Psychiatry Research 237 (2016) 90–96

Contents lists available at ScienceDirect

Psychiatry Research

journal homepage: www.elsevier.com/locate/psychres

Exploring the measurement structure of the Gambling Related Cognitions Scale (GRCS) in treatment-seekers: A Bayesian structural equation modelling approach

David Smith [a,*], Richard Woodman [b], Aaron Drummond [a], Malcolm Battersby [a]

[a] Department of Psychiatry, Flinders University, Adelaide, South Australia, Australia
[b] Centre for Epidemiology and Biostatistics, Flinders University, Adelaide, South Australia, Australia

ARTICLE INFO

Article history:
Received 24 July 2015
Received in revised form
31 January 2016
Accepted 3 February 2016
Available online 11 February 2016

Keywords:
Gambling disorder
Gambling related cognitions
Confirmatory factor analysis
Bayesian statistics

ABSTRACT

Knowledge of a problem gambler's underlying gambling related cognitions plays an important role in treatment planning. The Gambling Related Cognitions Scale (GRCS) is therefore frequently used in clinical settings for screening and evaluation of treatment outcomes. However, GRCS validation studies have generated conflicting results regarding its latent structure using traditional confirmatory factor analyses (CFA). This may partly be due to the rigid constraints imposed on cross-factor loadings with traditional CFA. The aim of this investigation was to determine whether a Bayesian structural equation modelling (BSEM) approach to examination of the GRCS factor structure would better replicate substantive theory and also inform model re-specifications. Participants were 454 treatment-seekers at first presentation to a gambling treatment centre between January 2012 and December 2014. Model fit indices were well below acceptable standards for CFA. In contrast, the BSEM model which included small informative priors for the residual covariance matrix in addition to cross-loadings produced excellent model fit for the original hypothesised factor structure. The results also informed re-specification of the CFA model which provided more reasonable model fit. These conclusions have implications that should be useful to both clinicians and researchers evaluating measurement models relating to gambling related cognitions in treatment-seekers.

1. Introduction

The cognitive approach to explaining gambling disorder is based on the principle that problem gamblers hold erroneous perceptions of randomness (e.g., the gambler's fallacy), erroneous beliefs (e.g. 'luck helps me win') and inaccurate perceptions (e.g. 'gambling makes things better for me') which are rewarded, learned, and become habitual (Ladouceur et al., 2001; Raylu and Oei, 2004). Evidence for this approach has come predominantly from 'think aloud' techniques where gamblers have verbalised their perceptions and beliefs during gambling activities (Gadboury and Ladouceur, 1989). Accordingly, cognitive restructuring plays an important role in gambling-specific therapy juxtaposed with behavioural approaches such as distraction, avoidance or exposure tasks (Gooding and Tarrier, 2009).

The emergent understanding and treatment of gambling related cognitions led to the development of the Gambling Related Cognitions Scale (GRCS) as a screening tool (Raylu and Oei, 2004). The scale is comprised of 5 factors that reflect the multidimensionality of gambling cognitions: interpretative control/bias, illusion of control, predictive control, gambling-related expectancies and a perceived inability to stop gambling (Raylu and Oei, 2004). Cognitive restructuring techniques have been shown to be effective in reducing a range of GRCS related symptoms such as the correction of misconceptions of the basic concept of randomness and increasing self-efficacy in high-risk gambling situations (Ladouceur et al., 2003, 2001; Smith et al., 2015). The instrument has been used in a range of gambling help settings for both treatment screening and outcome assessment, for example, (Michalczuk et al., 2011; Oei and Gordon, 2008; Oei and Raylu, 2015; Smith et al., 2010; Smith et al., 2015).

Past studies of GRCS psychometric properties have mostly (if not all) been conducted in community-based samples at an international level (Arcan and Karanci, 2015; Donati et al., 2015; Grall-Bronnec et al., 2012; Iliceto et al., 2015; Kale and Dubelaar, 2013; Oei et al., 2007; Taylor et al., 2014; Yang et al., 2014; Yokomitsu et al., 2015). The latent structure of the GRCS has generated varying findings including a 5-factor lower order model and a higher order single-factor model. The role of a higher order factor has mostly been to reduce collinearity of first-order latent

* Corresponding author.
E-mail address: david.smith@flinders.edu.au (D. Smith).

http://dx.doi.org/10.1016/j.psychres.2016.02.002

variables but is in the absence of any hypothesised relationships (Chen et al., 2006). This ex post facto approach is perhaps inimical to theory development. Furthermore, most GRCS- confirmatory factor analysis (CFA) models have produced less than optimal goodness-of-fit statistics, including significant discrepancies between observed and model-implied covariances in small to moderate sample sizes within a structural equation modelling (SEM) framework (Kline, 2011). This might be important from a substantive viewpoint as it suggests that the observed survey responses do not fit the hypothesised gambling-cognition frameworks. Nevertheless, the findings in relation to model fit are also not unforeseen as"*…many psychological instruments routinely used in applied research do not even meet the minimum criteria of acceptable fit, based on current ICM* (basic independent clusters model) *-CFA standards*" (Marsh et al., 2014) (p87).

Confirmatory factor analysis for continuous scale measurements commonly uses maximum-likelihood (ML) estimation to obtain model parameters (Kline, 2011). Although ML algorithms have numerous strengths they do apply "*…unnecessarily strict models to represent hypotheses derived from substantive theory*" (Muthén and Asparouhov, 2012) (p313). For instance, the fixing of cross-loadings to exact zero in GRCS-CFA may well not be a realistic characterisation of subjective reports of gambling related cognitions. This is because GRCS items potentially reflect multiple brain mechanisms coming together (Bechara, 2005; Clark, 2010). For example, Item 20 "Remembering how much money I won last time makes me continue gambling" is typically hypothesised to be an indicator of interpretive bias. It taps into the "availability heuristic" (Clark, 2010; Wagenaar, 1988) where sensory stimulation (e.g. cascading sounds of coins dropping into a slot machine tray) may elicit gambling related arousal involving brain structures such as the ventromedial prefrontal cortex (vmPFC) (Potenza et al., 2003). The vmPFC has also shown to be associated with tracking the subjective value of rewarding stimuli and has effects in depression and anxiety disorders, both highly prevalent co-morbid conditions in gambling disorder (Lorains et al., 2011; Myers-Schulz and Koenigs, 2012; Winecoff et al., 2013). This has potential implications for the role of GRCS factor 'gambling expectancies' (e.g. gambling to demonstrate one's worth or to relieve stress and tension) as an additional determinant of Item 20 (Raylu and Oei, 2004). Thus, if the underpinning neural substrates of gambling cognitions are linked to varying degrees, allowing cross-loadings in the GRCS factor structure may lead to more adequate model fit.

Similarities in the wording and context of GRCS questions may also lead to small residual covariances between items (Marsh et al., 2014; Muthén and Asparouhov, 2012). By forcing residual covariances to zero, which essentially equates to ignoring the possibility of parallel wording and similar contexts of various items in the GRCS, inflated correlations between factors may be induced, which in turn tempers discriminant validity and ultimately leads to incorrect model rejection (Marsh et al., 2014). Additionally, the fixing of residual covariances to zero may result in error propagation to other parts of a CFA model due to the presence of minor factors. For instance, Raylu and Oei (2004) theorised that there may be subtypes of gambling cognitions – such as gamblers who hold erroneous self-beliefs across multiple domains. These subtypes may result in patterns of responding on the GRCS (e.g., endorsement of self-related items) that reflects true non-zero residual covariances in the GRCS. However, if residual correlations and cross-loadings are instead set free rather than being constrained to zero in the CFA model then this may result in a non-identified model (Kline, 2011). In other words, the effective number of observations is reduced below the value of the number of estimated model parameters. Although guidance to the inclusion of specific non-zero loading paths (rather than all paths) using modification indexes will also improve model fit, this approach often yields changes that are non-additive, deficient of a theoretical basis and capitalize on chance (Kline, 2011; Marsh et al., 2014; Muthén and Asparouhov, 2012).

A complementary approach to CFA is Bayesian structural equation modelling (BSEM). In a single step analysis it enables the specification of the prior hypothesised major factor patterns as well as informative (close to zero but not exactly zero) small-variance priors for cross-loadings and residual correlations (Muthén and Asparouhov, 2012). These attributes support both developmental theory and at the same time provide a more realistic approximation of psychological measurement in everyday practice. Since the proposal of BSEM as a new approach to factor analysis (Muthén and Asparouhov, 2012) it has been applied to the widely used Hospital Anxiety and Depression Scale (HADS) (Fong and Ho, 2013), Wechsler Intelligence Scale for Children (WISC- IV) (Golay et al., 2013) and Utrecht Work Engagement Scale (UWES − 9) (Fong and Ho, 2015). Such studies have facilitated a better understanding of measurement structures relative to previous CFA findings. This is because CFA approaches have not always realistically reflected psychological theories whereas BSEM has offered a more flexible approach to balancing theoretical plausibility and empirical findings. In this current study we aimed to advance insights on the original GRCS 5- factor structure by firstly applying a standard ML based CFA approach to data collected from treatment-seeking problem gamblers. Subsequently, a Bayesian-subjective approach was used to explore any differences between a hypothesised GRCS-CFA model and the data. It was anticipated that BSEM would produce a better match between observed and model-implied covariances based on a more pragmatic take on the measurement of gambling-specific cognitions.

2. Methods

2.1. Study design

Data for the assessment of construct validity (subtypes convergent and discriminant validity) of the self-report measure GRCS was collected at each participant's first presentation to an outpatient gambling treatment centre between January 2012 and December 2014. Convergent validity was shown if correlations between observed items and factors were at least moderate. Discriminant validity was indicated if factor intercorrelations were not too high (Kline, 2011). The study was approved by the Southern Adelaide Health Service/Flinders University Human Research Ethics Committee and written consent was obtained from all participants.

2.2. Service and participants

The Statewide Gambling Therapy Service (SGTS) offers free cognitive–behavioural therapy (CBT) for help-seeking problem gamblers in South Australia. The service is staffed by a psychiatrist and therapists with professional registration in psychology, nursing or social work. All therapists have Masters level qualifications in CBT (Battersby et al., 2008). On first presentation to SGTS, patients are individually screened using an interview to assess their suitably for admission into the treatment programme. This is comprised of a gambling focused cognitive behavioural assessment including criteria for identifying problem gambling. Patients are also assessed for any co-morbid mental health problems such as alcohol dependence, anxiety and depression.

The dataset consisted of records for 454 adult treatment-seeking problem gamblers. Mean age of participants was 41.7 years (SD = 13.2 years). Gender was distributed as 280 (61.7%) males and 174 (38.3%) females. Based on the validated self-report questionnaire Problem Gambling Severity Index (PGSI), 432 (95.2%) of participants were classified as problem gamblers and met criteria for DSM − 5 Gambling Disorder (American Psychiatric Association, 2013; Ferris and Wynne, 2001).

2.3. GRCS

The GRCS is a self-report questionnaire that records common thoughts associated with problem gambling (Raylu and Oei, 2004). The 23 items of the GRCS contribute to five subscales reflective of the broader categories of gambling related cognitions that have been described in the literature: interpretative bias (GRCS-IB)