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Validating the Two-Factor Model of the Gambling Functional Assessment – Revised in a Mainland Chinese sample

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Abstract: The Gambling Functional Assessment – Revised (GFA-R) was developed to measure the degree to which gambling behavior is maintained by positive reinforcement and/or negative reinforcement. In the current study, the GFA-R, South Oaks Gambling Screen, and Problem Gambling Severity Index were translated into simplified Chinese and completed by university students from mainland China (N = 299). A confirmatory factor analysis was conducted on a subset of the sample who scored greater than 0 on the GFA-R (N = 112). Results of the confirmatory factor analysis revealed the previously validated two-factor model of the original GFA-R (i.e., positive reinforcement & negative reinforcement) adequately fit the data from the current sample. Five of the items from the GFA-R did not adequately load to either factor; cultural factors and translation issues were discussed as possible explanations. Consistent with previous research, gambling maintained by negative reinforcement was found to be more strongly correlated with gambling problems than gambling maintained by positive reinforcement. These results indicate the Chinese version of the GFA-R may be useful for identifying maintaining contingencies for gambling behavior in Chinese populations, which may be beneficial to practitioners when attempting to treat gambling problems.

Keywords: Factor Structure, Gambling, Positive Reinforcement, Negative Reinforcement, Foreign Language Translation, Scale Validation.

Introduction

Although previous research has validated measures to identify people with problematic and pathological gambling in Chinese populations (e.g., Tang et al., 2010), less research has been done to investigate gambling motivations (e.g., Wu & Tang, 2011; Wu et al., 2012). In 2011, Wu and Tang conducted a study to validate a Chinese version of the Gambling Motivation Scale (C-GMS). The authors tested the seven-factor model of the original French Gambling Motivation Scale (GMS; Chantal et al., 1994) and found their data from a Chinese sample supported the model. The seven factors for the GMS are: (1) knowledge, (2) accomplishment, (3) stimulation, (4) social reward, (5) stress relief, (6) external rewards, and (7) amotivation (i.e., no relationship between actions and gambling outcome). The Gambling Motives, Attitudes and Behaviors (GMAB) was developed and validated using Chinese samples (Tao et al., 2011; Wu et al., 2012). Implementing an exploratory factor analysis with the GMAB, the authors developed a five-factor model for gambling motivations. The five factors of the GMAB are (1) self-worth, (2) monetary gains, (3) sensation seeking, (4) boredom alleviation, and (5) learning.

Given the illicit nature of gambling in mainland China, there is a gap in the literature studying gambling in mainland Chinese populations, with most research on gambling in Chinese populations being conducted in Macau and Hong Kong (e.g., Cheung, 2016; Tang et al., 2010; Wu et al., 2015). Data from samples in Macau and Hong Kong may still provide information that is generalizable to mainland Chinese, but given the heterogeneity of Chinese communities, application of this information should be contextualized.

Understanding specific motivations is important to understanding gambling, but so too is understanding the contingencies that maintain the gambler's behavior. This is especially the case given that gambling problems have been more strongly associated with gambling maintained by negative, than by positive, reinforcement (Morasco et al., 2007). Along those lines, the current study aimed to validate the Gambling Functional Assessment - Revised (GFA-R) in a mainland Chinese sample. The GFA-R is a two-factor model designed to identify the contingency maintaining the respondent's gambling behavior. Its two subscales are positive and negative reinforcement. Further, the GFA-R has been validated in multiple samples, including in America (Weatherly et al., 2011), Italy (Iliceto et al., 2018), Japan (Weatherly et al., 2014a), and the United Kingdom (Weatherly et al., 2014b).

The Gambling Functional Assessment (GFA) was first introduced by Dixon and Johnson (2007). The GFA is a 20-item self-report measure created to measure factors for maintaining gambling behavior. The GFA has four subscales representing functions the authors theorized as maintaining pathological gambling: sensory experiences, escape, attention, and tangible rewards. An exploratory and confirmatory factor analysis later revealed a two-factor structure for the GFA (Miller et al., 2009) (See Note 1). The two factors in this model were determined to represent positive reinforcement and negative reinforcement. Four of the original items did not fit Miller et al.'s two-factor model. Subsequently, Weatherly et al. (2011) removed these items and created a 16-item revised version of the GFA (GFA-R) to measure gambling behavior that is contingent on positive reinforcement and/or negative reinforcement. Previous exploratory and confirmatory factor analyses of two different samples revealed eight of the GFA-R items loaded onto the positive reinforcement factor, and the other eight items loaded for negative reinforcement (Weatherly et al., 2011).

Gambling in mainland China has been outlawed since 1949. However, Chinese citizens can legally participate in gambling activities through state-approved sports, government-run lotteries, and traveling to Macau or abroad. Chinese citizens may also engage in illegal gambling activities anonymously online, in more informal underground operations, or in social contexts with friends and family. Despite this cultural distinction and social taboos surrounding excessive gambling, pathological and problem gambling is a growing concern in China (Wu & Lau, 2015).

Valid and reliable measurement of gambling behavior is essential for identifying pathological and problem gambling, but understanding why people gamble is essential for treatment. In the current study, the GFA-R was translated into simplified Chinese and administered to a sample of mainland Chinese university students. In addition to the GFA-R, respondents in the current study also completed translated versions of the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987) and the Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001).

The SOGS is one of the most widely used measures for assessing pathological gambling. The SOGS measures severity of pathological gambling by assessing lifetime gambling history. It was originally validated using a U.S. sample of pathological gamblers, university students, and hospital employees (Lesieur & Blume, 1987).

The Canadian Problem Gambling Index (CPGI) was created by a Canadian research team through the Canadian Centre on Substance Abuse and validated in a Canadian sample (Ferris & Wynne, 2001). The CPGI assesses aspects related to problem gambling (i.e., types of gambling activity, gambling frequency, and amount of money spent on gambling). The PGSI is comprised of the nine scored items from the 31-item CPGI. Items of the PGSI measure the severity of problem gambling through reported consequences of gambling behavior.

Both the SOGS and PGSI have been previously translated for use in Chinese speaking populations (e.g., Loo et al., 2011; Tang et al., 2010). However, the present authors performed their own translation because previously translated versions of the SOGS and PGSI were written in traditional Chinese, and the sample for this study was anticipated to primarily read and write in simplified Chinese. The present study is the first known administration of either measure in a research study with a mainland Chinese sample. The SOGS and the PGSI measure different aspects of problem and pathological gambling. Inclusion of these measures in the current study was important for establishing convergent validity of the GFA-R with the SOGS and PGSI in a mainland Chinese population. We expected to find positive correlations between all three measures. We also hypothesized the two-factor model previously reported in the literature would be a good fit for the GFA-R data, and that all 16 items of the GFA-R would load onto the same factors (i.e., positive reinforcement & negative reinforcement) seen in previous studies (e.g., Weatherly et al., 2010; Weatherly et al., 2014b).

Method

Participants

Participants were 299 students at a university located in a large metropolitan city of mainland China. Of this sample, 187 (62.5%) scored a 0 on the GFA-R. The GFA-R was developed to measure contingencies that maintain gambling behavior. Thus, a score of 0 on the GFA-R suggests the respondent either does not gamble or does not gamble for reasons measured by the GFA-R. Chi-square goodness-of-fit tests showed no significant differences in income or gender between the general sample and the subsample who scored above 0 on the GFA-R (N = 112). An independent sample t-test found no difference between the subsample's age and the general sample's age. Table 1 summarizes demographics for the general sample as well as demographics for the subsample of participants who scored greater than 0 on the GFA-R. Following Weatherly et al. (2011), data from the participants who scored greater than 0 on the GFA-R were used for factor analyses.

Table 1. Sample statistics

	General Sample $N = 299$	Sample (GRA-R scores > 0) $N = 112$
Gender		
Male	35.5%	37.5%
Female	64.5%	58.9%
Age	19.51 (1.71)	19.42 (1.76)
Annual personal income		
< 10,000	89.1%	85.8%
10,000-25,000	6.8%	7.5%
25,000-50,000	0.8%	1.9%
50,000-100,000	0.4%	0.9%
> 100,000	3.0%	3.8%
Annual household income		
< 10,000	21.7%	20.6%
10,000-25,000	28.5%	30.8%
25,000-50,000	21.7%	18.7%
50,000-100,000	14.6%	17.8%
> 100,000	13.5%	12.1%

Measures and Procedures

All measures in this study were administered in simplified Chinese. English versions of the measures were first blind translated into simplified Chinese, then back translated to English to assure each item retained its original meaning as accurately as possible. The translation and back-translation were conducted independently by two native Chinese speakers. Translated items are available in the Appendices. The order of the GFA-R, SOGS, and PGSI were randomized during administration.

The GFA-R (Weatherly et al., 2011) measures functions that maintain gambling behavior. The GFA-R is a 16-item questionnaire with two subscales that measure gambling behavior maintained by positive and negative reinforcement. Items such as, "I gamble when I feel stressed or anxious." are answered on a seven-point Likert-like scale (0 = Never to 6 = Always), and scores are calculated based on the sum of numerical answers for these items. The negative and positive reinforcement subscales each consist of eight items. For the subsample (*N* = 112), which only included the full scale GFA-R scores of participants who scored greater than 0, Cronbach's alpha coefficients for the full scale GFA-R, positive reinforcement subscale, and negative reinforcement subscale, were .83, .70, and .79, respectively.

The SOGS (Lesieur & Blume, 1987) assesses lifetime gambling history. Scores on the SOGS may be used to help identify problem gambling and pathological gambling. The SOGS has a total of 43 items, but only 20 items count toward a respondent's total score. Scores on the SOGS are calculated based on the sum of 'yes' answers to 20 items (e.g., "Did you ever gamble more than you intended to?") on the questionnaire. Previous research has indicated a score of 5 or more on the SOGS suggests the potential presence of pathological gambling, and scores of 3 or 4 may suggest problematic gambling (e.g., Weiss & Loubier, 2010). The SOGS has been previously tested for reliability and validity in a Hong Kong-based Chinese sample (Tang et al., 2010). Tang et al. found similar results for probable pathological gambling based on SOGS scores. In the current study, Cronbach's alpha was .79 for the general sample (*N* = 299) and .64 for the sample subset (*N* = 112).

The PPGSI (Ferris & Wynne, 2001) is a 9-item measure of gambling severity. Items such as "Have you felt that you might have a problem with gambling?" are answered on a 4-point Likert-like scale (0 = Never to 3 = Almost Always). Total scores on the PGSI are calculated based on the sum of numerical answers for each item. For the general sample (*N* = 299) and sample subset (*N* = 112), Cronbach's alpha coefficients for the PGSI were adequate at .66 and .64, respectively.

Results

To determine the model fit for our confirmatory factor analysis, we used cutoffs for CFI, RMSEA, and SRMR, as recommended by Hu and Bentler (1999) for samples of less than 250. SPSS 26 was employed to perform a confirmatory factor analysis on the GFA-R data for the current sample (see Table 2). Items were loaded to the corresponding latent factors as hypothesized in GFA-R.

Table 2. Descriptive statistics and factor loadings of GFA-R using Chinese sample

No.	Items	*M*	*SD*	Factor 1	Factor 2
Positive Reinforcement					
1	I gamble when my friends are gambling with me.	1.89	1.17	.28	
2	I find myself feeling a rush, and getting excited, when I gamble.	1.67	1.17	.54	
3	I really enjoy the complementary perks that come along with gambling, like free points, drinks, comp coupons, etc.	1.66	1.24	.75	
4	I enjoy the social aspects of gambling such as being with my friends or being around other people who are having a good time and cheering me on.	1.64	1.23	.53	
5	I gamble primarily for the money that I can win.	1.56	1.29	.35	
Negative Reinforcement					
6	I gamble after fighting with my friends, spouse, or significant other.	1.14	0.38		.51
7	I gamble when I feel stressed or anxious.	1.19	0.51		.56
8	If I have a hard day at work or school, I am likely to gamble.	1.24	0.61		.43
9	I gamble when I am feeling depressed or sad.	1.43	1.06		.74
10	I find that gambling is a good way to keep my mind off problems I have in other parts of my life.	1.33	0.71		.86
11	I gamble when I am in debt or need money.	1.20	0.57		.48

Notes: A confirmatory factor analysis was estimated with maximum likelihood. The model showed a good fit with the data, $\chi^2(43, N = 112) = 67.08$, $p = .01$, CFI = .91, RMSEA = .07, SMEA = .07. Latent factors were allowed to covary, but the error terms were not. Standardized factor loadings were reported and significant at .05.

An initial model included all 16 items of the GFA-R. Residuals of the observed indicators were not allowed to covary. A two-factor solution was tested with the responses from the participants who scored greater than 0 on the GFA-R. The overall fit indices suggested that the initial model could be improved, $\chi^2(103, N = 112) = 281.37$, $p < .01$, CFI = .69, RMSEA = .13, 90% CI [.11, .14], SRMR = .10.

According to the literature, there are two approaches to improving the model fit. The first approach is to correlate the error terms of the observed indicators from the same factor (e.g., positive or negative reinforcement). The correlation of measurement error in CFA may be justified when the specification is substantively interpretable and other identification requirements are met (Brown & Moore, 2012). Prior research on validating GFA-R in non-US samples found that correlated measurement errors with the same latent factor were needed to establish a reasonable model fit (Weatherly et al., 2014). The second approach is to remove items that may contribute to the poor model fit. This second approach assumes that the measurement error is random and the observed relationship between any two indicators arises from their loadings on the same, hypothesized latent construct.

Both of these approaches are reasonable but come with distinct trade-offs. Correlating measurement errors maximizes the number of items retained in the study but introduces uncertainty as to why the items are related. By contrast, removing items relies on fewer assumptions about shared variance between the items but makes it difficult to compare the results with prior studies that might use different sets of items. For a rigorous testing, we used both approaches in this study.

Following the first approach, we correlated the residuals of the items from the same latent factor (positive or negative reinforcement). Residuals of the items from different latent factors were not allowed to covary. The modification indices suggested a total of six covariance terms (four from the positive reinforcement subscale & two from the negative reinforcement subscale); the remaining were covariance terms across the latent factors. The model fit improved but did not reach the benchmarks recommended by Hu and Bentler (1999), $\chi^2(96, N = 112) = 222.39$, $p < .01$, CFI = .78, RMSEA = .11, 90% CI [.09, .13], SRMR = .09. The results suggested that accounting for the shared variance between items from the same latent factor alone may not be sufficient to establish the factor structure hypothesized in the GFA-R in this sample.

Using the second approach, we removed items that either poorly loaded on the hypothesized factor or substantially correlated with those from a different latent factor. Five items were removed: three items from the positive reinforcement subscale and two from the negative reinforcement subscale. The revised model with 11 GFA-R items showed a reasonable fit with the data, $\chi^2(44, N = 112) = 83.95$, $p < .01$, CFI = .85, RMSEA = .09, 90% CI [.06, .12], SRMR = .08. As a robust check, we further examined whether the 11 items conformed to one factor, as opposed to two hypothesized in GFA-R. The data were not consistent with the one-factor solution, $\chi^2(43, N = 112) = 67.08$, $p = .01$, CFI = .91, RMSEA = .07, 90% CI [.04, .10], SRMR = .07. Hence, we adopted the results based on the two-factor solution with 11 items.

Descriptive statistics and standardized factor loadings for the GFA-R items are presented in Table 2. All factor loadings were significant at $p \leq 0.05$. Consistent with previous studies, items 6, 7, 13, 14, and 16 factor loaded for positive reinforcement, and items 2, 3, 5, 10, 11, and 12 factor loaded for negative reinforcement. Factor loadings for the positive reinforcement items ranged from .28-.75. Factor loadings for the negative reinforcement items ranged from .43 to .86. Cronbach's alpha was .76 for the 11 GFA-R items, .60 for the five positive reinforcement items, and .75 for the six negative reinforcement items.

To validate the factor structure of the SOGS, we ran a one-factor CFA with items designated to show the at-risk responses (Lesieur & Blume, 1987). A total of 20 items were included. Error terms were not allowed to covary. The initial model showed a poor fit with the data, $\chi^2(170, N = 101) = 370.13$, $p < .01$, CFI = .50, RMSEA = .11, 90% CI [.10, .13], SRMR = .14. Inspecting modification indices showed that three pairs of error terms were highly correlated and hence were allowed to covary. The revised model showed a reasonable fit with the data, $\chi^2(158, N = 101) = 172.01$, $p = .21$, CFI = .97, RMSEA = .03, 90% CI [.00, .06], SRMR = .10. The findings suggested that 20 items of the SOGS assessed one latent construct (as intended by the original SOGS; Lesieur & Blume, 1987).

A one-factor model including nine items of the PGSI was estimated, with error terms of the observed indicators not being allowed to covary. The results showed a poor model fit, $\chi^2(df = 27, N = 106) = 69.16$, $p < .01$, CFI =.77, RMSEA = .12, 90% CI [.09, .16], SRMR =.09. After inspecting the modification indices and inter-item correlations, we found that three pairs of error terms were highly correlated. Thus, these terms were allowed to covary in the revised model. With these revisions, the model fit improved substantially, $\chi^2(df = 24, N = 106) = 69.16$, $p < .01$, CFI = .93, RMSEA = .07, 90% CI [.01, .11], SRMR = .07, suggesting that the nine items of the PGSI converged to assess one unified construct as originally intended.

Zero-order correlations between the study measures are presented in Table 3. As expected, GFA-R positive reinforcement was positively correlated with GFA-R negative reinforcement ($r = .47$, $p < 0.01$). GFA-R positive reinforcement scores were positively correlated with the SOGS ($r = .39$, $p < .01$) scores and the PGSI ($r = .24$, $p < .05$). GFA-R negative reinforcement scores were significantly positively correlated with both the SOGS ($r = .48$, $p < 0.01$) and the PGSI ($r = .28$, $p < 0.01$) scores. The SOGS and the PGSI were also significantly positively related ($r = .48$, $p < 0.01$).

Table 3. Zero-order correlations between scales ($N = 107$)

	1	2	3	4
1. GFA-R positive[a]				
2. GFA-R negative[b]	.47**			
3. SOGS[c]	.39**	.48**		
4. PGSI[d]	.24*	.28**	.48**	

***Notes*:**
[a]Positive-reinforcement factor of the Gambling Functional Assessment Revised scale
[b]Negative-reinforcement factor of the Gambling Functional Assessment Revised scale
[c]South Oaks Gambling Screen scale
[d]Perceived Gambling Severity Index scale
Age, gender, and income were not significantly correlated with any of the scales.
$^{*}p < .05$, $^{**}p < .01$

Discussion

In the current study, we translated the GFA-R (Weatherly et al., 2011) and two other widely used measures of gambling behavior—the SOGS (Lesieur & Blume, 1987) and PGSI (Ferris & Wynne, 2001)—into simplified Chinese. We administered these measures and a short demographic survey to students who attended a university in mainland China. Overall, the results generally supported our hypotheses.

We originally hypothesized that the two-factor structure validated in previous studies would adequately fit the data for the Chinese version of the GFA-R. We had also hypothesized all 16 items would load onto their respective factors in our two-factor model. Our confirmatory factor analysis revealed 11 of the 16 GFA-R items loaded onto their respective factors. Of the five items that did not load to either factor, three of these items were on the positive reinforcement subscale, and two items were on the negative reinforcement subscale.

The modifications needed to make the Chinese GFA-R conform to the theorized two-factor structure do not undermine the scale's validity. The current study showed that modifications were also needed to validate the other two established scales of gambling behavior—the SOGS (Lesieur &

Blume, 1987) and PGSI (Ferris & Wynne, 2001). The fact that all three scales require modification suggests that the Chinese gambling population does not perhaps perfectly match those found in other parts of the world, which is an important direction for future research.

One potential avenue for future research is the cultural distinction made in China that differentiates high-stakes gambling (e.g., gambling at casinos & betting) from social, small-stakes gambling (e.g., Mahjong with friends/relatives or government sanctioned lottery). ‘Social gambling’ or ‘gaming’ in Chinese culture represents smaller stakes betting for entertainment, typically amongst friends and family, and is considered more socially acceptable than high-stakes gambling (Loo et al., 2008; Wu & Lau, 2015). Based on the current results, we cannot conclude for certain whether answers to the GFA-R have to do with high-stakes gambling, small-stakes social gaming, or a combination of both. For example, two items that did not load to either factor were “I like the sound, lighting and excitement when I gamble.” and “When gambling, I will choose to play the game with the highest chance of winning.” These items may not be compatible with settings related to “social gambling.” Future research could explore whether changing the wording for the GFA-R to include distinctions between ‘social gambling’ and/or ‘gaming’ will yield data that would result in retaining more items from the original 16-item measure.

Our study does have some notable limitations. Our data were collected from university students, meaning our sample was comparatively younger, had lower individual income, and had a greater proportion of female participants, in comparison to the general population. Next, our sample was limited to only one region/province of China’s large and heterogeneous population. Additionally, the current data collection and past data collections of the GFA-R have been conducted in community samples, and not samples of those who have been identified as having gambling problems. Only one previous study (Weatherly & Terrell, et al., 2014) has validated use of the GFA-R in a sample of probable problem and pathological gamblers (i.e., participants who scored 3 or greater on the SOGS). Our current results may not generalize to populations of problem gamblers and pathological gamblers. Therefore, a logical next step is validation of the GFA-R with a Chinese sample from a more representative population, which would include problem and pathological gamblers.

Consistent with previous research, scores on the negative reinforcement GFA-R subscale were more strongly associated with problematic gambling than scores on the positive reinforcement subscale. This association was indicated by a larger correlation between GFA-R negative reinforcement and both the SOGS and the PGSI, compared to GFA-R positive reinforcement. Replicating this finding in a Chinese sample is important because scholars have previously assumed Chinese people only gamble to gain something (Chan et al., 2019). The present findings suggest that, consistent with other research, problems with gambling among this Chinese sample are related to gambling as an escape. This finding speaks to the potential utility of the GFA-R for identifying modes of treatment for problem gambling behavior. Indeed, the original GFA (Dixon & Johnson, 2007) was designed as function-based assessment to target behaviors that sustained problem gambling. Previous research (e.g., Guercio et al. 2012; Dixon et al., 2016) has found evidence supporting the use of behavior-based interventions to treat gambling behavior. Identifying behavioral function-based maintenance of gambling behavior with a measure such as the GFA-R, could have potential utility in clinical treatment planning. Dixon et al. (2018) point out the GFA-R two-factor structure deviates from their intended behavioral-analytic approach of the four-factor revised GFA-II (as well as the original GFA). However, this does not mean the GFA-R does not have clinical utility. We argue the two-factor GFA-R has utility for targeting areas of treatment such as potentially identifying whether gambling maintained by positive and/or negative reinforcement may be related to issues like work-related stress, relationship problems, or depression symptoms. Based on this conceptualization, the two-factor GFA-R can be viewed as complementary to the four-factor GFA-II (Dixon et al., 2018). Regardless, future research, both in the U.S. and internationally, will want to explore whether targeting life issues as a form of intervention can reduce problematic gambling behavior.

Previous research in Chinese populations has found demographic variables like age, gender, and income to be related to gambling behavior (Loo et al., 2008). However, in our current study, these demographic variables were not related the gambling behavior assessed by the GFA-R or the SOGS. Only age was found to have a weak negative correlation, $r(101) = -.21$, $p = .036$, with participant scores on the PGSI. Given age was not related to scores on the GFA-R or the SOGS, we speculate this significant correlation between age and PGSI scores may simply be due to chance. Both age and income had a restricted range in our sample because participants were university students. In our study, gender was not associated with gambling behavior. This non-significant relationship may be due to the restricted range and income of the sample. Future research could explore whether the relationship between gender and gambling in Chinese samples is moderated by age and income.

Overall, the 11-item model retained the original two-factor structure for the GFA-R and was a good fit for the data. Use of the GFA-R in Chinese populations may be helpful for identifying functional maintenance of gambling behavior, as well as motivations that are specific to positive and negative reinforcers. The GFA-R could be a valid measure for use in Chinese speaking populations with some revisions and/or removal of items that were not a good fit with our model. Additionally, the translated GFA-R offers convergent validity for our translated versions of the SOGS and PGSI. Our results reinforce the notion that gambling maintained by negative reinforcement is a potential indicator of gambling problems, and that this notion is maintained cross-culturally. As such, its use by practitioners may benefit tailoring successful treatment options by focusing attention on life issues and factors from which the gambler is attempting to escape.

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Declaration of conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study will be made publicly available on osf.io after publication of this manuscript. Data can also be requested from the corresponding author at kimberly.tom@und.edu.

Author's contributions

Jeffrey Weatherly and Xun Zhu contributed to the study conception and design. Material preparation was performed by Xun Zhu, Hsuan-Ying Liu, and Jeffrey Weatherly. Data collection was performed by Xun Zhu and Jeffrey Weatherly. Data analysis was performed by Xun Zhu and Kimberly Tom. The first draft of the manuscript was written by Kimberly Tom. Kimberly Tom, Xun Zhu, and Jeffrey Weatherly commented on and edited previous versions of the manuscript. All authors read and approved the final manuscript.

Ethics and informed consent

The questionnaires and methodology for this study was approved by the Institutional Review Board of the University of North Dakota (Ethics approval number: IRB-201912-141). All participants received informed consent information and participated voluntarily.

Note 1: More than a decade after publication of the GFA, Dixon, Wilson, Belisle, and Schreiber (2018) attempted to reestablish the validity of four-factor model for the GFA. This updated 10-item model is known as the GFA-II, which asserts itself as a tool that can be used more precisely or further developed to target gambling maintenance behaviors. Theoretical implications and comparisons between the GFA-R and the GFA-II are addressed in the discussion section.

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