be multidimensional, we have chosen to investigate the use of the GRCS in teenagers and young adults.

Methodological Issues with GRCS Development

In the original development of the GRCS scale, Raylu and Oei (2004) pooled all the data across 53 original items prior to distilling out the final 23 items. This large file was then split into two subfiles for the subsequent confirmatory factor analysis tests. Two problems with this approach is that, (1) it forces the fit, and (2) it is prone to capitalizing on chance and spurious correlations. A better method would have been to winnow out the inappropriate scale items on one half of the data (say the group A data) and then confirm the structure on the other half of the data (the group B data only). This method would have more effectively assessed the properties of the scale and would have reduced the chances of sample based spurious correlations causing future problems (Field, 1991).

Moreover, confirmatory factor analysis is sensitive to violations of assumptions, particularly in regards to violations of normality. Given that these data are collected on a community sample, it would be expected that most people would be answering at the bottom of the scale (showing no sign of cognitive distortions). This distribution of data could adversely affect the fit of the model, particularly when using any of the goodness of fit measures associated with the chi square (Marsh, Balla, & McDonald 1988; Hu and Bentler, 1998).

Furthermore, several recent studies have asserted that the GRCS accounts for only small amounts of variance in concurrent validity tests (Oei, et al., 2007, 2008). Taylor, et al. (2013) point out that the individual subscales show very little concurrent validity with various other scales also measuring gambling severity. In summary, given the face validity and extensive use of the GRCS, it may be an appropriate tool to use in assessing gambling-related cognitions among adult populations. However, there remain some reservations regarding its generalizability to other populations.

Method

Sample

The samples used in our study comprised of: (1) 2,000 teenagers, aged between 15-19 years living in the Australian State of Victoria (hereafter referred to as the "teenage sample"), and (2) 1,600 students drawn from three universities in Australia (hereafter referred to as the "university sample").

The teenage sample was provided by a private company that facilitates panel data collection through online surveys. To participate in the surveys, Australian consumers sign up on the company's website in return for points. Internet and social media advertising are used to recruit into the panel. If a member is selected to participate in a survey, the company sends out an invitation email. Participation in any survey is voluntary. This sample had a mean age of 17.03, was split almost equally between males and females (997 male, 1003 female), all respondents

were from the Australian state of Victoria, 97.3% were born in Australia and 98.7% spoke English at home. The teenage sample had 906 non-gamblers (45.3% had never gambled in their lives), 616 were non- problem gamblers (30.8% scored zero on the Problem Gambling Severity Index, see below for a description of the PGSI), 285 were low risk gamblers (14.3% scored between 1 and 2.5 on the PGSI), 75 were moderate risk gamblers (3.8% scored between 3 and 7.5 on the PGSI), while the remaining 118 were problem gamblers (5.9% scored 8 or more on the PGSI).

For the "university sample," international and domestic students were sampled from three Australian universities, two in Victoria and one in Queensland. After data cleaning, the final survey sample consisted of 764 international students and 836 domestic students across the three universities, a total sample of 1,600. This sample had a mean age of 23.56 (382 of this sample were teenagers, age range was 17 to 70), had more female than male respondents (948 female vs. 656 male), 43.15% were born in Australia, and 71.40% spoke English at home. The university sample had 1,118 respondents who were non-problem gamblers (69.6%), 244 were low risk gamblers (15.2%), 134 were moderate risk gamblers (8.3%), and 85 (5.3%) were identified as problem gamblers on the PGSI.

The GRCS was used in both samples and was correlated with other measures of gambling, such as Problem Gambling Severity Index (PGSI, Wynne &Ferris, 2001), and the Frequency of Gambling Scale (Moore & Ohtsuka, 1997). Our goal was to replicate the results of Raylu and Oei (2004) across both samples in order to assess whether the GRCS is robust and generalizable across younger populations. We sought to accomplish this goal by first examining its concurrent validity (ability to relate to other constructs in the same area – specifically the PGSI and the Frequency of Gambling Scale), and then to focus on the characteristics of the scale itself from a psychometric perspective.

Analysis

Concurrent Validity

One key way to establish validity for a construct is to demonstrate its links to other related constructs (Finn & Kayandé, 1997). Doing so demonstrates that the construct fits into the normal net of constructs in the literature. Here, we have the known link between GRCS and PGSI as a basis for establishing that the GRCS is working as expected. In our teenage data, the correlation between GRCS and PGSI was 0.664 ($p < 0.001$). For the university sample, the correlation between GRCS and PGSI was 0.563 ($p < 0.001$). These results show that the expected relationship between these two constructs exists.

We also investigated the link between GRCS and the Frequency of Gambling Scale, a slightly amended version of Moore and Ohtsuka's (1997) Gambling Behavior Scale. This scale relates to the frequency of gambling over the past 12 months across 12 different types of games (e.g., played cards or bet on sports). Frequency is measured on a 4 point Likert type scale, where 0 = (Not in the last year or never) and 3 = (Frequently, once a week or more). Scores are summed across the different games to create a total frequency score ranging from 0 to 36. Higher scores indicate higher frequencies of gambling.

In the teenage dataset, the correlation between GRCS and gambling frequency was 0.3 ($p < .001$). For the university sample, the correlation was even higher at 0.48 ($p < .001$). Table 1 provides basic comparative statistics using the findings reported by Raylu and Oei (2004), findings from the teenage sample, and those from the university sample. Having established concurrent validity, we next examined the factor structure of the GRCS.

Factor Structure

Table 1. GRCS properties across three different samples

GRCS properties	Raylu and Oei (2004)	Teenage sample	University sample
Cronbach's alpha	0.93	0.96	0.96
Number of factors (eigen value > 1)	5	2	2
Correlation with PGSI	N/A	0.664*	0.563*
Correlation with Gambling Frequency Scale	N/A	0.329*	0.479*

*Correlation is significant at $p < .001$.

Factor analysis of the data using principal axis factoring with varimax rotation as done in Raylu and Oei (2004) revealed several problems. For the teenage sample, the factor analysis of the 23 items comprising the GRCS resulted in two factors (using eigenvalue > 1), with the first containing 50.8% of the total variance. The same procedure was applied to the university sample. Once again, we were unable to replicate the five-factor solution uncovered by Raylu and Oei (2004) in their dataset. Specifically, the first factor accounted for over half the variance of the data (55%). Furthermore, as with the teenage sample, only two factors were extracted (using the eigenvalue > 1 rule). Finally, the rotated factors contained cross-loadings of 0.2 or greater for all 23 variables. These results are reported in Table 2 and Table 3.

Table 2. Rotated factor matrix for teenage data

	Factor	
GRCS Item	**1**	**2**
Gambling Expectancies		
1. Gambling makes me happier	0.597	0.179
6. Gambling makes things seem better	0.668	0.345
11. Gambling makes the future brighter	0.481	0.603
16. Gambling helps reduce tension and stress	0.586	0.305
Illusion of Control		
3. Praying helps me win in gambling	0.351	0.633
8. Specific numbers and colours can help increase my chances of winning	0.488	0.495
13. I collect specific objects that help increase my chances of winning	0.276	0.779
18. I have specific rituals and behaviours that increase my chances of winning	0.337	0.631
Predictive Control		
4. Losses when gambling are bound to be followed by a series of wins	0.691	0.447
9. A series of losses will provide me with a learning experience that will help me win later	0.491	0.356
14. When I have a win once, I will definitely win again	0.650	0.402
19. There are times when I feel lucky and thus, gamble those times only	0.459	0.416
22. I have some control over predicting my gambling wins	0.694	0.252
23. If I keep changing my numbers, I have less chance of winning that if I keep the same numbers every time	0.517	0.426
Inability to Stop Gambling		
2. I can't function without gambling	0.308	0.825
7. It is difficult to stop gambling as I am so out of control	0.342	0.67
12. My desire to gamble is often overpowering	0.522	0.679
17. I'm not strong enough to stop gambling	0.211	0.676
21. I will never be able to stop gambling	0.276	0.766
Interpretative Bias		
5. Relating my winnings to my skill and ability makes me continue gambling	0.812	0.241
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.569	0.586
15. Relating my losses to probability makes me continue gambling	0.652	0.376
20. Remembering how much money I won last time makes me continue gambling	0.742	0.277

Table 3. Rotated factor matrix for university data

	Factor	
GRCS Item	**1**	**2**
Gambling Expectancies		
1. Gambling makes me happier	0.617	0.205
6. Gambling makes things seem better	0.679	0.433
11. Gambling makes the future brighter	0.473	0.643
16. Gambling helps reduce tension and stress	0.601	0.41
Illusion of Control		
3. Praying helps me win in gambling	0.47	0.488
8. Specific numbers and colours can help increase my chances of winning	0.599	0.373
13. I collect specific objects that help increase my chances of winning	0.446	0.648
18. I have specific rituals and behaviours that increase my chances of winning	0.5	0.543
Predictive Control		
4. Losses when gambling are bound to be followed by a series of wins	0.639	0.399
9. A series of losses will provide me with a learning experience that will help me win later	0.669	0.385
14. When I have a win once, I will definitely win again	0.673	0.424
19. There are times when I feel lucky and thus, gamble those times only	0.586	0.275
22. I have some control over predicting my gambling wins	0.593	0.387
23. If I keep changing my numbers, I have less chance of winning that if I keep the same numbers every time	0.589	0.331
Inability to Stop Gambling		
2. I can't function without gambling	0.312	0.691
7. It is difficult to stop gambling as I am so out of control	0.358	0.772
12. My desire to gamble is often overpowering	0.332	0.865
17. I'm not strong enough to stop gambling	0.275	0.675
21. I will never be able to stop gambling	0.406	0.668
Interpretative Bias		
5. Relating my winnings to my skill and ability makes me continue gambling	0.726	0.294
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.588	0.506
15. Relating my losses to probability makes me continue gambling	0.669	0.414
20. Remembering how much money I won last time makes me continue gambling	0.708	0.287

This loadings pattern suggests that there may be common method variance at play (Podsakoff, et al., 2003). To address this possibility, we ran Harman's One Factor Test as a test for common method variance. Using the university sample, when we put the GRCS and an unrelated construct (respondents' adaptability to life at university) into a factor analysis, the GRCS variables loaded onto two factors (as before) while the Adaptability Scale loaded onto four distinct and separate factors. That is, there is very little cross loading between the two constructs, and nothing at a level (0.2 or greater) that would suggest method variance may be an issue.

Given we cannot demonstrate that the data collection process caused the inability to replicate the original factors from Raylu and Oei (2004), the disparity in results may be due to differences in the sample characteristics (specifically age) in the current study. This inference fits well with the conclusions drawn by Taylor, et al. (2013) and suggests that there may be a pattern to these deviations.

Of particular interest is the stability in the factor loadings between the data sets. Specifically, the factors do not follow the pattern set out by Raylu and Oei (2004) in that they do not all consistently load on one of the two factors. For example, in the Gambling Expectancies subscale, the item, "Gambling makes the future brighter," loads on factor two while the rest of the subscale loads on factor one. Furthermore, several of the items load almost equally on each of the factors. It is noted that the initial process used by Raylu and Oei (2004) specifically removed items from the original 53 point scale if their scores loaded on more than one factor. This means that one should see a clear structure in these data if the structure holds across samples. Factor loadings in both samples clearly show that there is a much more compact structure than initially suggested (two factors instead of five) and that there is not as much clarity in the structure as has been claimed by Raylu and Oei (2004).

Further Investigation

Given that confirmatory factor analysis can be adversely affected by violations of distribution assumptions (Hu & Bentler, 1998), we investigated whether floor effects in the response scale may be responsible for the inconsistency between our results and those of Raylu and Oei (2004).

We noted that both our datasets contain a disproportionate number of people who have answered "1" ("strongly disagree") on the GRC Scale. In the teenage sample, of the 1,094 respondents who had ever gambled, 206 answered "1" to each of the 23 GRCS questions. In the university sample, of the 1,191 who had ever gambled, 401 people answered "1" to each of the 23 GRCS questions. Across both of the datasets, a significant proportion of respondents indicated that the lowest possible GRCS score is the correct one for them. When we eliminate these people from further analysis, we get a slightly different view of the data.

Using the teenage data set, with those who answered one to all 23 GRCS questions removed, four factors (using the eigenvalue > 1 cut-off) were revealed. Using the university dataset, and after removing those who had answered one to all 23 items, three factors (with eigenvalue > 1) were revealed. A five factor solution was forced on both sets of modified data. The sums of squared loadings for the GRCS items for both samples are shown in Table 4.

Table 4. Loading for GRCS items allowing for a five factor solution on modified data

Sums of squared loadings for GRCS items

Teenage sample				University sample			
Initial eigen values	**Total**	**% Variance**	**% Cumulative**	**Initial eigen values**	**Total**	**% Variance**	**% Cumulative**
10.566	4.866	21.154	21.154	11.387	4.978	21.643	21.643
1.83	3.131	13.611	34.766	1.411	3.003	13.057	34.7
1.174	3.115	13.541	48.307	1.056	2.817	12.246	46.946
1.061	1.647	7.162	55.469	0.894	1.85	8.042	54.988
0.927	0.751	3.267	58.736	0.784	0.74	3.217	58.204

Examining these two factor analyses, we began to see some semblance of the pattern from Raylu and Oei (2004) in the factors. For the most part, however, the cross loadings were high and the factor structure was still unclear. These results are reported in Tables 5 (see Appendix A) and 6 (see Appendix B).

We further examined the factor loadings under Raylu and Oei's (2004) five dimensions of cognitions in Table 5 and Table 6. Across both datasets, very few scale items show maximum loadings that correspond to Raylu and Oei's (2004) results (shown in bold font in both tables), and loadings on several items actually contradict Raylu and Oei's (2004) findings (these are underlined in Table 5 and Table 6). These results call into question the stability and validity of the five GRCS dimensions across datasets. Our next step was to examine the data for only those people who had identified through the PGSI as having a low risk problem gambling score or higher. We reasoned that perhaps teenagers and young people who have only limited exposure to gambling have not had a chance to develop clear cognitions on gambling, a point made by Taylor, et al. (2013). We eliminated all such respondents from both datasets and used only those who were more prone to gambling in the hope of getting cleaner results. In the teenage data set, this process left us with 444 respondents, and in the university sample, we were left with 401 respondents; both of which are still more than enough to factor analyse 23 variables. Even with restricting the data to those who are somewhat at risk of being problem gamblers, we do not see clear factor structures in either data set. Data presented in Table 7 (see Appendix C) and Table 8 (see Appendix D) indicate no better congruence with Raylu and Oei's (2004) five dimensional model than before, where all respondents were included.

These results cast further doubts on the reliability and generalizability of the factor structure as reported by Raylu and Oei (2004). In neither data set could we replicate the original structure, and despite going to great lengths to replicate the original results of Raylu and Oei (2004), we were unable to find a set of filters that would allow us to produce similar factor structures. These results notwithstanding, the GRCS is highly correlated with problem gambling in all datasets, and thus is a useful screen for problem gambling diagnosis. Given that we are trying to confirm a factor structure, we really should be using Confirmatory Factor Analysis (CFA). However, CFA is far less forgiving than EFA, and if we cannot replicate the factors using an exploratory technique, CFA will definitely not result in a model that fits well. Ignoring this basic fact, we still proceeded

to test a measurement model for the five factors. The results were very poor (as expected), with goodness of fit levels (GFI) on the order of 0.6.

Discussion

We have used two separate data sets comprising of Australian teenagers and tertiary education students to attempt to replicate the factor analysis results of Raylu and Oei (2004). In the process, we have found that the factor structure is not replicable. Even after applying filters to eliminate from our sample those who are least likely to have established gambling cognitions, we were unable to replicate the original factor structure. We therefore conclude that the GRCS, while a reasonable proxy for problem gambling, is not generalizable across sub-populations. Hence, we suggest that use of GRCS be restricted to those populations where it has been shown to be both valid and reliable. This caveat especially applies in situations where the scale may be used as a diagnostic tool for treatment selection (Grall-Bronnec, et al., 2012). The lack of reliability of the scale across populations suggests that cognitive therapy for individual dimensions of the scale should not be recommended, based on the respondent's score on the five GRCS dimensions. In other words, given that the items do not load onto the same sets of factors in different populations, there is the danger that inappropriate treatments may be assigned to problem gamblers.

Future Research

Given that we were unable to replicate Raylu and Oei's (2004) original findings, we recommend that future research should focus on finding the limits of the applications of the GRCS, since understanding gamblers' cognitions is such an important step in cognitive behavioural therapy. Looking at the clear results that Raylu and Oei (2004) found, and the strong face validity they reported for the scale, we suggest that there may be some experience requirements pertaining to gambling that are not being met with our two samples. As Taylor, et al. (2013) observe, "the lack of differentiation among GRCS dimensions in the present [younger] sample may reflect age appropriate levels of cognitive abilities that are less sophisticated than those typically found in adult respondents." Therefore, future research should focus on finding a more generalizable scale and also exploring the boundaries of the existing GRCS in order to develop a more robust scale that is independent of age and other boundary variables that future research may identify. It is entirely possible that, besides age, social psychological and cultural factors create differences in gambling related cognitions across populations. Any gambling diagnostic instrument should accommodate these differences.

References

Beck, A. T., Wright, F .D., Newman, C. F., &Liese, B. S. (1993). *Cognitive therapy of substance abuse.* New York: Guilford Press.

Grall-Bronnec, M., Bouju, G. Sebille-Rivain, V., Gorwood, P., Boutin, C., Venisse, J. L. & Hardouin, J. B. (2012). A French adaptation of the Gambling-Related Cognitions Scale (GRCS): A useful tool for assessment of irrational thoughts among gamblers. *Journal of Gambling Issues, 27,* 1-21.

Clark L., Lawrence A. J., Astley-Jones F., & Gray N. (2009). Gambling near-misses enhance motivation to gamble and recruit win-related brain circuitry. *Neuron, 61,* 481-490.

Coulombe, A., Ladouceur, R., Desharnais, R., & Jobin, J. (1992). Erroneous perceptions and arousal among regular and occasional video poker players. *Journal of Gambling Studies, 8,*: 235-244.

Emond, M. S., & Marmurek, H. H. C. (2010). Gambling related cognitions mediate the association between thinking style and problem gambling severity. *Journal of Gambling Studies, 26:* 257-267.

Ferland F., Ladouceur R., & Vitaro F. (2002). Prevention of problem gambling: Modifying misconceptions and increasing knowledge. *Journal of Gambling Studies, 18,* 19-29.

Ferris, J., & Wynne, H. J. (2001). *The Canadian Problem Gambling Index final report.* Ottawa, ON: Canadian Centre on Substance Abuse.

Finn, A., & Kayandé, U. (1997). Reliability assessment and optimization of marketing measurement. *Journal of Marketing Research, 34,* 262-275.

Gilovich T. & Douglas C. (1986). Biased evaluations of randomly determined gambling outcomes. *Journal of Experimental Social Psychology, 22,* 228-241.

Hu, L.T. and Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 34,* 424-453.

Joukhador, J., Maccallum, F., & Blaszczynski, A. (2003). Differences in cognitive distortions between problem and social gamblers. *Psychological Reports, 92,* 1203-1214.

Ladouceur R. (2004). Gambling: the hidden addiction. *Canadian Journal of Psychiatry, 49,* 501-3.

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indices in confirmatory factor analysis: Effects of sample size. *Psychological Bulletin, 103,* 391-411.

Michalczuk R., Bowden-Jones H., Verdejo-Garcia A., & Clark L. (2011). Impulsivity and cognitive distortions in pathological gamblers attending the UK National Problem Gambling Clinic: A preliminary report. *Psychological Medicine, 41,* 2625-2635.

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,* 257–274.

Moodie, C. (2008). Student gambling, erroneous cognitions, and awareness of treatment in Scotland. *Journal of Gambling Issues, 21,* 30-55.

Moore, S. M., & Ohtsuka, K. (1997). Beliefs about control over gambling among young people, and their relation to problem gambling. *Psychology of Addictive Behaviors, 13,* 339-347.

Oei, T. P. S., Lin, J., & Raylu, N. (2007) Validation of the Chinese Version of the Gambling Related Cognitions Scale (GRCS-C). *Journal of Gambling Studies, 23,* 309–322.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88,* 879-903.

Raylu, N., & Oei, T. P. S. (2004). The Gambling Related Cognitions Scale (GRCS): Development, confirmatory factor validation and psychometric properties. *Addiction, 99,* 757–769.

Sharpe, L., & Tarrier N. A. (1992). Cognitive-behavioral treatment approach for problem gambling. *Journal of Cognitive Psychotherapy 6*, 193-203.

Sharpe L. (2002). A reformulated cognitive–behavioral model of problem gambling: A biopsychosocial perspective. *Clinical Psychology Review, 22,* 1-25.

Tang, C. S. K. & Wu, A. M. S (2012). Gambling-related cognitive biases and pathological gambling among youths, young adults, and mature adults in Chinese societies. *Journal of Gambling Studies, 28,* 139-154.

Taylor, N. T., Parker, J. D. A., Keefer, K. V., Kloosterman, P . H., & Summerfeldt L. J. (2013). Are gambling related cognitions in adolescence multidimensional?: Factor structure of the gambling related cognitions scale. *Journal of Gambling Studies,* DOI 10.1007/s10899-013-9368-7.

Toneatto, T. (1999). Cognitive psychopathology of problem gambling. *Substance Use and Misuse, 34,* 1593-1604.

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

Young, M. M., & Wohl, M. J. A. (2008). The gambling craving scale: Psychometric validation and behavioral outcomes. *Psychology of Addictive Behaviors, 23,* 512-522.

Appendices

Appendix A

Table 5. Rotated factor matrix for teenage data[a]

GRCS Item	Factor 1 Inability to Stop	2 Interpretive Bias	3 Gambling Expectancies	4 Predictive Control	5 Illusion of Control
1. Gambling makes me happier			*0.305*		0.486
2. I can't function without gambling	**0.799**				
3. Praying helps me win	0.563		0.359		
4. Losses when gambling, are bound to be followed by a series of wins	0.318	0.423	0.48	*0.334*	
5. Relating my winnings to my skill and ability makes me continue gambling		*0.456*	0.594		
6. Gambling makes things seem better		0.444	*0.405*		0.326
7. It is difficult to stop gambling as I am so out of control	**0.579**			0.332	
8. Specific numbers and colours can help increase my chances of winning	0.399	0.325	0.401		
9. A series of losses will provide me with a learning experience that will help me win later				**0.76**	
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.465	*0.459*	0.4		

Table 5. Rotated factor matrix for teenage data[a] *(continued)*

GRCS Item	Factor 1 Inability to Stop	2 Interpretive Bias	3 Gambling Expectancies	4 Predictive Control	5 Illusion of Control
11. Gambling makes the future brighter	0.529		*0.509*		
12. My desire to gamble is so overpowering	**0.575**	0.342	0.458		
13. I collect specific objects that help increase my chances of winning	0.757				
14. When I have a win once, I will definitely win again			0.521		
15. Relating my losses to probability makes me continue gambling		**0.787**			
16. Having a gamble helps reduce tension and stress			**0.716**		
17. I'm not strong enough to stop gambling	**0.695**				
18. I have specific rituals and behaviours that increase my chances of winning	0.56	0.438			
19. There are times that I feel lucky and thus, gamble those times only	0.326	0.488			
20. Remembering how much money I won last time makes me continue gambling		**0.57**	0.338		
21. I will never be able to stop gambling	**0.738**			0.327	
22. I have some control over predicting my gambling wins		0.358	0.348	**0.483**	
23. If I keep changing my numbers, I have less chance of winning than if I keep the same numbers every time	0.337	0.453			

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. [a]Rotation converged in 13 iterations

Bolded entries show max loadings that correspond to Raylu and Oei (2004)

Underlined entries show maximum loadings that contradict Raylu and Oei (2004)

Italicized entries show cross loadings that correspond to Raylu and Oei (2004) main loadings

Appendix B

Table 6. Rotated factor matrix for university data[a]

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Illusion of Control	4 Gambling Expectancies	5 Interpretive Bias
1. Gambling makes me happier				**0.556**	
2. I can't function without gambling	**0.672**				
3. Praying helps me win	0.431		*0.387*		
4. Losses when gambling, are bound to be followed by a series of wins	0.323	**0.445**	0.436		
5. Relating my winnings to my skill and ability makes me continue gambling		0.657		0.371	
6. Gambling makes things seem better	0.364	0.383	0.309	**0.571**	
7. It is difficult to stop gambling as I am so out of control	**0.739**				
8. Specific numbers and colours can help increase my chances of winning		0.403	**0.594**		
9. A series of losses will provide me with a learning experience that will help me win later	0.315	**0.643**			
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.444	0.433	0.366		
11. Gambling makes the future brighter	0.599			*0.306*	

Table 6. Rotated factor matrix for university data[a] *(continued)*

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Illusion of Control	4 Gambling Expectancies	5 Interpretive Bias
12. My desire to gamble is so overpowering	**0.837**				
13. I collect specific objects that help increase my chances of winning	0.595		*0.398*		
14. When I have a win once, I will definitely win again	0.355	**0.436**	0.392		
15. Relating my losses to probability makes me continue gambling	0.358	0.526			*0.375*
16. Having a gamble helps reduce tension and stress	0.351		0.354	**0.523**	
17. I'm not strong enough to stop gambling	**0.654**				
18. I have specific rituals and behaviours that increase my chances of winning	0.481		**0.489**		
19. There are times that I feel lucky and thus, gamble those times only			0.583		
20. Remembering how much money I won last time makes me continue gambling		0.323	0.422		**0.441**
21. I will never be able to stop gambling	**0.649**				
22. I have some control over predicting my gambling wins	0.341	**0.465**			
23. If I keep changing my numbers, I have less chance of winning than if I keep the same numbers every time			0.468		

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. [a]Rotation converged in 13 iterations.

Bolded entries show max loadings that correspond to Raylu and Oei (2004)

Underlined entries show maximum loadings that contradict Raylu and Oei (2004)

Italicized entries show cross loadings that correspond to Raylu and Oei (2004) main loadings

Appendix C

Table 7. Rotated factor matrix teenage data with "no ones" on GRCS and PGSI > 0[a]

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Interpretive Bias	4 Unknown	5 Gambling Expectancies
1. Gambling makes me happier					**0.595**
2. I can't function without gambling	**0.773**				
3. Praying helps me win	0.605				
4. Losses when gambling, are bound to be followed by a series of wins	0.384	*0.356*	0.409		
5. Relating my winnings to my skill and ability makes me continue gambling		0.408	**0.576**		
6. Gambling makes things seem better		0.621			*0.382*
7. It is difficult to stop gambling as I am so out of control	**0.704**			0.42	
8. Specific numbers and colours can help increase my chances of winning	0.305	*0.322*			
9. A series of losses will provide me with a learning experience that will help me win later	0.339			0.717	
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.463	0.44	*0.339*	0.328	
11. Gambling makes the future brighter	0.482		0.648		

Table 7. Rotated factor matrix teenage data with "no ones" on GRCS and PGSI > 0[a] *(contiunued)*

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Interpretive Bias	4 Unknown	5 Gambling Expectancies
12. My desire to gamble is often overpowering	**0.543**	0.384	0.405	0.32	
13. I collect specific objects that help increase my chances of winning	0.745				
14. When I have a win once, I will definitely win again		**0.518**	0.465		
15. Relating my losses to probability makes me continue gambling		0.719			
16. Gambling helps reduce tension and stress			0.828		
17. I'm not strong enough to stop gambling	0**.77**				
18. I have specific rituals and behaviours that increase my chances of winning	0.645				
19. There are times when I feel lucky and thus, gamble those times only	0.331	**0.554**			
20. Remembering how much money I won last time makes me continue gambling		0.494			
21. I will never be able to stop gambling	**0.795**			0.335	
22. I have some control over predicting my gambling wins		*0.323*		0.668	
23. If I keep changing my numbers, I have less chance of winning that if I keep the same numbers every time	0.518				

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. [a]Rotation converged in 13 iterations.

Bolded entries show max loadings that correspond to Raylu and Oei (2004)

Underlined entries show maximum loadings that contradict Raylu and Oei (2004)

Italicized entries show cross loadings that correspond to Raylu and Oei (2004) main loadings

Appendix D

Table 8. Rotated factor matrix for university data with "no ones" on GRCS and PGSI > 0[a]

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Ilusion of Control	4 Interpretive Bias	5 Gambling Expectancies
1. Gambling makes me happier					**0.61**
2. I can't function without gambling	**0.657**				
3. Praying helps me win	0.378		**0.477**		
4. Losses when gambling, are bound to be followed by a series of wins			0.553		
5. Relating my winnings to my skill and ability makes me continue gambling		0.533	0.317		0.429
6. Gambling makes things seem better	0.32	0.303	0.313		**0.548**
7. It is difficult to stop gambling as I am so out of control	**0.718**				
8. Specific numbers and colours can help increase my chances of winning			**0.557**	0.314	
9. A series of losses will provide me with a learning experience that will help me win later		**0.527**	0.436		0.304
10. Relating my losses to bad luck and bad circumstances makes me continue gambling	0.36	0.333	0.385		
11. Gambling makes the future brighter	0.526				*0.307*

Table 8. Rotated factor matrix for university data with "no ones" on GRCS and PGSI > 0[a] *(continued)*

GRCS Item	Factor 1 Inability to Stop	2 Predictive Control	3 Ilusion of Control	4 Interpretive Bias	5 Gambling Expectancies
12. My desire to gamble is so overpowering	**0.786**		0.313		
13. I collect specific objects that help increase my chances of winning	0.558			0.324	
14. When I have a win once, I will definitely win again	0.317	**0.466**		0.354	
15. Relating my losses to probability makes me continue gambling	0.316	0.583			
16. Having a gamble helps reduce tension and stress	0.324			0.377	**0.428**
17. I'm not strong enough to stop gambling	**0.67**				
18. I have specific rituals and behaviours that increase my chances of winning	0.517			0.4	
19. There are times that I feel lucky and thus, gamble those times only				0.629	
20. Remembering how much money I won last time makes me continue gambling		0.416		**0.465**	
21. I will never be able to stop gambling	**0.659**				
22. I have some control over predicting my gambling wins	0.322	**0.609**			
23. If I keep changing my numbers, I have less chance of winning than if I keep the same numbers every time		0.307		0.41	

Rotation Method: Varimax with Kaiser Normalization. Extraction Method: Principal Axis Factoring. [a]Rotation converged in 13 iterations.

Bolded entries show max loadings that correspond to Raylu and Oei (2004)

Underlined entries show maximum loadings that contradict Raylu and Oei (2004)

Italicized entries show cross loadings that correspond to Raylu and Oei (2004) main loadings