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Validating the Gambling Functional Assessment-Revised in a Sample of Probable Problem/Disordered Gamblers

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The Gambling Functional Assessment-Revised (GFA-R) was designed to measure whether the respondent's gambling is maintained by positive reinforcement or escape. However, it has only been administered in samples dominated by non-problem gamblers. One hundred five adult participants who scored three or more on the South Oaks Gambling Screen (SOGS) completed the GFA-R and the Problem Gambling Severity Index (PGSI). Confirmatory factor analyses showed that a 15-item GFA-R demonstrated a sound factor structure. The internal consistency of the GFA-R subscales was good to excellent for both probable problem and disordered gamblers. Participants scored significantly higher on gambling for positive reinforcement than as an escape. However, probable disordered gamblers endorsed gambling as an escape significantly more than probable problem gamblers. Gambling as an escape, but not for positive reinforcement, was also a significant predictor of participants' PGSI scores independent of their SOGS scores. The results suggest that the GFA-R may be a valid and useful measure for both researchers and practitioners. The results also highlight the prominent role gambling as an escape plays in problem and disordered gambling.

Keywords: Disordered Gambling; Problem Gambling; Gambling Functional Assessment-Revised; Escape; Positive Reinforcement

A number of diagnostic screening measures have been created to detect the presence of gambling problems. One widely used measure is the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987), but others are also frequently employed (e.g., the Problem Gambling Severity Index [PGSI]; Ferris & Wynne, 2001). Other instruments have been developed to measure gamblers' motivations or expectancies (e.g., Gambling Expectancies Questionnaire; Gillespie, Derevensky, & Gupta, 2007). Still others have been developed in an attempt to determine the reinforcement contingencies maintaining the respondent's gambling behavior (e.g., Gambling Functional Assessment [GFA]; Dixon & Johnson, 2007; Weatherly, Miller, & Terrell, 2011).

Dixon and Johnson (2007) were the first to introduce a measure for assessing the contingencies maintaining gambling behavior, coined the GFA. This measure is a 20-item self-report questionnaire designed to measure four different possible maintaining reinforcement contingencies (tangible outcomes, social/attention, sensory experience, & escape). Subsequent psychometric research determined that the GFA produced relatively reliable data (Miller, Meier, & Weatherly, 2009b), but that it did not measure four distinct contingencies (Miller, Meier, Muehlenkamp, & Weatherly, 2009a). Rather, Miller et al. (2009a) identified two underlying constructs, which they labeled positive reinforcement and escape (i.e., negative reinforcement). Further, Miller et al. found that not all items loaded onto one of the two constructs or loaded onto the construct for which the item was originally intended.

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As a result of these psychometric deficits, Weatherly et al. (2011) developed the Gambling Functional Assessment-Revised (GFA-R). The GFA-R is a 16-item self-report questionnaire designed to measure whether the respondent's gambling behavior is being maintained by positive reinforcement and/or escape. Eight of the items are dedicated to each contingency. Weatherly et al. (2011) reported that all items loaded strongly onto their intended construct and subsequent cross-cultural research has found that the data reliably fit the original factor structure (Weatherly, Aoyama, Terrell, & Berry, in press a; Weatherly, Dymond, Samuels, Austin, & Terrell, in press b). Research also indicates that the internal consistency and temporal reliability of the data produced by the GFA-R are good to excellent, and are superior to that of the original GFA (Weatherly, Miller, Montes, & Rost, 2012).

Although the existing research suggests that the GFA-R produces reliable and valid data, its psychometric properties have only been examined using data from samples consisting mostly of non-problem gamblers. If the GFA-R is going to be a useful tool for identifying the contingencies maintaining the gambling behavior of those who may be suffering from gambling problems, then its psychometric properties need to be examined using such a sample. Until these tests are completed, the validity of the GFA-R for use with problem or disordered gamblers[1] is only speculative.

A fair amount of basic research has been conducted with the GFA-R and that research has reliably produced two results. First, nearly all respondents who complete the GFA-R score higher on the positive reinforcement, than on the escape, subscale (e.g., Weatherly et al., in press a, b; Weatherly & Derenne, 2012). These results suggest that the gambling behavior of nearly all respondents is, at least in part, maintained by trying to obtain something. Second, although participants' gambling is maintained at least partially by positive reinforcement, it is the escape subscale score on the GFA-R that is far more strongly associated with potential gambling problems than is the score on the positive reinforcement subscale (e.g., Weatherly et al., in press b; Weatherly & Derenne, 2012; Weatherly & Miller, 2013).

Finding that the contingency of escape is strongly related to gambling problems is perhaps not surprising. Gambling as an escape was an explicit symptom of pathological gambling in the previous version of the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2003), although escape is no longer directly referenced in the newest version of that publication (American Psychiatric Association, 2013)[2]. Theories for why people develop gambling problems have long indicted escape as playing a major role (e.g., Blaszczynski & Nower, 2002). Likewise, a plethora of empirical research has linked gambling problems to escape (e.g., Rockloff, Greer, Fay, & Evans, 2011; Wood & Griffiths, 2007). What may be surprising, however, is just how strong the relationship may be. For instance, Weatherly and Derenne (2012) reported that nearly 50% of the variance of participants' score on the SOGS could be accounted for by their score on the escape subscale of the GFA-R.

As with the psychometric properties of the GFA-R, the basic research that has used the GFA-R has been conducted using samples that consist of mostly non-problem gamblers. One exception was Weatherly (2013b), who collected data from a sample of 25 university students who scored 3 or more on the SOGS. Results indicated that GFA-R positive rein-

[1] Pathological gambling has been replaced with the label disordered gambling (American Psychiatric Association, 2013).

[2] The symptoms do included gambling when one feels distressed, which can be considered an indirect reference to the contingency of escape.

forcement subscale scores were significantly higher than the escape subscale scores. But results also showed that GFA-R escape, but not positive reinforcement, scores were significantly correlated with participants SOGS scores. Those results, however, were limited by the fact that the study had a relatively small sample size and all participants were university students.

The present study recruited both university students and adults from across the United States to complete the GFA-R, SOGS, and PGSI. Data from participants who qualified as probable problem or disordered gamblers (i.e., who scored 3 or more on the SOGS) were then analyzed. We predicted that previous results from studies on the GFA-R would be replicated. First, we predicted that the same factor structure of the GFA-R identified by Weatherly et al. (2011) would describe well the data from the present sample. We also predicted the internal consistency of the GFA-R would be good or better. Next, we predicted that participants would endorse gambling for positive reinforcement to a significantly greater extent than they would endorse gambling as an escape. However, we predicted that participants who qualified as probable disordered gamblers would display significantly higher GFA-R escape scores than would participants who qualified as probable problem gamblers. Further, we also predicted that GFA-R escape scores, but not their positive reinforcement scores, would be significant predictors of how participants scored on the PGSI.

METHOD

Participants

The participants were 105 individuals (52 males; 53 females) who scored 3 or more on the SOGS. These individuals were taken from a sample of 305 adult participants who completed the materials via Amazon's Mechanical Turk (MTurk; http://www.mturk.com) and a sample 249 adult participants who completed the materials via their enrollment in a psychology course at the University of North Dakota.[3] Twenty-five of the participants were between 18-20 years of age, 27 were between 21-24 years of age, 31 were between 25-34 years of age, and the remaining 22 participants were 35 years of age or older. Seventy-seven participants (73.3%) self-reported as Caucasian, while the remaining participants reported to be Hispanic (4; 3.8%), African American (13; 12.4%), American Indian (4; 3.8%), or Asian (7; 6.7%). Participants completing the materials on MTurk were paid for their participation. Participants who completed the materials as part of their enrollment in a psychology class earned (extra) course credit for their participation.

Materials and Procedure

All participants were first presented with information about the study as approved by the Institutional Review Board at the University of North Dakota. Continued participation in the study after being presented with this information constituted the granting of informed consent.

Participants who completed the materials via MTurk did so by logging onto their MTurk account. The university participants completed the materials via an online data-management system (SONA Systems, Ltd; Version 2.72; Tallinn, Estonia) that was available to them through their enrollment in a psychology class. All participants completed the same materials, which were presented in random order across participants.

Demographic Information. Participants completed a total of four measures. The first was a demographic questionnaire that asked about the participant's sex, age, and ethnicity.

[3] In neither case was gambling involvement required to be involved in the data collection. All 554 individuals completed the materials described herein, but only data from the 105 participants are reported.

GFA-R. The second measure was the GFA-R (Weatherly et al., 2011). The GFA-R has 16 items, with eight designed to identify whether the respondent's gambling behavior is maintained by positive reinforcement and eight designed to identify whether the respondent's gambling is maintained by escape. All items are answered on a scale of 0 (Never) to 6 (Always) and subscale scores are calculated by summing the scores from the eight questions from that subscale. A complete version of the GFA-R can be found in Weatherly et al. (2011). Previous research has suggested that the GFA-R has high internal consistency ($\alpha = 0.91$; Weatherly et al., 2012) and good test-retest reliability ($r = 0.80$ at four weeks and $r = 0.81$ at 12 weeks; Weatherly et al., 2012). The factor structure of the GFA-R has also been replicated in samples from Japan and the United Kingdom (Weatherly et al., in press a, b).

SOGS. The third measure participants completed was the SOGS (Lesieur & Blume, 1987). The SOGS has 20 questions pertaining to the respondent's gambling history. Scores between 0-2 on the SOGS have been interpreted as the likely absence of problem or pathological gambling. Researchers (e.g., Weiss & Loubier, 2010) have interpreted scores of 3-4 on the SOGS as indicating the probable presence of problem gambling (i.e., subclinical). Lesieur and Blume (1987) originally suggested that scores of 5 or more on the SOGS can be interpreted as indicating the probable presence of pathological gambling. Lesieur and Blume originally reported that the internal consistency of the SOGS was excellent ($\alpha = 0.97$), but subsequent research has suggested that its internal consistency ranges from fair ($\alpha = 0.69$; Stinchfield, 2002) to good ($\alpha = 0.81$; Stinchfield, 2003). Research has also demonstrated that the test-retest reliability of the SOGS is good ($r = 0.89$ at four weeks and $r = 0.67$ at 12 weeks; Weatherly et al., 2012). The validity of the SOGS has also been replicated cross-culturally (e.g., Kido & Shimazaki, 2007).

PGSI. The fourth measure participants completed was the PGSI (Ferris & Wynne, 2001). The PGSI was designed to measure the negative experiences respondents have encountered because of their gambling. The PGSI has 12 questions with each answered on a four-point scale ranging from 0 (Never) to 3 (Almost always). A participant's score on the PGSI is calculated by summing the responses from the first nine questions. Ferris and Wynne suggested that the PGSI measured four categories: no problems with gambling (scores of 0), few negative outcomes (scores of 1-2), experiencing some negative outcomes as a result of gambling (scores of 3-7), and experiencing negative outcomes because of gambling (scores ≥ 8). Ferris and Wynne, along with subsequent researchers (McMillen & Wenzel, 2006), reported that the PGSI is psychometrically sound. Ferris and Wynne (2001) reported that the internal consistency was good ($\alpha = 0.84$; Ferris & Wynne, 2001), which has also been supported by subsequent research (Holtgraves, 2009). Ferris and Wynne (2001) also reported that the test-retest reliability of the PGSI was good ($r = 0.78$; Ferris & Wynne, 2001).

RESULTS

Forty-six of the participants scored between 3-4 on the SOGS whereas 59 scored 5 or more. The descriptive statistics on each of the three gambling measures for each group are presented in Table 1.[4]

Factor Structure of the GFA-R

The data from the 105 participants were used in a confirmatory factor analysis that employed Mplus 6.0 structural equation

[4] The descriptive statistics for the GFA-R positive reinforcement subscale have been calculated excluding item number one of the GFA-R because the confirmatory factor analysis suggested that this item did not load onto its intended construct.

Table 1. Descriptive statistics for the three gambling measures for each group of participants. Scores for the GFA-R positive reinforcement subscale were calculated excluding item 1 (i.e., across seven items).

	SOGS = 3-4 (*n* = 46)			
	Mean	(SD)	Median	Range
GFA-R Positive	22.57	9.15	24.00	0-37
GFA-R Escape	7.33	7.06	5.00	0-26
SOGS	3.41	0.50	3.00	3-4
PGSI	3.30	4.11	2.00	0-18
	SOGS $\geq$ 5 (*n* = 59)			
	Mean	(SD)	Median	Range
GFA-R Positive	24.46	8.87	25.00	7-42
GFA-R Escape	16.56	10.96	16.00	0-48
SOGS	8.53	3.45	8.00	5-18
PGSI	10.66	7.16	10.00	0-36

modeling software (Muthen & Muthen, 2010). This analysis used MLMV estimation because the response distributions for several of the GFA-R items were skewed. MLMV estimations use "maximum likelihood parameter estimates with standard errors and a mean- and variance-adjusted chi-square statistic that are robust to non-normality" (Muthen & Muthen, 2010, p. 533).

Fit of the model was assessed using multiple indices. They were: a chi-square test of model fit (recommended $\chi^2 \leq 0.01$: Hu & Bentler, 1999; Yu, 2002), the root mean square error of approximation (RSMEA; recommended RSMEA $\leq$ 0.05; Hu & Bentler, 1999; Rigdon, 1996; Yu, 2002), the Comparative Fit Index (CFI; recommended CFI $\geq$ 0.95 for good fit and CFI $\geq$ 0.90 for adequate fit; Hu & Bentler, 1999; Rigdon, 1996; Yu, 2002), and the standardized root mean square residual (SRMR; recommended SRMR $\leq$ .07; Hu & Bentler, 1999).

For models based on samples between 75-200 cases, chi-square provides a reasonable measure of model fit. The null hypothesis when using chi-square as a measure of model fit is that the model provides an adequate fit. Therefore, a failure to reject the null suggests an adequate fit. Because the present analysis was based on a sample of 105 participants, chi-square was expected to be a reasonable indicator of model fit. RMSEA is an absolute fit measure. Absolute fit measures presume that the best fitting model has a fit of zero, so such measures of fit indicate how far the model is from perfect fit. Thus, larger values indicate worse model fit. CFI, on the other hand, is an incremental fit index where a value of zero indicates the worst possible model and a value of one indicates the best possible model. SRMR is a measure of the discrepancy between the sample and model covariance matrices, which can vary from zero to one.

The positive reinforcement items of the GFA-R (items 1, 4, 6, 7, 8, 13, 14, & 16) were specified to load on Factor 1, while Factor 2 was composed of the escape items (items 2, 3, 5, 9, 10, 11, 12, & 15). Modification indices that yielded a chi-square change equal to or greater than four were requested. Based on the modification indices, as well as the interpretability of the suggested modifications, some pairs of residuals were allowed to correlate.[5] The modification indices also suggested

[5] The correlations among residuals were as follows: items 8 and 16 = .30; items 7 and 8 = .47; items 6 and 14 = .30; items 7 and 14 = - .52.

Table 2. Unstandardized loadings (standard errors) and standardized loadings for the two-factor confirmatory model.

	Unstandardized (S.E.)		Standardized	
Item	Factor 1	Factor 2	Factor 1	Factor 2
4	1.00 (---)		.75 (.05)	
6	0.75 (0.12)		.61 (.07)	
7	0.79 (0.10)		.70 (.06)	
8	0.36 (0.14)		.30 (.11)	
13	1.19 (0.11)		.83 (.03)	
14	1.14 (0.13)		.82 (.05)	
16	0.59 (0.15)		.44 (.10)	
2		1.00 (---)		.92 (.02)
3		1.00 (0.06)		.88 (.03)
5		0.94 (0.14)		.78 (.07)
9		0.89 (0.07)		.69 (.05)
10		1.18 (0.07)		.92 (.02)
11		0.99 (0.08)		.76 (.05)
12		0.93 (0.08)		.72 (.05)
15		0.96 (0.07)		.83 (.04)

Note: Dashes (---) indicate that the standard error was not estimated.

that better model fit could be obtained if Item 1 ("After I gamble, I like to go out and celebrate my winnings with others") was allowed to cross-load on both factors.

Given our preference for a factor solution that captured positive reinforcement and escape as distinct constructs, we opted to omit Item 1 entirely. The factor loadings for this model (7 positive reinforcement items and 8 escape items) are presented in Table 2. The items in the final model all loaded significantly onto their respective factors ($p < .01$) and the two factors were moderately correlated, $r = .30$ ($SE = .09$), $p < .01$. An examination of the fit indices indicated adequate model fit: χ^2 (85) = 111.40, $p = .03$; CFI = 0.95; RMSEA = .05; and SRMR = .08. The chi-square was significant and the SRMR was slightly higher than optimal, suggesting a less-than-good model fit. The CFI and RMSEA measures, on the other hand, suggest a good model fit. The model is illustrated in Figure 1.

Internal Consistency

The internal consistency of the GFA-R subscales was examined separately for the participants who scored 3-4 or 5 or more on the SOGS. For 46 participants who scored 3-4 on the SOGS, Cronbach's alpha for the 15-items of the GFA-R identified by the confirmatory factor analysis was $\alpha = 0.87$. The internal consistency for the seven items on the positive reinforcement subscale was $\alpha = 0.83$ and for the escape subscale it was $\alpha = 0.90$.

For 59 participants who scored 5 or more on the SOGS, Cronbach's alpha for the 15-items of the GFA-R identified by the confirmatory factor analysis was $\alpha = 0.89$. The internal consistency for the seven items on the positive reinforcement subscale was $\alpha = 0.84$ and for the escape subscale it was $\alpha = 0.93$. Thus, the internal consistency of the GFA-R ranged from good to excellent, with the internal consistency being higher for the probable disordered gamblers than for the probable problem gamblers.

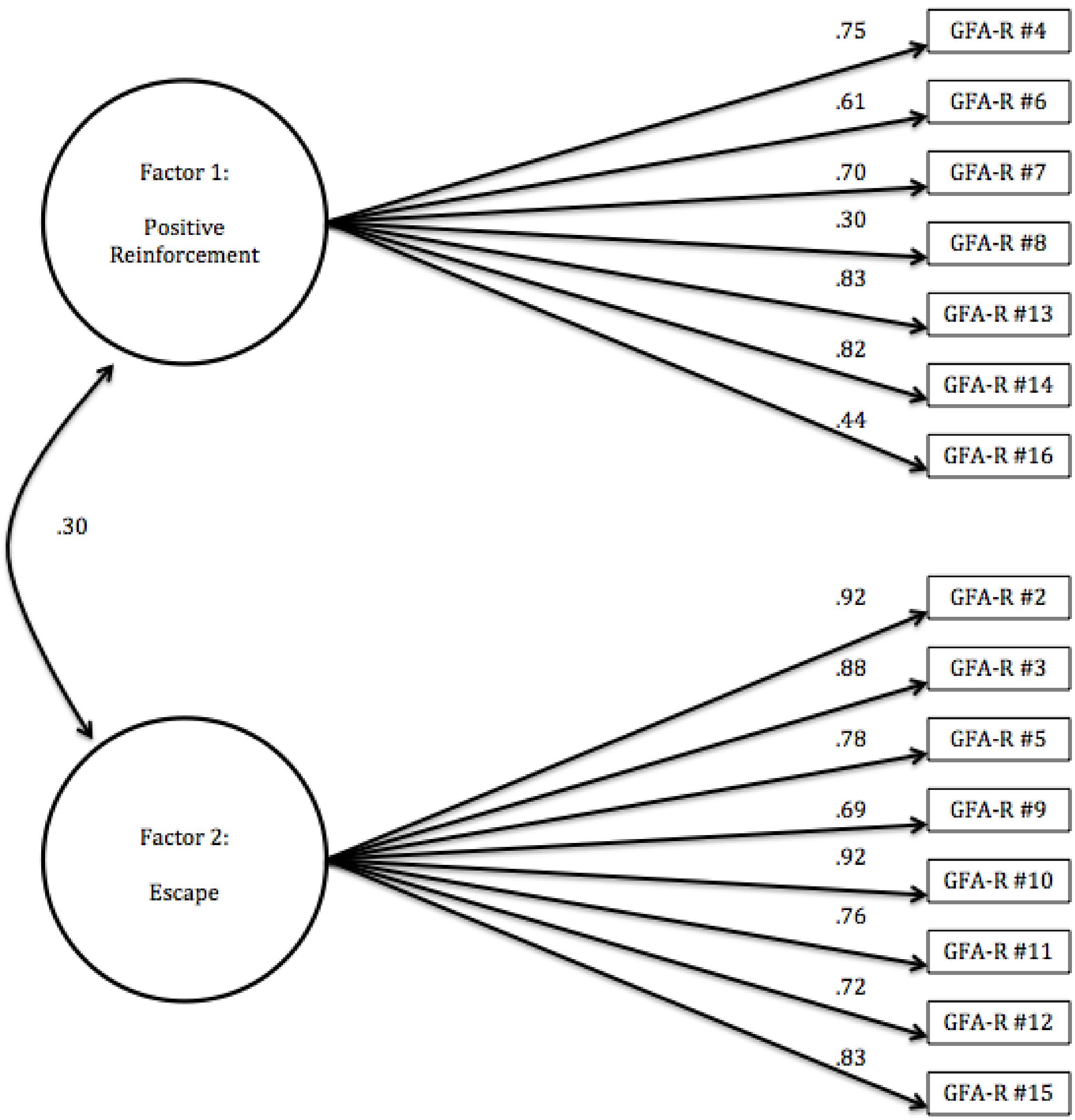

Figure 1. Standardized factor loadings for each GFA-R subscale with each item and the inter-correlation between factors.

Comparing the GFA-R Subscales

Prior to conducting statistical tests on whether scores differed between the GFA-R subscales (or between groups), analyses were completed to determine if scores from either of the GFA-R subscales were skewed. These analyses indicated that the escape subscale scores, but not the positive reinforcement subscale scores, were positively skewed. Thus, nonparametric statistics were employed.

Again, scores for the GFA-R positive reinforcement subscale were calculated and tested using only the seven items identified by the confirmatory factor analysis (i.e., excluding Item 1).

For each group, overall scores from the two GFA-R subscales were compared using a related-samples Wilcoxon Signed Rank test. For participants who scored between 3-4 on the SOGS, scores on the GFA-R positive reinforcement subscale were significantly higher than scores on the escape subscale ($p < .001$). Likewise, for participants who scored 5 or more on the SOGS, scores on the GFA-R positive reinforcement subscale were significantly higher than scores on the escape subscale ($p < .001$). Thus, regardless of whether participants were probable problem or disordered gamblers, their positive reinforcement subscale score was higher than their escape subscale score.

Comparisons between the two groups were made by conducting independent-samples Mann-Whitney U tests. These analyses indicated that participants scoring 5 or more on the SOGS did not have significantly different GFA-R positive reinforcement subscale scores than participants scoring 3-4 on the SOGS ($p = .442$). However, participants scoring 5 or more on the SOGS had significantly higher GFA-R escape subscale scores than participants scoring 3-4 on the SOGS ($p < .001$). Thus, as severity of potential gambling problems increased, so too did endorsing gambling as an escape. However, a concomitant change was not observed for endorsing gambling for positive reinforcement.

Predicting PGSI Scores

Before conducting linear regressions to determine if either of the GFA-R subscale scores were significant predictors of PGSI scores, a test was conducted to determine whether PGSI scores were skewed. Results indicated that they were positively skewed. Thus, PGSI scores were recoded to approximate linearity (i.e., to allow for a linear regression to be conducted). The raw data were recoded according to the categories suggested by Ferris and Wynne (2001), with scores of 0 remaining 0, scores of 1-2 being recoded as 1, scores of 3-7 being recoded as 2, and scores of 8 or more being recoded as 3.

Because previous tests of skewness had determined that GFA-R escape subscale scores were also positively skewed, the raw data for this subscale were also recoded to approximate linearity. GFA-R escape scores of 0 remained 0, scores between 1-5 were recoded as 1, and scores of 6 or more were recoded as 2. These categories were used based on previous research (Miller, Dixon, Parker, Kulland, & Weatherly, 2010; Weatherly, 2013a; Weatherly & Miller, 2013). GFA-R positive reinforcement subscale scores were not skewed and were therefore not transformed.

Next, the correlations between all of the predictor variables were examined to detect any potential problems with collinearity. Knight (1984) suggested that predictor variables that correlate at 0.8 or more should not be used in the same regression analysis because the regression coefficients could become inaccurate. None of the predictor variables correlated at 0.8 or higher, so all were retained.

The regression analysis was a simultaneous multiple linear regression. The transformed PGSI scores served as the dependent measure. GFA-R positive reinforcement (7 items) and transformed escape subscale scores served as predictor variables. Whether or not the participant was a probable problem or disordered gambler (determined by SOGS scores) was also entered into the model, with probable problem gamblers coded as 0 and probable disordered gamblers coded as 1. These SOGS categories were entered as a predictor variable because the goal was to determine how much of the participants' PGSI scores could be predicted by their GFA-R subscale scores independent of whether the participants were probable problem or disordered gamblers.

The resulting regression model was statistically significant, $F(3, 101) = 19.19$, $p < .001$, $R^2 = .363$. GFA-R positive reinforcement subscale scores were not a significant predictor of PGSI scores, β = .006, $p = .941$. However, GFA-R escape subscale scores, β = .329, $p < .001$, and SOGS category, β = .410, $p < .001$, were both significant predictors of PGSI scores. Thus, whether or not one was a probable problem versus disordered gambler was the strongest predictor of PGSI scores. However, endorsing gambling as an escape was also significant predictor of PGSI scores independent of one's gambling status. The extent to which participants endorsed gambling for positive reinforcement did not predict whether or not they had experienced negative experiences due to their gambling, as measured by the PGSI.

DISCUSSION

The first hypothesis was that the same factor structure of the GFA-R identified by Weatherly et al. (2011) would describe the data from a sample of probable problem or disordered gamblers. That hypothesis was partially supported. When all 16 items from the GFA-R were included in the confirmatory factor analysis, the model proposed by Weatherly et al. (2011) did not provide a very good fit to the data. However, with the minor alteration of excluding one item from the positive reinforcement subscale, an adequate model fit was obtained. The second hypothesis was that the internal consistency of the GFA-R would be good or better. That hypothesis was supported. The third hypothesis was that participants would endorse gambling for positive reinforcement to a significantly greater extent than they would endorse gambling as an escape. That hypothesis was supported. The fourth hypothesis was that participants who qualified as probable disordered gamblers would display significantly higher GFA-R escape scores than would participants who qualified as probable problem gamblers. That hypothesis was also supported. The final hypothesis was that GFA-R escape scores, but not their positive reinforcement scores, would be significant predictors of how participants scored on the PGSI. That hypothesis was also supported.

Unlike previous studies that have examined the factor structure of the GFA-R, the present study employed only participants who scored 3 or more on the SOGS (i.e., probable problem or disordered gamblers)[6]. Finding that the original factor structure did not provide a strong fit to the present data is informative in that researchers and practitioners working with this particular population should likely not use the GFA-R as it was originally designed. Rather, as the present confirmatory factor analysis indicated, the first item of the GFA-R should be omitted from the calculations of subscale scores. This change leaves seven items in the positive reinforcement subscale and the original eight items in the escape subscale.

This change does not imply that the first item of the GFA-R should be eliminated altogether. Previous research with samples consisting of mostly non-problem gamblers have found that this item loads onto the construct labeled as positive reinforcement (Weatherly et al., 2011; Weatherly 2013a, b). Thus, this item may be informative for that particular population. Likewise, attempts to replicate the present study may find that this item does load as originally intended. It is also common to find instruments that include items that are not ultimately used in the final calculation of the respondent's score. The SOGS and PGSI are both examples. The present results suggest that the GFA-R scores should be calculated using 15 of the 16 items, at least when

[6] The SOGS may not be a perfect measure of whether the respondent is a problem or disordered gambler, however, so one should not mistake the present sample for a clinical sample.

one is working with probable problem or disordered gamblers.

It is also worth noting that Item 1 on the GFA-R ("After I gamble, I like to go out and celebrate my winnings with others.") is the only one of the 16 items that refers to something that occurs after one gambles. The other 15 items either refer to antecedent conditions or to things that occur while gambling. Item 1 may load onto the positive reinforcement construct for non-problem gamblers but not for probable problem/disordered gamblers because the latter group is more focused on the actual gambling situation, or what leads to it, than is the former group. Testing this possibility would seem to be an interesting topic for future research.

As with previous research, the internal consistency of the GFA-R and its subscales was good or better. What is interesting was that the internal consistency measures were higher among the probable disordered gamblers than they were among the probable problem gamblers. This outcome may be linked to this particular data set. Alternatively, it may suggest that reinforcement contingencies exert increasing control over a gambler's behavior as the individual goes from being a problem to a disordered gambler. Future research that attempts to replicate the present findings will be needed to address which of these possibilities, if either, is correct. In any event, existing research suggests that the GFA-R's internal consistency is good or better regardless of what population is tested.

The present findings would seem to suggest that the gambling behavior of probable problem or disordered gamblers is maintained to a greater extent by things the gambler potentially gains by gambling than by things that the gambler is trying to escape. This conclusion is made even stronger when it is considered that the GFA-R positive reinforcement subscale scores were significantly higher than escape subscale scores even when one of the positive reinforcement subscale items was excluded. The existing research would suggest that the vast majority of individuals gamble more for positive reinforcement than as an escape. Likewise, the vast majority of individuals who gamble do not develop into problem or disordered gamblers (e.g., see Petry, 2005). With that said, one could argue that the positive reinforcement and escape subscales of the GFA-R vary in the scale that they measure their respective latent variable (i.e., reinforcement contingencies), which may at least partially account for the observed difference in subscale scores.

Although the vast majority of people who gamble do not develop gambling problems, a certain proportion of the population does develop into problem or disordered gamblers. The present results indicate that endorsing gambling as an escape is associated with those categories. The results actually suggest that, as the disorder develops from potentially subclinical to potentially clinical, there is a significant increase in gambling as an escape. Practitioners who are working with individuals who qualify as problem, but not disordered, gamblers might be well served to address escape-maintained behaviors in therapy. Doing so may prevent that individual from becoming a disordered gambler.

The link between endorsing gambling as an escape and gambling problems is further strengthened by the present finding that scores on the PGSI were significantly predicted by GFA-R escape, but not positive reinforcement, subscale scores. Perhaps just as interesting is the finding that the predictive value of GFA-R escape scores was significant above and beyond whether the individuals qualified as probable problem or disordered gamblers. Phrased differently, finding that people experience more negative consequences due to their gambling as their gambling problems increase in severity is not a surprising finding. If anything, it is intuitive. However, finding that endorsing gambling as an escape is related to experiencing negative consequences from one's gambling independent of one's level of gambling problem is a novel finding. Future research should focus on determining the direction of this relationship. Does gambling as an escape lead to experiencing negative consequences, do negative consequence lead to turning to gambling as an escape, or both? The answer to these questions would have both theoretical and therapeutic implications.

One aspect of the present data that is worth noting is that the 105 participants came from an original sample of 554 adults. This number suggests that nearly 19% of the original sample were probable problem or disordered gamblers; a higher percentage than one would expect to see in the population (see Petry, 2005). There are several potential reasons for this high percentage. First, one criticism of the SOGS is that it tends to overestimate the presence of gambling problems (e.g., see Gambino, 1997). It is possible that not all of the 105 individuals identified as probable problem or disordered gamblers were actually such. Second, the title of the study, on both MTurk and the SONA Systems websites, informed potential participants that the study related to gambling. This fact may have attracted people who gamble to participate and/or dissuaded those who do not gamble from participating. Neither of these possibilities can be ruled out. However, the fact that A) scores on the GFA-R escape subscale differed significantly as a function of participants' SOGS scores and B) SOGS scores were significant predictors of PGSI scores would seem to both favor the latter possibility.

There are a number of aspects of the current study that should promote caution when generalizing its results. For one, all of the measures used in the study were self-report in nature. One cannot assume that participants' responses perfectly match their actual behavior or experiences. Secondly, despite the fact that the present sample included both university students and adults from across the United States, the sample was racially homogenous. Given that race is a risk factor for disordered gambling (see Petry, 2005), one cannot assume that the same results would have been observed had the sample been more racially diverse. Finally, the sample of probable problem and disordered gamblers was identified using SOGS scores. This sample does not qualify as a clinical sample and the conclusions drawn from the present study cannot be directly applied to the treatment-seeking population of disordered gamblers. Future research on the GFA-R should include testing it using treatment-seeking gamblers.

In summary, the present results indicate that a 15-item GFA-R has a sound factor structure and solid psychometric properties. The results also suggest that probable problem and disordered gamblers likely gamble more for positive reinforcement than as an escape. However, probable disordered gamblers are more likely than probable problem gamblers to endorse gambling as an escape. Endorsing gambling as an escape, but not for positive reinforcement, is also a significant predictor of whether one has had negative experiences from gambling, independent of whether or not the person is a probable problem or pathological gambler. Thus, the GFA-R would appear to be a valid and potentially informative measure for researchers and practitioners interested in knowing the contingencies maintaining the respondent's gambling behavior. And despite gambling as an escape no longer being explicitly listed as a symptom of disordered gambling (APA, 2013), the present results highlight that understanding gambling as escape will be a key component to understanding the disorder itself.

REFERENCES

American Psychiatric Association. (2003). *Diagnostic and Statistical Manual of Mental Disorders* (4th ed., Text Revision). American Psychiatric Association: Washington, D. C. http://dsm.psychiatryonline.org//book.aspx?bookid=22

American Psychiatric Association (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th Ed). American Psychiatric Association: Arlington, VA. http://dsm.psychiatryonline.org/book.aspx?bookid=556

Blaszczynski, A., & Nower, L. (2002). A pathways model of problem and pathological gambling. *Addiction, 97*, 487-499. doi: 10.1046/j.1360-0443.2002.00015.x

Dixon, M.R., & Johnson, T.E. (2007). The gambling functional assessment (GFA): An assessment device for identification of the maintaining variables of pathological gambling. *Analysis of Gambling Behavior, 1*, 44-49.

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

Gambino, B. (1997). The correction for bias in prevalence estimation with screening tests. *Journal of Gambling Studies, 13*, 343-351. doi: 10.1023/A:1024971521887

Gillespie, M.M., Derevensky, J., & Gupta, R. (2007). I. Adolescent problem gambling: Developing a gambling expectancy instrument. *Journal of Gambling Issues*, *19*, 51-68. doi:10.4309/jgi.2007.19.3

Holtgraves, T. (2009). Evaluating the Problem Gambling Severity Index. *Journal of Gambling Studies, 25*, 105-120. doi: 10.1007/s10899-008-9107-7

Hu, L., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6,* 1-55. doi: 10.1080/10705519909540118

Kido, M., & Shimazaki, T. (2007). Reliability and validity of the modified Japanese version of the South Oaks Gambling Screen (SOGS). *Japanese Journal of Psychology, 77*, 547-552. doi: 10.4992/jjpsy.77.547

Knight, G.P. (1984). A survey of some important techniques and issues in multiple regression. In D.E. Kieras & M.A. Just (Eds.), *New Methods in Reading Comprehension Research* (pp. 183-219). Hillsdale, N.J.: Lawrence Erlbaum Associates.

Lesieur, H.R., & Blume, S.B. (1987). The South Oaks Gambling Screen (SOGS): a new instrument for the identification of pathological gamblers. *American Journal of Psychiatry, 144*, 1184-1188.

McMillen, J., & Wenzel, M. (2006). Measuring problem gambling: Assessment of three prevalence screens. *International Gambling Studies, 6*, 147-174. doi: 10.1080/14459790600927845

Miller, J.C., Dixon, M.R., Parker, A., Kulland, A.M., & Weatherly, J.N. (2010). Concurrent validity of the gambling function assessment (GFA): Correlations with the South Oaks Screen (SOGS) and indicators of diagnostic efficiency. *Analysis of Gambling Behavior, 4*, 61-75.

Miller, J.C., Meier, E., Muehlenkamp, J., & Weatherly, J.N. (2009a). Testing the validity of Dixon & Johnson's (2007) gambling functional assessment. *Behavior Modification, 33*, 156-174. doi: 10.1177/0145445508320927

Miller, J.C., Meier, E., & Weatherly, J.N. (2009b). Assessing the reliability of the Gambling Functional Assessment. *Journal of Gambling Studies, 25*, 121-129. doi: 10.1007/s10899-008-9109-5

Muthén, L.K., & Muthén, B.O. (1998-2007). *MPlus User's Guide*. Fifth Edition. Los Angeles, CA: Muthén & Muthén.

Petry, N.M. (2005). *Pathological gambling: Etiology, comorbidity, and treatment.* Washington, D.C.: American Psychological Association. doi: 10.1037/10894-000

Rigdon, E.E. (1996). CFI versus RMSEA: A comparison of two fit indexes for structural equation modeling. *Structural Equation Modeling, 6,* 369-379.

Rockloff, M.J., Greer, N., Fay, C., & Evans, L.G. (2011). Gambling on electronic gaming machines is an escape from negative self reflection. *Journal of Gambling Studies, 27*, 63-72. doi: 10.1007/s10899-010-9176-2

Stinchfield, R. (2002). Reliability, validity, and classification accuracy of the South Oaks Gambling Screen (SOGS). *Addictive Behaviors, 27*, 1-19. doi: 10.1016/S0306-4603(00)00158-1

Stinchfield, R. (2003). Reliability, validity, and classification accuracy of a measure of DSM-IV diagnostic criteria for pathological gambling. *American Journal of Psychiatry, 160*, 180-182. doi: 10.1176/appi.ajp.160.1.180

Weatherly, J.N. (2013a). The relationship between endorsing gambling as an escape and the display of gambling problems. *Journal of Addiction, 2013*, 7 pages. doi: 10.1155/2013/156365

Weatherly, J.N. (2013b). The relationship of the GFA-R subscales to negative consequences of gambling in a sample of potential problem and pathological gamblers. *Analysis of Gambling Behavior, 7*, 25-30.

Weatherly, J.N., Aoyama, K., Terrell, H.K., & Berry, J.C. (in press a). Comparing the Japanese version of the Gambling Functional Assessment – Revised to an American sample. *Journal of Gambling Issues*.

Weatherly, J.N., & Derenne, A. (2012). Investigating the relationship between the contingencies that maintain gambling and probability discounting of gains and losses. *European Journal of Behavior Analysis, 13*, 39-46.

Weatherly, J.N., Dymond, S., Samuels, L., Austin, J.L., & Terrell, H.K. (in press b). Validating the Gambling Functional Assessment – Revised in a United Kingdom sample. *Journal of Gambling Studies*. doi: 10.1007/s10899-012-9354-5

Weatherly, J.N., Miller, J.C., Montes, K.S., & Rost, C. (2012). Assessing the reliability of the Gambling Functional Assessment – Revised. *Journal of Gambling Studies, 28*, 217-223. doi: 10.1007/s10899-011-9275-8

Weatherly, J.N., Miller, J.C., & Terrell, H.K. (2011). Testing the construct validity of the Gambling Functional Assessment – Revised. *Behavior Modification, 35*, 553-569. doi: 10.1177/0145445511416635

Weatherly, J.N., & Miller, K.B. (2013). Exploring the factors related to endorsing gambling as an escape. *International Gambling Studies, 12,* 52-64. doi: 10.1080/14459795.2012.703214

Weiss, S.M., & Loubier, S.L. (2010). Gambling habits of athletes and nonathletes classified as disordered gamblers. *The Journal of Psychology, 144*, 507-521. doi: 10.1080/00223980.2010.503248

Wood, R.T.A., & Griffiths, M.D. (2007). A qualitative investigation of problem gambling as an escape-based coping strategy. *Psychology and Psychotherapy: Theory, Research and Practice, 80*, 107-125. doi: 10.1348/147608306X107881

Yu, C.Y. (2002). Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes. Dissertation for the degree Doctor of Philosophy in Education. University of California, Los Angeles.

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