Problem Gambling Severity Index Final Report

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Ipsos UK

Contents

1 Introduction to PGSI

1.1 Background

The Problem Gambling Severity Index (PGSI) is a validated screening tool, widely used to estimate gambling harm, including Health Survey for England, Scottish Health Survey and Welsh Problem Gambling Survey. It is also used by GambleAware to help inform the development of prevention campaigns and the evaluation of treatment and support services.

However, PGSI has not been developed as a clinical tool and there is some debate surrounding how best to use the instrument as a tool for identifying and measuring risk and gambling harms.

One of the key features of PGSI is that it applies classical test score theory, which treats all items with equal weight of severity when summing the item scores together to create an overall PGSI summary score. Other features include the relatively limited domains of harm covered within the Treatment and Support Survey (TSS) against which to compare the PGSI, i.e., psychological distress, problem alcohol use; also available are deprivation, experience of disability and presence of mental health conditions. PGSI further only captures the harm of individual gamblers (not affected others).

Additional research and analysis are therefore beneficial to explore the description and inference of gambling harms from the PGSI scale and any external validation variables assessing harm indicators, such as health and wellbeing.

1.2 The Problem Gambling Severity Index (PGSI)

The problem gambling severity index (PGSI) is a nine-question instrument to measure gambling behaviour and consequences. Each answer is scored on a four-point scale:

- Never = 0
- Sometimes = 1
- Most of the time = 2
- Almost always = 3

Summing the items scores across the nine items gives a total PGSI score ranging between 0 to 27. Depending on the score, respondents can be classified as[1]:

- 'Non-problem gamblers' (PGSI = 0),
- 'Low risk' (PGSI = 1-2) experiencing a low level of gambling problems with few or no negative consequences identified),

[1] Gambling Commission, September 2021. *Statistics and research release. Problem gambling screens*. www.gamblingcommission.gov.uk/statistics-and-research/publication/problem-gambling-screens

- ‘Moderate risk’ (PGSI = 3-7) experiencing a moderate level of gambling problems leading to some negative consequences) and
- ‘Problem gamblers’ (PGSI = 8+) gambling with negative consequences and a possible lack of control.

The nine PGSI question items cover three domains, relating to behaviour, personal consequences and social consequences (Table 1.1). We have used the labels for each dimension applied by Samuelson et al. (2018)[2] as a shorthand to refer to each item in this report.

Table 1.1: PGSI items

Item	Dimension	Label
Have you bet more than you could really afford to lose?	Behaviour	Control
Have you needed to gamble with larger amounts of money to get the same excitement?	Behaviour	Tolerance
When you gambled, did you go back another day to try and win back the money you lost?	Behaviour	Chasing
Have you borrowed money or sold anything to get money to gamble?	Behaviour	Borrowing
Have you felt that you might have a problem with gambling?	Personal Consequence	Felt problem
Has gambling caused you any mental health problems, including stress or anxiety?	Personal Consequence	Negative health
Have people criticised your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?	Personal Consequence	Criticism
Has your gambling caused any financial problems for you or your household?	Social Consequence	Financial problems
Have you felt guilty about the way you gamble or what happens when you gamble?	Personal Consequence	Guilt feelings

Note: adapted from Samuelsson et al., 2018

Despite this mix of three domains of questions, previous results have generally shown support for the assumption of a single underlying dimension (e.g., Miller et al.,2013; their study and the references cited) of gambling disorder as measured by the nine items. We corroborate this finding, below.

Classical test-score theory assumes that each PGSI item measures the severity of gambling harm to the same extent as all other items. Consequently, as an example, scores of ‘Sometimes’ = 1 and ‘Most of the time’ = 2, summing to three on Items 1 & 2 (zero elsewhere) indicate the same level of severity as a score of three on any one item (with zero across the other eight items). In other words, what is important

[2] https://www.researchgate.net/publication/332300897_Gamblers%27_mis-interpretations_of_Problem_Gambling_Severity_Index_items_Ambiguities_in_qualitative_accounts_from_the_Swedish_Longitudinal_Gambling_Study

in measuring severity is not the pattern of responses across the different items, simply the overall score summed across the nine items.

The PGSI mini-screen scale was designed as a short form of the PGSI scale[3] and includes three of the usual nine PGSI questions:

1. Control: Have you bet more than you could really afford to lose?
2. Criticism: Have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?
3. Guilt feelings: Have you felt guilty about the way you gamble or what happens when you gamble?

Each question is scored between zero and three and summed to obtain a short-form PGSI score. The score is recoded as follows:

0. Non-problem gambler (PGSI short form score = 0)
1. Low risk gambler (PGSI short form score = 1)
2. Moderate risk (PGSI short form score = 2, 3)
3. Problem Gambler (PGSI short form score 4+)

1.3 Use of PGSI

The PGSI was developed in Canada in 1999 and revised in 2003. It was developed for use in general population surveys. It was recognised that screening tools that had been developed for use in clinical settings for a treatment population and had limitations when applied to the general population of people who gamble[4].

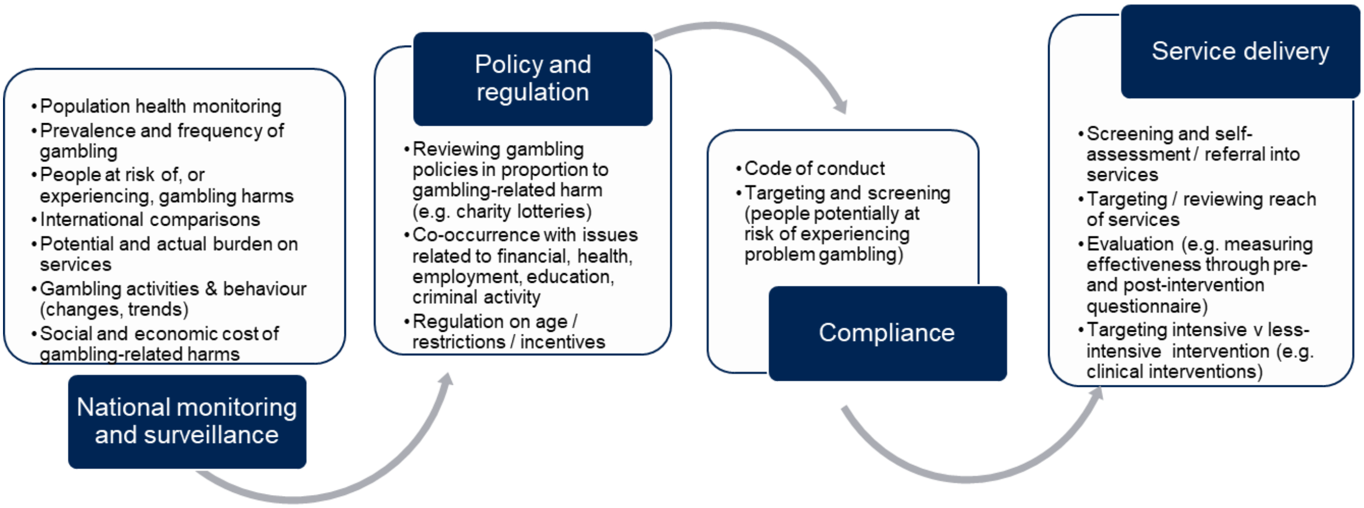
Today, the way in which the PGSI is used could be grouped into the following four themes:

- National monitoring and surveillance
- Policy and regulation
- Compliance
- Service delivery

These themes and how they inter-relate are illustrated below.

[3] https://www.gamblingcommission.gov.uk/statistics-and-research/publication/problem-gambling-screens

[4] Other tools for measuring the extent of problem gambling include: South Oaks Gambling Screen SOGS – designed for use in clinical context. DSM-IV - designed for diagnosis by clinicians of pathological gambling. An adapted version was developed for the British Gambling Prevalence Survey (BGPS). It is a ten-question tool with a four-point scale. A total score between 0 to 10. Each item is dichotomised to show whether a person meets the criteria or not; meeting at least three of the DSM-IV criteria is used to define problem gambling. It does not have thresholds for level of risk but clinicians currently use a threshold of 5 to represent pathological gambling. International Classification of Diseases (ICD) Gambling Assessment Module (GAM-IV-S)



PGSI is used both **retrospectively** (to consider the impact of policies) and **proactively** (to inform guidelines, service policies and targeting interventions). It is used **alongside** other data and measures to understand:

- Behaviours by different demographics
- Outcome of interventions
- Co-occurring mental health, substance use, social behaviours, crime
- Harms of different types of gambling activity

The PGSI is used to inform strategies designed to reduce the risk of gambling related harm, for example to inform:

- codes of conduct for gambling providers (for example 'responsible gambling strategies' to identify and provide the right support to customers exhibiting higher-risk behaviours[5] and advertising best practice[6]);
- marketing and advertising strategies to reduce saturation to vulnerable groups based on PGSI score 1+; demographics and previous gambling behaviours) and target prevention and support to those at risk of harm;[7]
- to inform policy messages relating to sector regulation. For example, a Lotteries Council-funded report to support their policy position on a proportionate sector levy, based on likely harm of different types of gambling.[8]

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[5] Flutter. March 2022. A deep dive into Flutter's UK&I Safer Gambling Strategy – 'Discover'. www.flutter.com/news-and-insights/insights/a-deep-dive-into-flutter-s-uk-i-safer-gambling-strategy-discover/ [accessed 12/1/23]
[6] Advertising Standards Authority (ASA) CAP and BCAP Gambling Review https://www.asa.org.uk/static/uploaded/fe806aae-4a9c-4408-a012a29d1b418ba7.pdf [accessed 31/03/23]
[7] GambleAware. November 2022. Background to World Cup prevention campaign. www.begambleaware.org/sites/default/files/2022-11/Background%20to%20World%20Cup%20prevention%20campaign.pdf
[8] Saxton J. April 2021. Responsible Play - Charity Lotteries and gambling-related harms: a call for proportionate regulation. NFP Synergy. https://nfpsynergy.net/free-report/responsible-play-charity-lotteries-and-gambling-related-harms-call-proportionate

The PGSI is used by gambling harm support services:

- For targeting interventions to understand and better reach populations most at risk of harm or those who do not access support services for various reasons, such as women, those with lower incomes and people with a lower risk of 'problem gambling' (PGSI less than 8).[9] [10]
- Within self-assessment tools for people to self-refer, and in measuring outcomes of gambling support services.[11] For example, annual statistics for 2020-21 from the National Gambling Treatment and Support Service (NGTS) show that 94% of referrals received a PGSI score of 8+ at the start of treatment, and that 81% of those accessing treatment had improved their PGSI score as captured at the start and end of treatment (27% of individuals experienced a reduction of 20-27 points).[12]

The PGSI is used by researchers (commissioned by policy-makers, regulators and campaign groups):

- To inform national policy development to explore the prevalence and impact of gambling in the population, including the economic impact, impact on various dimensions of health and relationships;[13]
- To consider the different behaviours and trends, such as a connection between youth gambling behaviours and experience of gambling harms as an adult.[14] [15] [16]
- To explore the impact on policies and regulations on harmful gambling, such as the impact on gambling behaviours from the closure venues and cancellation of live sporting events during the COVID-19 pandemic[17] [18]; and
- To explore the prevalence, impact and trajectory of harmful gambling alongside other health and social issues such as socio-economic deprivation and long-term health conditions[19].[20]

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[9] YouGov. July 2020. Treatment and support needs among women. GambleAware. www.begambleaware.org/sites/default/files/2020-12/gambleaware_treatment-and-support__women_debrief_webinar_final.pdf

[10] Horch, J. and Hodgins, D. 2015. Self-stigma coping and treatment-seeking in problem gambling. International Gambling Studies, [Online] 15(3), pp.470-488. Available at: https://www.tandfonline.com/doi/abs/10.1080/14459795.2015.1 078392.

[11] Hickman B , Chakraborty B. Analysis of NGTS Treatment Impact (Tier 3 and 4 service users , 2018-2021). July 2022. GambleAware

[12] GambleAware. 2021. Annual Statistics from the National Gambling Treatment Service www.begambleaware.org/sites/default/files/2021-11/FINAL_GA_Annual%20stats_report_2020-21_English.pdf

[13] OHID. January 2023. The economic and social cost of harms associated with gambling in England. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1128002/The-economic-cost-of-gambling-related-harm-in-England_evidence-update-2023.pdf

[14] Forrest, D., & McHale, I.G. 2020. Transmission of problem gambling between adjacent generations. Journal of Gambling Studies. doi: https://doi.org/10.1007/s10899-020-09977-8

[15] Newall PWS, Russell AMT, Sharman S, Walasek L. Associations between recalled use of legal UK youth gambling products and adult disordered gambling. J Behav Addict. 2020 Aug 20;9(3):863-868. doi: 10.1556/2006.2020.00048. PMID: 32817588; PMCID: PMC8943655.

[16] Vadlin, S., Åslund, C., & Nilsson, K. W. 2017. Stability of problematic gaming and associations with problematic gambling: A three-year follow-up study of adolescents in the SALVe-cohort. European Psychiatry, 41, S882. https://doi.org/10.1016/j.eurpsy.2017.01.1782

[17] PHE. 2021. The impact of COVID19 on gambling behaviour and associated harms. A rapid review. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1020748/Gambling_review_COVID_report.pdf

[18] Gabriel A. Brooks, Luke Clark, Associations between loot box use, problematic gaming and gambling, and gambling-related cognitions, Addictive Behaviors, Volume 96, 2019, Pages 26-34 https://doi.org/10.1016/j.addbeh.2019.04.009.

[19] Kruse, K., White, J., Walton, D. K., & Tu, D. 2016. Changes in risky gambling prevalence among a New Zealand population cohort. International Gambling Studies, 0(0), 1–19. http://doi.org/10.1080/14459795.2016.1183033

[20] OHID. January 2023. Gambling-related harms evidence review: summary https://www.gov.uk/government/publications/gambling-related-harms-evidence-review/gambling-related-harms-evidence-review-summary--2

- It is also used for international comparisons, with limitations as, although the PGSI is common, not all national health surveys use a standard measure[21].

1.4 Interpretation

Despite its wide use, there is some concern about the validity and application of PGSI in different settings. Key criticisms include:[22]

- **Thresholds**: the 'problem gambler' threshold at PGSI 8+ is considered high: 'at risk' could include people who are showing signs of problematic behaviour and experience gambling harm but remain below the 8+ threshold[23]. However, moving the 'problem gambler' threshold below PGSI 8+ would suggest a higher prevalence of gambling harms among people currently being reported as being in the 'low' and 'moderate risk' groups[24].

- **Conflation of probability vs impact**: being 'at-risk' can suggest that people will progress up the scale to become a 'problem gambler' (PGSI 8+). Studies suggest this isn't always the case[25]. Furthermore, it does not quantify the degree of harm providing more nuanced understanding of health impact[26].

- **Context of use**: how respondents' answers can be influenced by the context of the survey. For example, within different national surveys, how it is influenced by the questions that precede or follow it[27]. Within treatment support interventions, how it is influenced by familiarity and recall.

- **Mode effects**: differences in how it is administered (self-completion online or on paper, telephone, face-to-face) – issues of social desirability bias, confidentiality, anonymity[28].

- Use of **short-form** PGSI compared to longer-form version where the prevalence estimates are not directly comparable[29].

Given these challenges, there are notable differences in the estimates produced by different studies that use PGSI to estimate the risk of gambling harms in society. Table 1.2 below provides an overview of PGSI estimates considered by Sturgis (2020) in a recent study to examine mode effects. This compared

[21] Curran M. April 2022. Monitoring Gambling engagement and problem gambling prevalence within selected European jurisdictions. European Gaming and Betting Association. www.city.ac.uk/__data/assets/pdf_file/0007/667609/Monitoring-Gambling-Engagement-and-Problem-Gambling-within-selected-European-jurisdictions-April-2022.pdf

[22] Gambling Commission, September 2021. *Statistics and research release. Problem gambling screens*. www.gamblingcommission.gov.uk/statistics-and-research/publication/problem-gambling-screens

[23] O:\LON_Files_SRI_PublicAffairs\PSU\Data_Analytics\Projects\DfE_Multiply

[24] [24] Delfabbro, P., N. Georgiou, and D.L. King, 2020. Measuring Gambling Harm: The Influence of Response Scaling on Estimates and the Distribution of Harm Across PGSI Categories. Journal of Gambling Studies, 2020. 18: p. 18

[25] Kruse, K., White, J., Walton, D. K., & Tu, D. 2016. Changes in risky gambling prevalence among a New Zealand population cohort. International Gambling Studies, 0(0), 1–19. http://doi.org/10.1080/14459795.2016.1183033

[26] Browne, M., et al.. 2017 What is the harm? Applying a public health methodology to measure the impact of gambling problems and harm on quality of life. Journal of Gambling Issues, 2017. 36: p. 28-50.

[27] Sturgis, P., 2020. *An assessment of the accuracy of survey estimates of the prevalence of problem gambling in the United Kingdom.* Department of Methodology, London School of Economics, London.

[28] Sturgis, P., 2020. *An assessment of the accuracy of survey estimates of the prevalence of problem gambling in the United Kingdom.* Department of Methodology, London School of Economics, London.

[29] Sturgis, P., 2020. *An assessment of the accuracy of survey estimates of the prevalence of problem gambling in the United Kingdom.* Department of Methodology, London School of Economics, London.

telephone, online panel, online random probability, face to face and paper methodologies[30]. It concluded that the combined health surveys are likely to be an under-estimate because of under-coverage and non-response among groups with higher rates of people experiencing gambling harm and measurement error due to socially desirable responding and content of the questions preceding the PGSI. The online survey conducted by YouGov for GambleAware likely over-estimate prevalence due to sample composition [31]. Furthermore, a recent pilot commissioned by the Gambling Commission to test a new push to web methodology produced higher prevalence estimates - both for gambling activities in the previous 12 months and for low or moderate risk or problem gambling - in comparison with both HSE 2018 and the trend-adjusted HSE figures[32].

After analysis of the combined health surveys and a YouGov population study, Dinos et al (2020) also conclude that the true level of problem gambling lies somewhere in between the estimates reported by the two surveys[33]. The mode effects have a significant impact on estimating demand and planning help and support services. Based on varying estimates, the report calculates that demand for treatment and support ranges from between 385,112 to 1,210,351 adults across Great Britain (among those identified as PGSI 1+).

Table 1.2: Comparison of the prevalence of gambling between different surveys

Table 1 Prevalence estimates of problem gambling from different UK surveys 2010 to 2019

						PGSI Score			
Survey	Year	Mode	Sampling	sample size	response rate	Low-risk	Moderate-risk	Problem Gambler	Total
Gambling Commission	2018	phone/RDD	quota	4000	-	3.3%	1.5%	0.5%	5.3%
GambleAware/YouGov	2019	online	quota	16000	-	7.2%	3.3%	2.7%	13.2%
Combined health surveys	2016	f-t-f /paper	random	12161	55%	2.4%	1.1%	0.7%	4.2%
Combined health surveys*	2015	f-t-f /paper	random	8034	57%	2.8%	1.1%	0.6%	4.5%
Combined health surveys*	2012	f-t-f /paper	random	7676	56%	3.2%	1.0%	0.4%	4.6%
Gambling Prevalence Survey	2010	f-t-f /CASI	random	7748	47%	5.6%	1.8%	0.7%	8.1%
NI Gambling Prevalence Survey	2016	f-t-f /CASI	random	1003	53%	6.7%	4.9%	2.3%	13.9%
ALSPAC (aged 24)	*2017-18*	*online/paper*	*Non-random*	*1921*	*(<20%)*	*15.9%*	*4.4%*	*1.5%*	*21.8%*
Health Survey for England (20 to 29)	*2016*	*f f-t-f /paper*	*random*	*972*	*55%*	*6.5%*	*2.0%*	*1.0%*	*9.5%*
GambleAware/YouGov (18 to 34)	*2016*	online			-	*9.0%*	*4.0%*	*5.0%*	*18.0%*

*England and Scotland Only

Note: Taken from Sturgis (2020)

[30] Sturgis, P., 2020. An assessment of the accuracy of survey estimates of the prevalence of problem gambling in the United Kingdom. Department of Methodology, London School of Economics, London.

[31] This is due to under-coverage of the offline population, a group the study reports is less likely to experience gambling harms

[32] Gambling Commission. May 2022. Participation and Prevalence: Pilot methodology review report. Pilot methodology review report

[33] Dinos, S., and others. Treatment needs and gap analysis in Great Britain: Synthesis of findings from a programme of studies. 2020, NatCen Social Research: London

1.5 Completing PGSI

As part of the research for this project, the authors conducted a small sample of ten cognitive interviews with a range of people who gamble to better understand how respondents answer PGSI items. The findings suggest that although the index does provide a reasonable estimation of potential risk of harm, it is imperfect. Participants felt that the index had good coverage of key items, but that these did not have equal severity and may be open to underreporting.

- **Coverage –** participants were largely satisfied with the range of items included within PGSI. Most did not spontaneously suggest any other dimensions that would help assess potential risk of harm. However, some suggested that it would be important to add more direct reference to impact on relationships. Others acknowledged that there were other early signs of potential risk of harm, such as betting late at night, that are not covered.

- **Equivalence** – participants did not feel that PGSI items presented equivalent levels of severity. For example, participants commented that feeling 'guilty' was less severe than feeling that there was 'a problem'. Some participants placed greater importance on financial items which were seen as more likely to be accurate and a pre-curser to other outcomes; others placed greater emphasis on items that demonstrated a direct outcome (e.g., impact on mental health) over early signs of 'risky' gambling behaviour.

- **Honesty and prevalence –** a common concern among participants was whether respondents would answer honestly. This was particularly relevant to items which consider personal consequence, and whether an individual feels guilty or that they may have a 'problem'. Participants felt it was likely that someone who is experiencing significant impact from gambling may be inclined to answer 'sometimes' if they are unable or unwilling to acknowledge the significant impact on their lives or want to 'play down' the impact. It was further suggested that an individual may genuinely not feel guilty or perceive there to be a problem, even if they were experiencing harm. This would in turn underestimate the prevalence of those scoring 3-7 and 8+. Participants generally favoured statements that were seen as more factual (e.g. Borrowing money) which were seen as likely to be more accurate and less open to interpretation.

1.6 Research Objectives

Our focus was on exploring the internal consistency of the PGSI as it is currently defined and its relationship with wellbeing measures. The analytic approach distinguished three phases, which are detailed in Section 2.2. Potential issues around the comprehensiveness and coverage of the nine items in terms of potentially omitted other items are beyond the remit of this paper, though some insight into this is provided by the cognitive interview results. Similarly, we focus on risk and potential harms to gamblers themselves and not to affected others.

In Section 2, the analytic approaches are described with an overview of the methods used in each phase of the analysis. Section 3 describe the results and Section 4 provides a series of recommendations, supported through reference to the analytic results.

2 Methods

2.1 Data

Two years (2020 & 2021)[34] of the Treatment and Support Survey[35] (TSS) dataset were pooled together to provide a large sample size for analysis[36], which is especially relevant to analysis of the ‘problem gambler’ group and people with larger PGSI scores generally. Analysis was carried out either on the 21,172 who had responded to the PGSI (the population of people with gambling experience) or to the subset of 4,632 who had scored 1+ on the PGSI, as is described for each analytic approach. Additionally, the analysis showing the relationship between PGSI score and harm also included 15,745 people with no gambling experience. The TSS is carried out using an online panel of respondents and a survey weight is available to adjust the profile of respondents to be representative of the population of adults. The results in this study are generally reported on the weighted data[37], with the exception of the latent class analysis, the Rasch model (Section 3.2.1) and the network modelling (Section 3.2.3).

2.2 Design

To meet the project aims, we distinguished three broad phases of analysis. The first explored the intrinsic nature of the PGSI scale and its component items. The second explored prevalence, first through comparing the full PGSI with the short form, ‘mini’ screen responses, and second through splitting the 8+ group into two subgroups distinguishing between those whose PGSI score was 20+ and those whose PGSI score was between 8-19[38]. The third phase explored links between the overall scale and wellbeing to test ‘construct validity’, i.e., the extent to which the PGSI at risk scale (and individual items) is correlated with wellbeing measures. Statistical approaches are described in Section 2 of this document and the results in Section 3.

[34] The 2019 data were excluded because of questionnaire changes between the waves.

[35] https://www.begambleaware.org/annual-gb-treatment-support-survey

[36] The 2019 dataset was excluded due to questionnaire changes between waves.

[37] In many cases we also conducted analysis on the unweighted data and found the weights typically had little effect on the results.

[38] This grouping was taken from Hickman & Chakraborty (2022) who found that Tier 4 entrants for gambling treatment had a mean PGSI score of 19 (Table 21, page 40).

2.3 Item analysis

2.3.1 Factor Analysis and Reliability

The standard procedure of summing the PGSI items assumes that only a single underlying dimension exists ('at risk of problem gambling') and that each question item contributes equally to the summing procedure.

Factor analysis is a statistical technique that reveals underlying common dimensions (factors, or 'latent variables') which explain statistical relationships between multiple items. It can be used to reveal if there is a single common dimension which explains the relationship between responses to the nine PGSI question items or if there is more than one dimension. The existence of more than a single dimension would show that the nine items are measuring more than a single underlying factor and that simple summing of the nine items into a single summary score would not be appropriate. We used an exploratory factor analysis approach, with principal components extraction. The principal components approach extracts as many underlying factors[39] as there are variables. However, traditionally only components with a value greater than 'one' are accepted[40].

The factor analysis was used to provide corroborating evidence of a single underlying factor and we assessed the internal consistency (reliability) of responses using Cronbach's alpha (α). Cronbach's α is a measure of how closely related items are, in this case how related the PGSI items are. Scores range between 0 and 1, with 0 indicating the items are completely unrelated whilst 1 showing a perfect relationship.

	Analysis	Objective/value
1. Item Analysis	1.1 Identifying more and less PGSI severe items using Rasch Models	To identify the more severe markers of harm on the PGSI scale, and comparatively more minor markers of harm
	1.2 Network analysis to establish how PGSI items are correlated together	Visual display: analyses of the relationships and associations between different PGSI items.
	1.3 Probability Analysis	To identify which items are more commonly experienced at higher frequencies
	1.4 Latent Class analysis of PGSI items	Segmentation: analyses of the relationships and associations between different PGSI items.
2. Prevalence	2.1 Crosstabs and logistic regression	To identify if the mini-screen, compared to the full screen, differs when estimating prevalence
	2.2 Logistic regression	To identify the differences between who our campaigns target (PGSI 8+) compared to who presents at treatment (mean score of 20 among those presenting to NGTS for support)
3. Association with Harms	3.1 Regression and drivers analysis	To identify if some items are more closely tied to other health outcomes than others
	3.2 'Pinch-point' classification algorithms	To understand how severity of harm increases and whether there is a point in the scale where harms increase rapidly creating a 'pinch point'

[39] For simplicity, we treat components and factors as interchangeable terms in this paper. In practice, PCA utilises all variance in the correlation matrix of observed variables whereas factor analysis relies only on common variance.

[40] Under principal components analysis, each variable contributes an item variance of 'one' to the total variance of the correlation matrix of responses to the nine items. The sum of these standardised item variances is partitioned into the eigenvalues of the solution, with the first component explaining the greatest amount of the total variance. Consequently, a component with an eigenvalue less than one explains less than any one item in the model and is therefore considered redundant.

2.3.2 Rasch Model

The Rasch model is based on a mathematical model that assumes a single underlying dimension. It is often used in educational testing and distinguishes between an item's difficulty and a person's ability. In the current context, the focus is on the item difficulty, which translates in the current context to the 'inherent severity' of 'problem gambling'[41]. In other words, are some items more - or less - indicative of problem gambling? The aim of a Rasch model is to choose items from a larger pool which incrementally increase in 'difficulty' to create an interval scale. However, we do not aim to construct a Rash scale from the PGSI items. Our interest simply lies in using the model to explore evidence for differences in the inherent severity of items. For ease of interpretation, each item was recoded into a dichotomous variable such that never = 0 and sometimes, most of the time, or almost always = 'one'.

2.3.3 Network Mapping

The strength of the relationship between each of the nine PGSI items is known from the correlation between each item. However, the basic correlation coefficient includes both the relationships between two variables that is unique to those two variables and also the relationship which is also shared with one or more of the seven other variables. The unique association is useful to know because it allows us to focus more directly on the extent to which people respond to those two items irrespective of how often they respond also to other items giving a clearer view of the strength of relationship between each of the pairs of items. This unique association is stored in a partial correlation matrix. The partial correlations are reproduced as a network map, which identifies the strength of the relationship between each item using a thicker line to denote a stronger relationship and a thinner line a less strong relationship. Items with more connections to others are placed towards the centre of the graph[42].

2.3.4 Item Probabilities

The probability of selecting each of the nine items among people with gambling experience was calculated as the simple proportion of people who had selected the item. For each item, we then calculated the proportion of people who fell into the 1-2, 3-7 and 8+ groups to assess the extent to which some items were more - or less - strongly associated with a classification of 'problem gambler'.

2.3.5 Latent Class Analysis

Latent class analysis (LCA) is a technique which groups each person into a class with other people who have similar patterns of responses across the nine PGSI items (using their original coding of 0= 'Never' to 3 = 'Almost always'). The aim of the LCA was to attempt to reproduce the PGSI classification, excluding people in the PGSI zero class. Thus, three classes were chosen and people in each of these classes were compared to the standard classification of 1-2, 3-7 and 8+.

We used discriminant function analysis (DFA) to predict membership of both the three LCA produced classes and the standard three PGSI groups (1-2, 3-7 and 8+) using the nine PGSI items as predictors of the classes to assess the extent of the accuracy of the prediction of the classes using the two different classification procedures (LCA and standard PGSI).

[41] The person ability would translate into a person's predisposition towards problem gambling. However, that is not the focus of our interest in this analysis.

[42] In this analysis, correlations between all variables were positive, but it is worth noting that more generally, negative correlations are also possible.

2.4 Prevalence of PGSI

2.4.1 Short Form Classification

People with gambling experience were classified into their at-risk groups using the short form classification procedure (Section 1.2). People's classification on the short form was then compared to their corresponding at-risk classification group using the full 9-item scale. Standard statistical classification measures (sensitivity and precision) were used to assess the extent to which the prevalence of each risk group was accurately predicted from the short form through assessing false positive and false negative predictions alongside true positive and negative prediction rates, where the standard 9-item scale classification was taken as the 'true' measure.

2.4.2 Distinguishing the 8+ Group

We also used the 9-item summary score to explore the extremes of 'problem gamblers'. Those with a PGSI score between 8 and 19 were distinguished from those with a score between 20-27. As described above, Hickman & Chakraborty (2022) found that the average PGSI score of people presenting for NGTS treatment was 19. We used a score of 20 to distinguish between those more and less likely to be presenting for treatment in the 8+ group. With only 84 (weighted) cases in the 'treatment-more-likely' group, there is limited scope to distinguish between many sociodemographic characteristics distinguishing between those more and less likely to present for treatment. Chi-square auto interaction detector (CHAID) was used to identify the characteristics most strongly discriminating between the more and less likely treatment groups. CHAID first identifies the characteristic with the most discriminant capability and then the second most etc.

2.5 Association with Harms

2.5.1 Pinch-point Analysis

A 'pinch-point' analysis seeks to identify any sharp changes in a wellbeing outcome associated with an increase in the PGSI score. Any such change suggests that wellbeing worsens more substantially around that increase from one PGSI score to the next. Any such pinch-point changes may represent appropriate cut-off thresholds for PGSI scores for corresponding classes of wellbeing. The pinch-point analysis was undertaken visually using a scatterplot of the average wellbeing score on the wellbeing outcome plotted against each PGSI score.

Two outcomes were chosen for the pinch-point analysis: K-10 (psychological distress) and Audit-C (alcohol harm assessment tool). The key aim was to identify any thresholds where the outcome score changed substantially as the PGSI score scale increases. Each of the 28 PGSI scores (0-27) was treated as a separate group and, within each of these groups, the weighted average of the outcome score was calculated. Ideally, the average outcome would deteriorate as the PGSI group score increases in severity and one (or more) sudden changes in the outcome scores would be observed.

3 Results

3.1 Internal Scale Consistency of PGSI

3.1.1 Factor Analysis and Reliability

Overall, there was strong evidence that the nine items measure a single underlying dimension with each item working to improve the overall internal consistency of the scale. This confirms previous findings cited in Miller et al. (2013) who used confirmatory factor analysis in their study and who also cited other corroborative findings supporting the one-dimensionality of the scale.

The factor analysis was conducted on all people with experience of gambling who had provided a response to the PGSI (0 thru 27). In support of the standard procedure of summing all items on a single 'at-risk' scale, the factor analysis extracted a single factor, which explained 67% of the variation between the nine items (Table 3.1). All items showed a moderately high loading on the factor, indicating a strong association between each item and the factor. That there was little variation between the size of the factor loadings of the items onto the factor supports the standard procedure of summing them into their PGSI total score without first making any item more - or less – important in contributing to the summary score.

Additionally, as shown by the moderately high communality and squared multiple correlation (SMC) figures, there was a strong association between each item and all of the other items (Table 3.1). A high communality, e.g., Problem = 0.738, indicates a strong association between the item and other items making up the scale, under the factor analysis model. Conversely, a smaller communality, e.g., Chasing = 0.597, is indicates that other PGSI items are less strongly associated with the item. The SMC provides the same information for the reliability analysis as the communality does for the factor analysis[43]. In both cases, items with low communality or SMC suggest they may not belong in the scale because they are not strongly associated with other scale variables. The results below (Table 3.1) reveal no such concerns.

The nine items showed a great deal of consistency in the way people respond to them with an alpha coefficient, which at 0.94 is very high (with a maximum attainable value of 'one'). This provides strong support for treating the items as measuring the same underlying 'at risk' dimension. Further, none of the items appear to be redundant to the scale, in that removal of any of the items does not improve the alpha statistic (Table 3.1). Moreover, all item-total correlations show a strong association with the overall scale score.

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[43] The communality measures in the factor analysis differ from the squared multiple correlation in the reliability analysis because the factor analysis uses the loadings from the factor model to account for the explained variance in an outcome whereas the reliability analysis treats the item weights as unity.

Table 3.1: Factor scores and reliability results for the nine items

Item	Factor analysis		Reliability		
	Load-ing	Commun-ality	Corrected Item-Total Corre-lation	Squared Multiple Correl-ation	Cronbach's Alpha if Item Deleted
Control: Have you bet more than you could really afford to lose?	0.835	0.697	0.784	0.620	0.926
Tolerance: Have you needed to gamble with larger amounts of money to get the same excitement?	0.816	0.665	0.759	0.589	0.928
Chasing: When you gambled, did you go back another day to try and win back the money you lost?	0.772	0.597	0.715	0.518	0.932
Borrow: Have you borrowed money or sold anything to get money to gamble?	0.828	0.685	0.770	0.628	0.928
Felt Problem: Have you felt that you might have a problem with gambling?	0.859	0.738	0.814	0.668	0.925
Negative Health: Has gambling caused you any mental health problems, including stress or anxiety?	0.843	0.711	0.794	0.638	0.926
Criticism: Have people criticised your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?	0.784	0.615	0.723	0.531	0.930
Financial Problems: Has your gambling caused any financial problems for you or your household?	0.849	0.721	0.797	0.664	0.926
Guilt Feelings: Have you felt guilty about the way you gamble or what happens when you gamble?	0.779	0.607	0.723	0.543	0.931

Cronbach's alpha = 0.936 and 67% of variance was explained by the first factor.

3.1.2 Latent Class Model

Latent class analysis (LCA) is a data driven technique which uses the associations between the items to assign them to higher-order categories. These higher-order classes may represent different patterns of co-occurrence between the variables. LCA permits an investigation into the appropriate number of classes, i.e., what number of statistical classes provide the best fit? It also permits an understanding of the meaning of each class through understanding which items have higher and lower probabilities of association with each class. However, the purpose of the LCA in this study was to assess how a data driven three-class solution compares to the three traditional groups created from the PGSI summary score. Consequently, exploring the best fitting latent class model was outside the current remit of the studyt[44]. Additionally, no exploration was made of the pattern of item loadings for each item on the three classes.

The development of a statistical model on a single sample opens the potential risk of 'overfitting', i.e., the model fits the sample data well but does not work well with data from a new sample. Therefore, the model was developed on a random 'training' subsample of 66% of the total sample with 34% reserved for testing the model (validation sample).

Using only people who had responded with a score of 1+ to the PGSI scale, we estimated a three-class solution to correspond to the three PGSI risk groups (low, moderate and high). We then explored the degree of correspondence between the classes and the grouped PGSI score classification 1-2, 3-7 and 8+. The original 0-3 coding was used for each of the nine items to produce the model. In the following, we label the LCA classes as Class 1, Class 2 and Class 3. We assign 'meaning' to these classes through identifying the relationship between the nine PGSI items and each latent class. Given that our interest lies in the PGSI summary score, we show how each class relates to the average summary score (Table 3.2) and Class 1 indicates a higher level of at risk, Class 2 a low level of at risk and Class 3 a moderate level of at risk. These findings are equivalent across the training, validation and overall sample solutions. Additionally, the validation sample reproduces the percentages of people in each latent class, within a tolerance of one percentage point.

Table 3.2: Average PGSI score by latent class

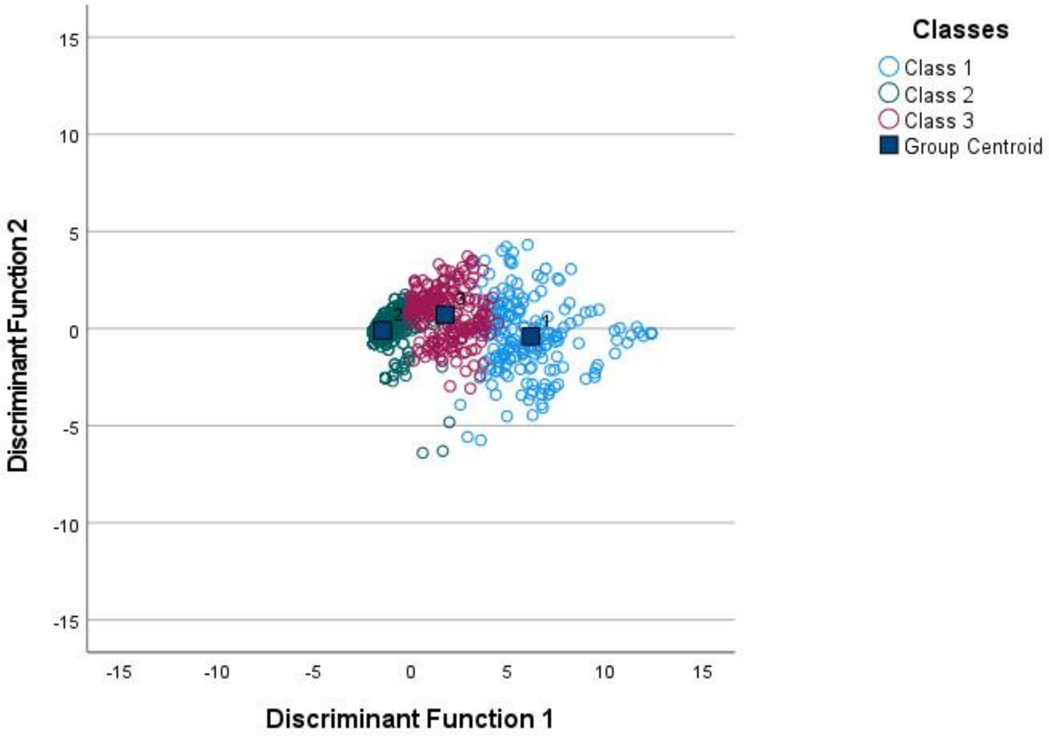
	Training sample			Validation sample			Total sample		
	Mean	n (%)	SD	Mean	n (%)	SD	Mean	n (%)	SD
Class 1	15.3	13%	4.0	15.5	12%	3.8	15.3	13%	4.0
Class 2	1.9	71%	1.2	1.9	72%	1.2	1.9	71%	1.2
Class 3	7.7	16%	1.9	8.0	17%	2.1	7.6	16%	1.9
Total	4.5	2,929	5.0	4.5	1,595	5.0	4.5	4,524	5.0

Note: weighted data

We initially assessed the quality of the model through a discriminant function analysis (DFA) using the nine PGSI items to predict membership of the latent classes on the validation subsample. DFA is a technique used to predict membership of the classes using the scores on the nine PGSI items as predictors. As is shown in Figure 3.1, the separation between the classes is very good with only a moderate amount of overlap into other classes. Each of the three predicted classes is identified through its colour scheme and a smaller overlap of the colours in the figure indicates a better prediction. Conversely, if the colours largely randomly overlie each other then the PGSI items are not very predictive of class membership. Given the nine items were used in the development of the classes through the LCA we anticipate that they will differentiate well between membership of the classes. Consequently, the DFA has largely succeeded in predicting class membership from each person's combination of scores across the nine items.

[44] Models were run for a two-class, three-class and four-class model. The corresponding entropy scores were 0.96, 0.92 and 0.84, suggesting a two-class model marginally provides a better fit than the three class model and both are better than the four-class model.

Figure 3.1: Predicted class membership of the 3 classes from the model



DFA works by creating 'discriminant functions' from the combination of scores across the nine items. Consistent with the findings from the factor analysis, that the variables load onto a single factor, nearly all the predictive power arose from the first discriminant function (98% of the variance). A higher loading indicates that more influence is being given to an item in predicting membership of the class. The loadings of the variables onto the three classes showed that for Class 1 (higher PGSI), Borrow (Item 4), Tolerance (Item 2) and Financial Problems (Item 8) had the highest loadings, whereas Guilty (Item 9) had the lowest loading (Table 3.3). These findings suggest that the scores for Borrow and Financial Problems were more influential than average, whereas Guilty was less influential. Given that Class 1 corresponds to the higher PGSI score, these results accord with the findings reported below, suggesting these items were not having an equal impact on the measurement of 'at risk of problem gambling', and, perhaps were indicative of a more severe form of at risk. Nevertheless, as shown in Table 3.2, the model is compatible with the summed PGSI score. Consequently, whilst the LCA derived classes from the nine items which were not consistent with the PGSI groups of 1-2, 3-7 and 8+, the latent classes were defined by their PGSI summary scores.

Table 3.3: DFA Classification Coefficients

Classification Function Coefficients

	Validated3		
	1	2	3
Have you bet more than you could really afford to lose?	6.301	2.835	4.957
Have you needed to gamble with larger amounts of money to get the same excitemen	8.382	3.590	5.561
When you gambled, did you go back another day to try and win back the money you	6.708	3.653	5.080
Have you borrowed money or sold anything to get money to gamble?	12.155	4.231	5.786
Have you felt that you might have a problem with gambling?	6.885	2.631	4.906
Has gambling caused you any mental health problems, including stress or anxiety?	6.501	2.668	4.708
Have people criticised your betting or told you that you had a gambling problem,	5.615	2.733	3.801
Has your gambling caused any financial problems for you or your household?	7.962	3.046	5.091
Have you felt guilty about the way you gamble or what happens when you gamble?	5.215	3.093	4.418
(Constant)	-91.743	-17.528	-43.335

Fisher's linear discriminant functions

The latent class model has produced an alternative potential grouping of the PGSI summary score to the traditional 1-2, 3-7 and 8+ groups. However, the correspondence between the latent class model and the traditional grouping of the PGSI scores is not particularly high. We see from Table 3.4 that the ’problem gambling’ (8+) group comprises all but one of the Class 1 (high PGSI score) cases but also just under half of the Class 3 (moderate PGSI score) cases. The Class 2 cases are predominantly low risk, but a substantial minority are moderate risk.

Table 3.4: Correspondence between the latent classes and the grouped PGSI

		PGSI Group			
		1-2	3-7	8+	Total
LCA	1	0	1	200	201
	2	868	291	0	1159
	3	0	125	147	272
Total		868	417	347	1632

Validation subsample

To the best of our knowledge, the traditional PGSI grouping was not based on a statistical model but on more practical considerations. Consequently, whether the traditional or latent class grouping is more appropriate is a question for debate. Nevertheless, it is of interest to know how well the individual PGSI items predict the traditional PGSI groupings, i.e., 1-2, 3-7 and 8+. A DFA was used to predict the traditional grouping of the PGSI from the nine individual items. Whilst this was a good model in that it correctly predicted 87% of the classification scores, this prediction rate was lower than that achieved when predicting the latent classes (at 95%). In particular, 41% of the moderate risk group were predicted as low-risk by the model and 15% of the 'problem gambler' group were predicted as moderate-risk (Table 3.5).

Table 3.5: Prediction of Traditional PGSI Classes from DFA using the nine item scores

			Predicted Group Membership			
		Grouped PGSI	1-2	3-7	8+	Total
Original	Count	1-2	2461	0	0	2461
		3-7	454	659	0	1113
		8+	2	142	807	951
		Ungrouped cases	16753	0	0	16753
	%	1-2	100.0	.0	.0	100.0
		3-7	40.8	59.2	.0	100.0
		8+	.3	14.9	84.9	100.0
		Ungrouped cases	100.0	.0	.0	100.0

a. 86.8% of original grouped cases correctly classified.

3.1.3 Revised PGSI Grouped Score

Using the full dataset, the PGSI summary score was re-grouped to correspond more closely to the three-class model solution, as shown in Table 3.6. The revised grouping ran from 1-4, 5-10 and 11+. Class 1 is primarily made up of people scoring 11 or more on the PGSI (n=565), although 19 score between 5 and 10. Class 2 is predominated by people who scored 1-4 on the PGSI (n=3,137), although 88 scored between 5 and 10. Class 3 is comprised mainly of people who scored 5-10 (n=658), although 55 fell into the 11+ group and two into the 1-4 group.

Table 3.6: Correspondence between the latent classes and the revised PGSI classification

		PGSI Group			
		1-4	5-10	11+	Total
LCA	CLASS1	0	19	565	584
	CLASS2	3137	88	0	3225
	CLASS3	2	658	55	715
Total		3139	765	620	4524

A DFA was run to predict membership of the revised grouping of the PGSI score and showed a 95% overall accuracy, which is superior to the 88% found when predicting the traditional grouping. From Table 3.7, we see that the 1-4 group was predicted with 100% accuracy, the 11+ group with 89% accuracy and the 5-10 group with 82% accuracy.

Table 3.7: Prediction of Revised PGSI Classes from DFA using the nine item scores

		PGSI group	Predicted Group Membership			
			1-4	5-10	11+	Total
Original	Count	1-4	3139	0	0	3139
		5-10	136	623	5	765
		11+	0	65	555	620
		Ungrouped cases	16753	0	0	16753
	%	1-4	100.0	.0	.0	100.0
		5-10	17.8	81.5	.7	100.0
		11+	.0	10.6	89.4	100.0
		Ungrouped cases	100.0	.0	.0	100.0

a. 95.4% of original grouped cases correctly classified.

3.2 Item Severity

3.2.1 Rasch Model

The Rasch model addresses the question, are some items more - or less - indicative of 'problem gambling'? For ease of interpretation, a dichotomous (one/zero) coding of the nine items, was used for the Rasch model. The model is described in more detail in Section 2.3.2.

The focus of the analysis is on the 'inherent severity' of gambling risk, which is shown on the right-hand scale of risk of Figure 3.2, which is displayed as a logit estimate. A lower logit indicates the item has a weaker association with at-risk gambling and, conversely, a higher logit indicates the item has a stronger association with 'at risk' gambling. The results of the Rasch model showed, Figure 3.2, that the following three items were higher on the 'problem severity' scale (right hand axis):

- Borrow: Have you borrowed money or sold anything to get money to gamble? (logit = 5.3, SE = 0.03)
- Financial Problems: Has your gambling caused any financial problems for you or your household? (logit = 4.9, SE = 0.04)
- Tolerance: Have you needed to gamble with larger amounts of money to get the same excitement? (logit = 4.8, SE = 0.04)

These results are similar to those of Miller et al. (2013) who reported, from their Rasch model analysis, that Negative Health, Financial Problems and Borrowing Money were indicative of high levels of severity.

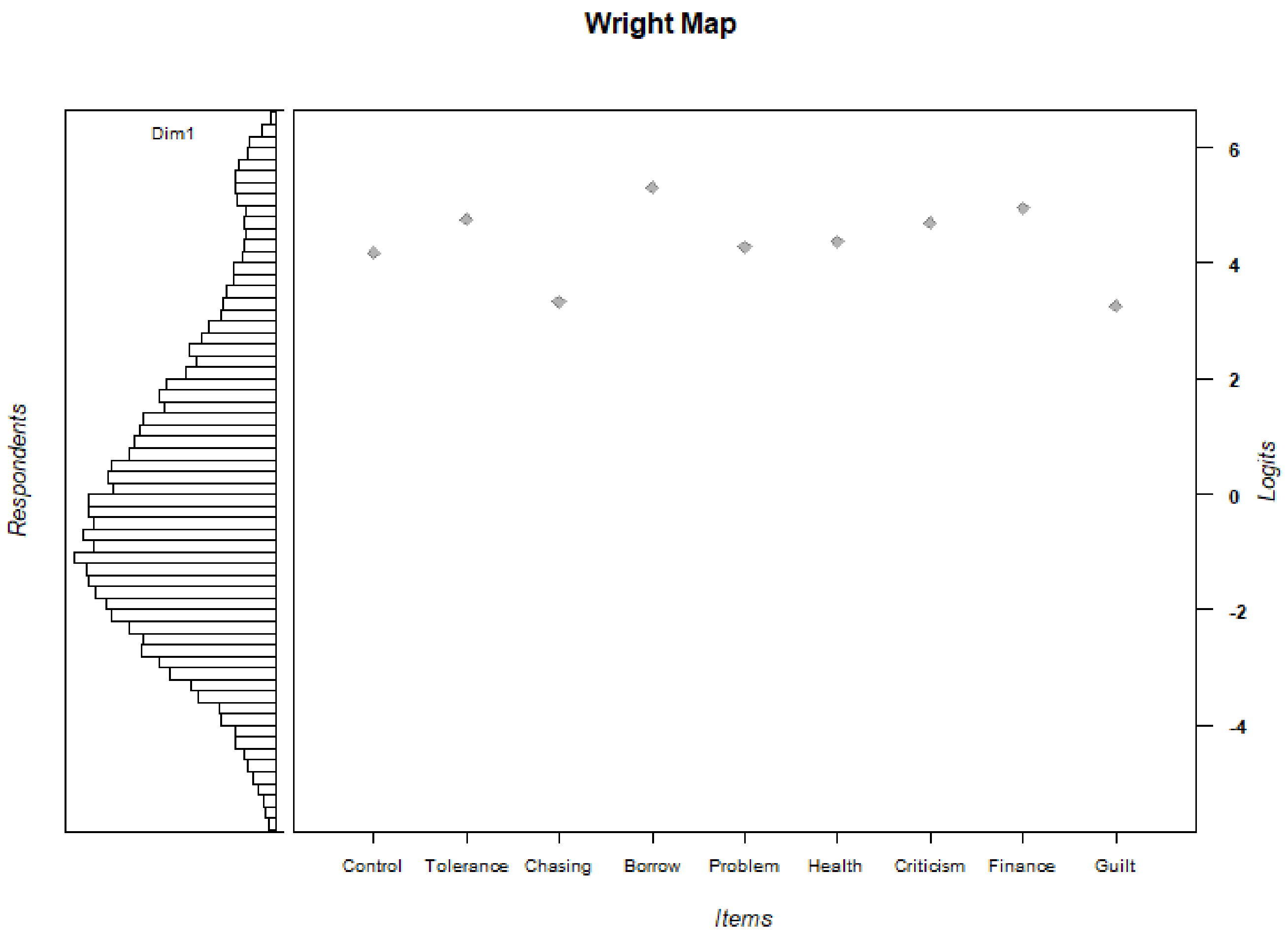
Conversely, Figure 3.2 showed that two items were indicative of lower inherent severity:

- Chasing Losses: When you gambled, did you go back another day to try and win back the money you lost? (logit = 3.3, SE = 0.03)

- Guilt feelings: Have you felt guilty about the way you gamble or what happens when you gamble? (logit = 3.3, SE = 0.03)

Again, this finding accords with Miller at al. (2013).

Figure 3.2: Item measures of inherent problem gambling severity



3.2.2 Item Probabilities

A more detailed breakdown of item associations using the probability of the occurrence of each item is given in Table 3.8, using the dichotomous coding described above. The column headed 'P' shows the frequency of occurrence of each item (coded as zero/one) among the gambling population. The least likely item to be selected by respondents was Borrowing Money (4%), followed by Financial Problem (5%), Tolerance (6%) and Criticism (6%). Conversely, Guilt (13%) and Chasing Losses (12%) were the most frequently endorsed items. Clearly, the items most likely to be endorsed were those which showed least severity and those that were least likely to be endorsed were of higher severity in the Rasch model, as shown above.

Moreover, people who responded positively to high severity items, e.g., Borrowing Money and Financial Problems, had a greater probability of a higher PGSI score than people who responded positively to other items. For example, whilst only four per cent reported Borrowing Money, of those who did, 83% were in the PGSI 8+ group. Similarly, only five per cent endorsed Financial Problem but of these, 73% scored eight or above on the PGSI summed scale. At the other extreme, Feeling Guilty was selected by 13% of people with gambling experience but just under one-third of these were in the low-risk group (a

PGSI score of 1-2) with just under a third in each of the 8+ and 3-7 groups. Similarly, 12% of people with gambling experience mentioned Chasing Losses, but of those who did, 38% were in the 1-2 group, 29% the 3-7 group and 34% in the 8+ group. In summary, selecting high severity items typically corresponded to being in the 8+ group, whereas selecting low severity items meant a higher likelihood of a low or moderate 'at risk' classification.

Table 3.8: Probability scores for the nine PGSI items

			Conditional Probability		
Label	**Item**	**P**	**1-2**	**3-7**	**8+**
Borrow	Have you borrowed money or sold anything to get money to gamble?	0.04	0.05	0.12	0.83
Financial Problem	Has your gambling caused any financial problems for you or your household?	0.05	0.06	0.21	0.73
Tolerance	Have you needed to gamble with larger amounts of money to get the same excitement?	0.06	0.11	0.26	0.63
Criticism	Have people criticised your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?	0.06	0.16	0.26	0.58
Negative health	Has gambling caused you any mental health problems, including stress or anxiety?	0.07	0.11	0.33	0.56
Felt problem	Have you felt that you might have a problem with gambling?	0.08	0.11	0.35	0.54
Control	Have you bet more than you could really afford to lose?	0.08	0.19	0.31	0.50
Chasing	When you gambled, did you go back another day to try and win back the money you lost?	0.12	0.38	0.29	0.34
Guilty	Have you felt guilty about the way you gamble or what happens when you gamble?	0.13	0.36	0.32	0.32

Note: results are based on weighted data. P refers to the proportion of gamblers and the three columns headed 'Conditional Probability' are based on those endorsing the corresponding P, giving the probability they fall into the low (1-2), moderate (3-7) and high (8+) risk PGSI grouped classification.

3.2.3 Network Mapping

Partial correlation shows the unique relationship directly between two variables excluding any indirect association they might have through being related indirectly to other variables in the network. Figure 3.3 depicts the partial correlations between each of the variables, with the strength of relationship apparent from the thickness and colour hue of the inter-connecting line.

Not only were Borrowing Money, Financial Problems and Tolerance indicative of higher severity, as shown by the Rasch model and probability analysis, but they tended to co-occur among the same people. Figure 3.3 shows that Borrowing Money was strongly connected to Financial Problem and Tolerance. The tendency for people who borrowed money to gamble also to have financial problems makes intuitive sense.

Problem recognition was most central to the network (Figure 3.3), i.e., it acted as a pathway for many other items to connect to each other. Given the generic nature of the statement, 'Have you felt that you might have a problem with gambling?', this is perhaps to be expected. Problem recognition had the highest measure of network strength (Figure 3.4), i.e., was most strongly connected to other items and of 'closeness', i.e., was the most influential in terms of interconnections between items. Additionally, it had a much higher level of 'betweenness' than other items, i.e., it is the most important connection between all other items.

Financial Problem was also quite central to the network, whereas Chasing Losses and Criticism were more peripheral than other items. It is also noteworthy that Chasing Losses and Guilt Feelings had a strong direct relationship with each other as well as being indicative of the least severity of the items, i.e., if one of these items was chosen by someone with gambling experience, it is highly likely the other item was also selected.

Figure 3.3: Network map of partial correlations between the nine PGSI items

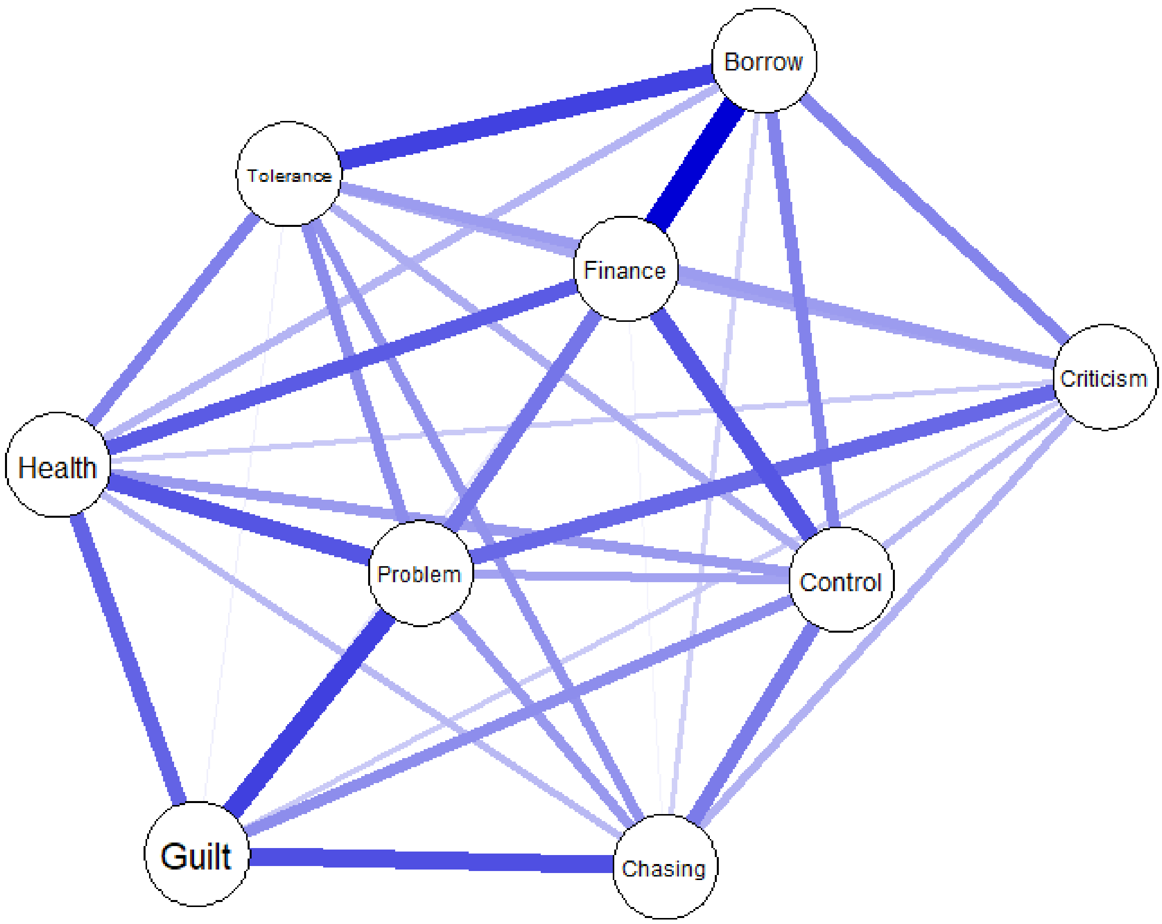
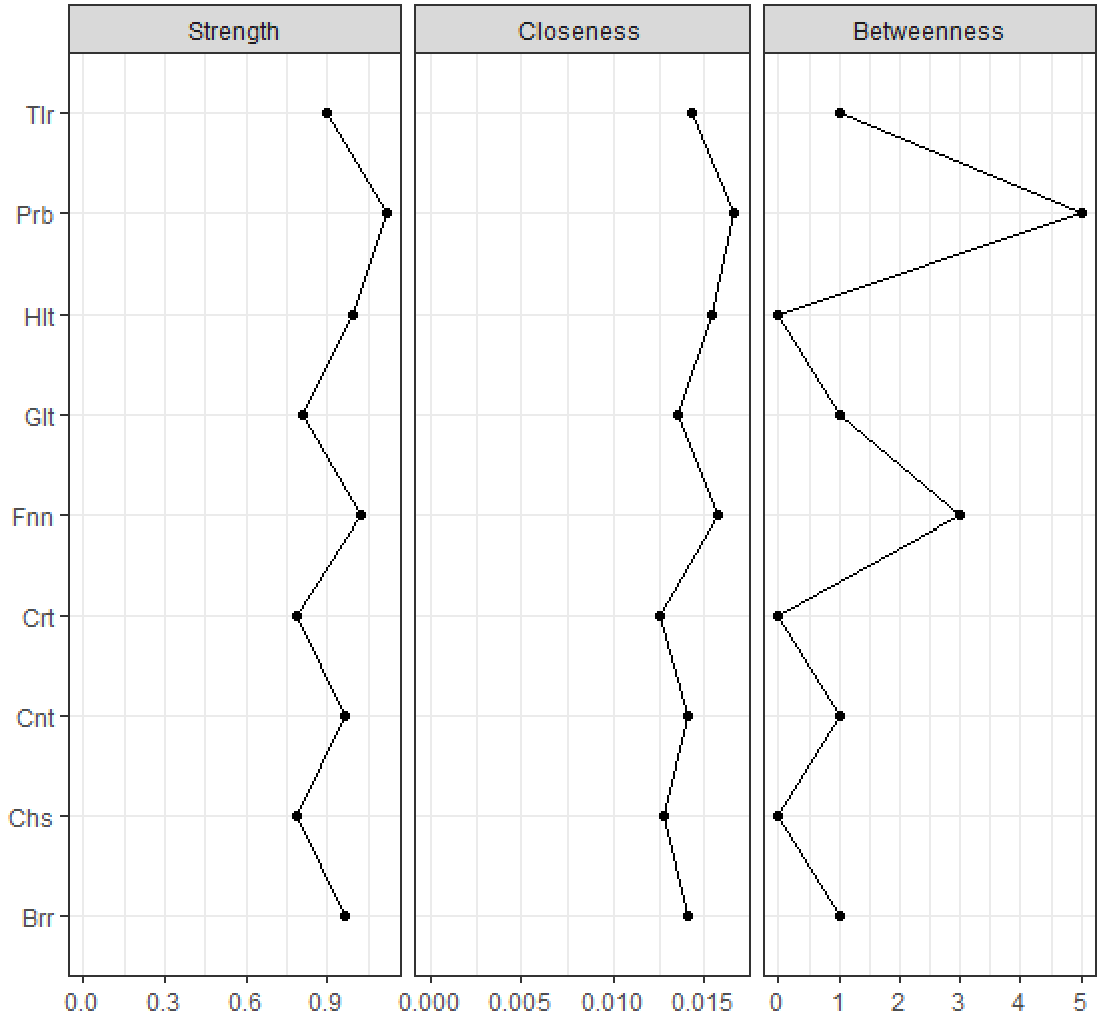


Figure 3.4: Network centrality measures



3.2.4 Short Form Analysis

A key question for the short form version of the PGSI is how well it identifies ‘problem gamblers’. It is unlikely that it will capture all people who gamble who would be identified as at risk (whatever the level of risk) using the full PGSI. In other words, the prevalence of the short form will be different to the prevalence for the full form. However, we are also interested in assessing how well the 3-item short-form grouping concurs with the 9-item grouping.

Various quality measures exist to quantify how well the predicted classification (from the short-form) predicts the ‘true’ classification score (as defined by the 9-item long-form), which are described below. These measures are based on the concept of positive and negative predictions which can be correct (true) or incorrect (false). There are four separate groups: no risk, low-risk, moderate-risk and ’problem gambler’, each of which has their own set of classification statistics.

From Table 3.9, we see that there were 950 ’problem gambler’ cases identified by the long form. The short form under predicts at 634 cases, of which 595 were accurate predictions (true positives). With only three of the nine items in the short form, it is no surprise that the total number is under predicted, though it is reassuring that relatively few of those predicted as ’problem gamblers’ are false positives

(39). Overall, the short form correctly classifies 63% (636/950) of long form ‘problem gamblers’, which is known as the ‘sensitivity’ of the test, i.e., the proportion of a long form classification group accurately predicted by the short form. Conversely, the short form misses 37% (355/950) of problem gamblers, which would be a concern in many practical contexts. However, of those it does predict as ‘problem gamblers’, it accurately classifies 94% (595/634) of them, i.e., it has a ‘precision’[45] of 94%.

Table 3.9: Crosstabulation of risk groupings between the short and long form scores

	Long Form				
Short Form	**None**	**Low**	**Moderate**	**’Problem’**	**Total**
None	16,753	1,043	83	2	17,881
Low	0	1,291	321	15	1,627
Moderate	0	126	669	338	1,133
‘Problem’	0	0	39	595	634
Total	16,753	2,460	1,112	950	21,275

Note: table shows the relationship between the classification on the short-form and the classification on the long-form.

For the non-problem gambler group, all 16,753 no risk cases are predicted by the short-form scale, so sensitivity is ‘one’ (Table 3.10). For low-risk cases, sensitivity is 0.52, i.e., nearly half (48%) of the low-risk cases are missed by the short-form. For moderate risk and ’problem gambler’ cases, sensitivity is 0.6 and 0.63, respectively, i.e., the short form misses 40% of moderate risk cases and 37% of ‘problem gambler’ cases. Consequently, the short-form scale is missing substantial minorities of low, moderate and ’problem gambler’ cases.

Precision is the proportion of predicted short form cases that are correctly predicted. For the non-problem gambler and ’problem gambler’ groups, precision is high at 0.94, i.e., of those the short form predicts as non-problem or ‘problem’ gamblers, it is mostly correct. However, for the low-risk group precision is lower at 0.79 and decreases more substantially to 0.59 for the moderate risk group.

[45] The proportion of predicted short form cases that are correctly predicted.

Table 3.10: Short-form quality measures

	True Positive	False Negative	False Positive	True Negative	Sensitivity	Precision
No risk	16,753	0	1,128	3,394	1.00	0.94
Low risk	1,291	1,169	336	18,479	0.52	0.79
Moderate risk	669	443	464	19,699	0.60	0.59
Problem gambler	595	355	39	20,286	0.63	0.94

Note: For each row, taking the row group as positive and any other group as negative.
True Positive: row group is correctly predicted
True Negative: row group is correctly predicted as 'other'
False Positive: row group is predicted but other group is correct
False Negative: row group is correct but other group is predicted

Overall, the utility of the short form measure is debatable. On the plus side, of those predicted as 'problem gamblers' 94% were accurately predicted, as were 94% of those not at risk. Additionally, none of those not at risk were missed by the short form. However, it missed one-third of people who were 'problem gamblers' according to the long-form. The performance of the short form was worse for identifying low risk and moderate risk groups than it was at identifying problem gamblers. This result is not surprising, given the use of three items rather than nine in the short form. Further work would benefit from exploring the relationships between the items not used and measures of harm. The three short form items include two of the least severe, but most frequently endorsed items, as described above; but the most 'severe' items are excluded from the short form.

3.2.5 Profiling the 20+ PGSI Group

The TSS sample size permits some insight to be shone on people reporting PGSI scores at the higher end of the summary score scale. The Hickman & Chakraborty (2022) study of people presenting for NGTS treatment found an average PGSI score of 19 at the start of treatment, so we used a grouping of 8-19 and 20-27 to roughly proxy a group who might be similar to those seeking treatment, at least according to this particular NGTS study. There are 1001 (unweighted) cases who fall into the PGSI 'problem gambling' group, which reduces to 951 when weighted. This classification shows 9% (weighted n = 84) fall into the 20+ group.

We have used a CHAID model, described above, to profile the characteristics of the more and less extreme members of the 8+ group. CHAID works by extracting characteristics in their order of importance in explaining the difference between the group members. When using weighted data, CHAID rounds up weights according to combinations of tables, hence the weighted base for CHAID differs from the sum of the weights in the dataset[46]. Consequently, the base in Figure 3.4, below, is 986 rather than 951.

Social Class/Grade[47] is a broad grouping of people which relates to occupation, hence socio-economic status, income and other potentially relevant characteristics. The small sample size for this analysis

[46] https://www.ibm.com/support/pages/why-weighted-n-parent-node-chaid-tree-different-compared-weighted-n-within-file
[47] The TSS includes a standard measure of Social Class, a socioeconomic classification produced by ONS based on people's occupations.

limits the number of variables it is practical to use, so Social Class was chosen because it is relatively cross-cutting across several potentially relevant characteristics. It was the primary distinguishing variable to discriminate between the 8-19 and 20+ groups. There are five classes or grades[48]:

- A: High managerial, administrative or professional
- B: Intermediate managerial, administrative or professional
- C1: Supervisory, clerical and junior managerial, administrative or professional
- C2: Skilled manual workers
- D: Semi and unskilled manual workers
- E: State pensioners, casual or lowest grade workers, unemployed with state benefits only

Social Classes C1/D made up 43% of the 8+ group and 9% of people in Social Class C/D1 were in the 20+ group. Further breakdowns of the C1/D class are based on small numbers and should be taken as indicative rather than robust findings. However, there is a suggestion that unemployment, particularly among non-widowed C1/D social class 8+ 'problem gamblers' predisposed towards membership of the 20+ group.

People in Social Class A and Social Class E (in the 8+ group) were proportionately more likely to be in the 20+ group. These people made up 27% of 'problem gamblers' and 14% of 'problem gamblers' with Social Class A/E were in the 20+ group.

'Problem gamblers' (8+) from Social Classes B/C2 were least likely to be in the 20+ group. They made up 30% of 'problem gamblers' but only 4% were in the 20+ group.

3.3 Relationship between PGSI and wellbeing

3.3.1 Well-being Outcomes

Whilst the PGSI is not a measure of gambling harm per-se, we anticipate that people at higher risk of 'problem gambling' will also be more likely to experience harm. In order to test this hypothesis, we have explored the association between the PGSI scores and wellbeing. Various measures of well-being are available from the TSS, and we have used the following:

- K-10 psychological distress score, which is constructed from ten items designed to measure global distress based on anxiety and depressive symptoms over the last four weeks (prior to interview). It is constructed from summing the 10 relevant questions. Both the raw K-10 score is

[48] https://www.ipsos.com/sites/default/files/publication/6800-03/MediaCT_thoughtpiece_Social_Grade_July09_V3_WEB.pdf

used alongside the standard grouping of 10-19 = ‘well’; 20-24 = ‘mild’; 25-29 = ‘moderate’; 30-50 = ‘severe’.

- Audit-C alcohol dependency score, which is based on three items asking about alcohol consumption in the past 12 months (prior to the interview). It is constructed from summing the 3 base items. Both the raw and grouped Audit-C scores are used with the groups comprising: 0-4 = ‘low’; 5-7 = ‘increasing’; 8-10 = ‘higher’; 11-12 = ‘dependence’.
- IMD deprivation indicator that the person resides in an area in the bottom 30% of deprived areas.
- Total number of self-reported disabilities (0-7)
- Total number of self-reported mental health issues (0-21)

3.3.2 Pinch-point Analysis

Overview

The aim of the pinch-point analysis is to identify a sudden rate of change in the wellbeing score as we ascend the PGSI score[49]. A dramatic change in wellbeing associated with a pinch-point PGSI change would then serve as a potential indicator of a critical period to intervene or provide support. The average outcome score (K10, Audit-C) is plotted against the PGSI group score for each of the outcomes. Two lines are plotted onto each of the charts shown below. The straight blue line is the fitted linear regression line from predicting the outcome mean from the PGSI score group. Ideally, the observations should cluster close to this line and be randomly scattered above and below the line. The red line is a smoothed plot (loess) which provides a fit closer to the observed data than the straight-line linear assumption and shows deviations from a straight-line relationship.

We note that the number of available cases to summarise the mean outcome score declines substantially after a score of 19 on the PGSI scale and the outcome means for groups above this PGSI score are not very precise. Consequently, observations towards the top of the PGSI distribution should be treated with caution.

Psychological Distress

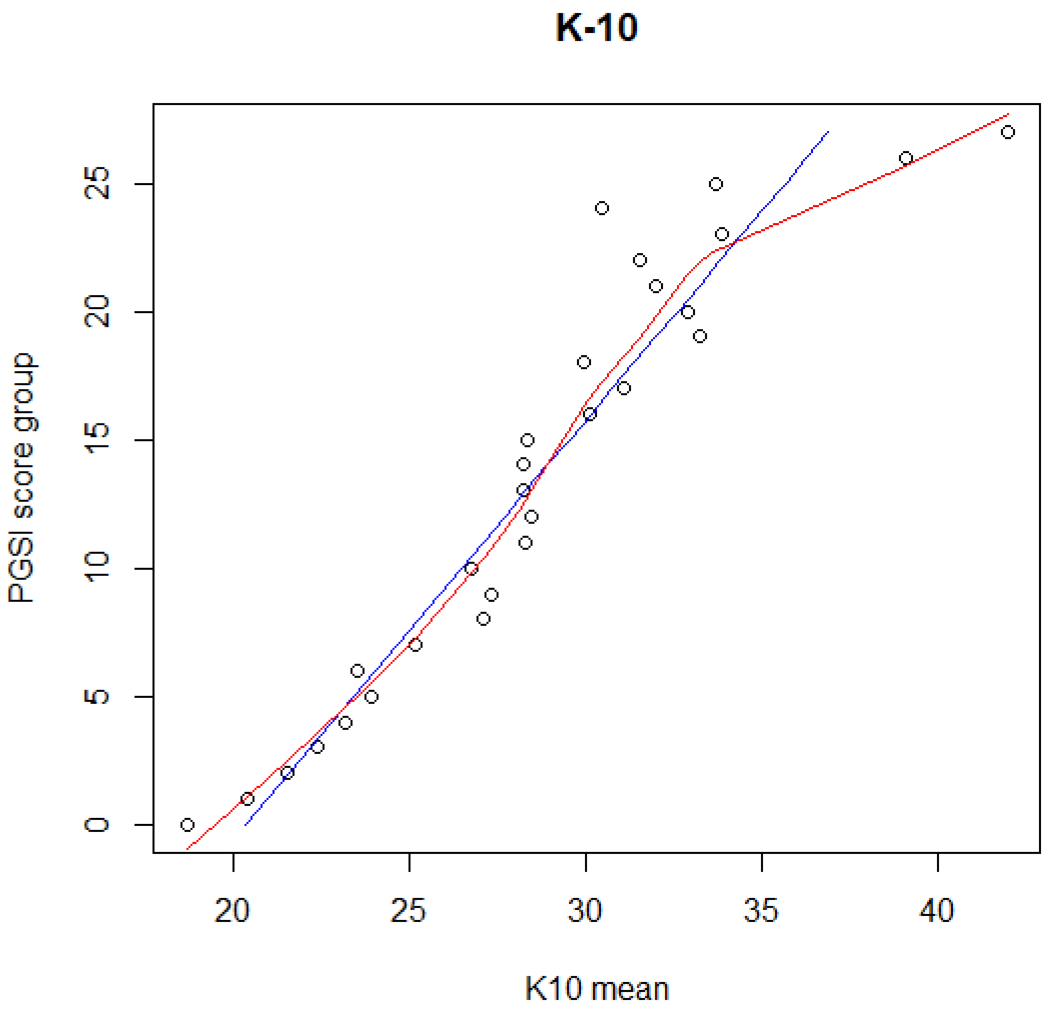
As the PGSI score increased, so too did psychological distress (Figure 3.5). The regression line (blue) generally showed a good fit between the two sets of scores, i.e., the scores are close to the regression line, until we reach the top end of the PGSI distribution. Given that sample sizes get small after a PGSI score of about 19, a poorer fit at the top end of the scale is not surprising. The loess (red) line is fairly close to the regression line, except at the top end of the PGSI distribution, where sample sizes lead to unreliable observations.

There does appear to be a potential pinch-point around a PGSI score of 6, with a change from an average outcome score of 23.5 to 25.2 for PGSI=7. There is another jump from PGSI score 7 to 8, with the K-10 average increasing from 25.2 to 27.1, respectively. Consequently, the current PGSI ‘problem gambler’ grouping at 8+ seems to represent an appropriate cut-off point, especially given that the K-10 grouping of ‘moderate’ distress runs from 25-29. Consequently, a score of 8+ on the PGSI is indicative of moderate psychological distress.

Another potential pinch-point seemed to occur between PGSI scores 15 and 16, with the K-10 average score increasing from 28.3 to 30.1. The K-10 classification of 'severe’ ranges between 30 and 50, so if the PGSI is being used for screening purposes, a PGSI score of 16+ is likely to reflect severe psychological distress and would suggest further investigation into the person’s condition.

[49] We initially looked at statistical measures to identify significant differences in the average outcome score as we ascended the PGSI scale. However, the comparatively large sample size resulted in too many significant differences and obfuscated the results. Hence, we decided to rely in a visual inspection of rate of change.

Figure 3.5: Scatterplot of K-10 average scores against PGSI score



Three groups were created from the PGSI score based on the pinch-point analysis, shown in Table 3.11, from which it appeared that the pinch-point split performs reasonably well in separating the K-10 scores for people with experience of gambling. The average K-10 score for the 16+ PGSI group is substantially higher than that of the 8-15 group and, and the between PGSI group differences in average K-10 scores in Table 3.11 are substantial. We repeat again that the K-10 classification of 'severe' distress is a score of 30+, which is exceeded by 60% of people in the PGSI 16+ score group and by 30% in the PGSI score of 8-15. Consequently, someone presenting with a PGSI score of 8+ would likely benefit from further psychological screening and someone with a score of 16+ should be considered for further investigation.

Table 3.11: K-10 score by PGSI group

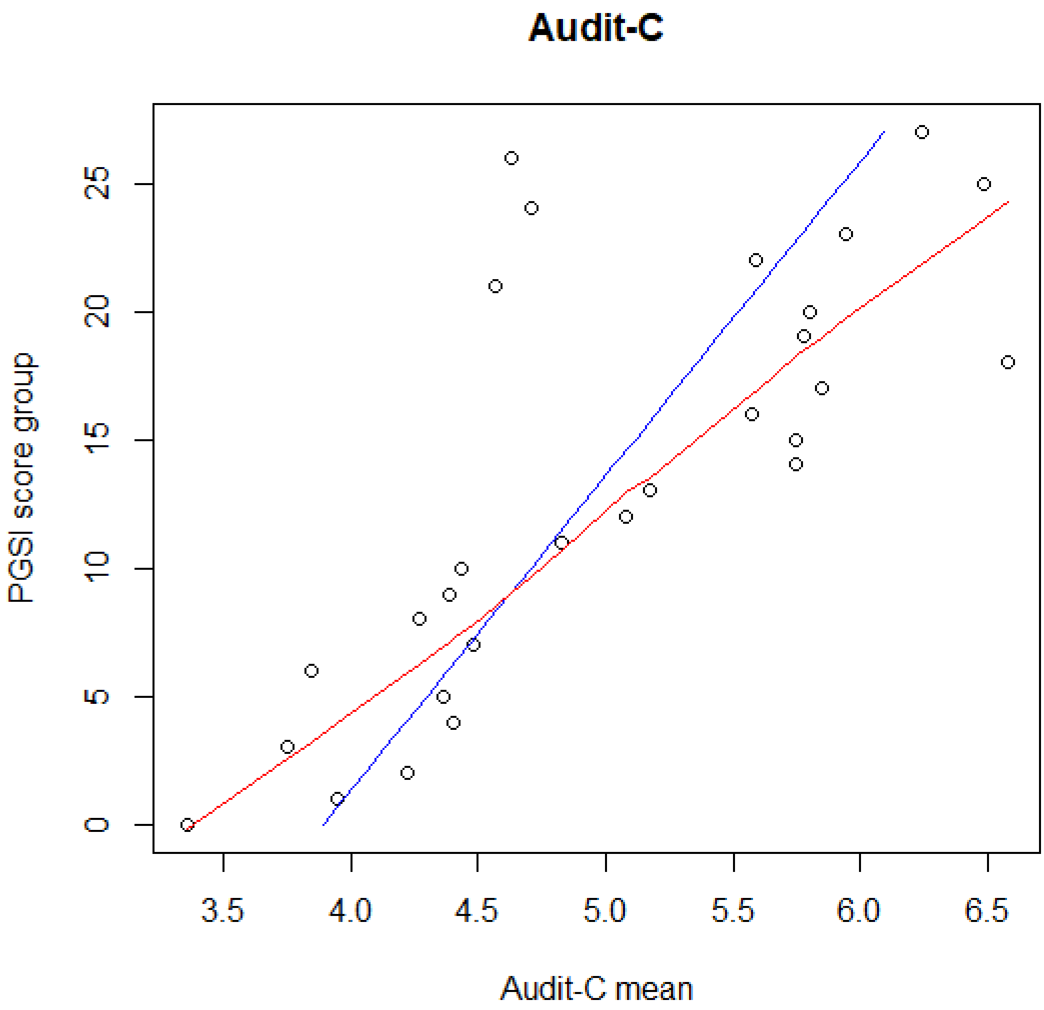
	K-10 score		
PGSI group	Mean	N	Std. Deviation
No gambling experience	20.0	15640	8.8
0-7	18.5	20327	8.3
8-15	27.8	745	7.5
16+	32.3	206	8.3
Total	19.4	36917	8.6

Note: PGSI group is defined from the K-10 pinch-point analysis.

Alcohol use

The relationship between the Audit-C score and the PGSI was less clear than that between K-10 and the PGSI. The observations tended to be further away from the regression (blue) line and the loess (red) line deviated substantially from the regression line. Nevertheless, a PGSI score of around 10 appeared to indicate a potential pinch-point though we found the average Audit-C score changed only from 4.3 to 4.11 between PGSI scores of 10 and 11. Another case can be made for a PGSI score of 13, which had an average Audit-C score of 5.2, which rose to 5.7 for a PGSI score of 14.

Figure 3.6: Scatterplot of Audit-C average scores against PGSI score



3.3.3 Relationship between PGSI Groups and Wellbeing Scores

Traditional PGSI Grouped Score

Table 3.12 shows strong evidence that the PGSI score reflected lower well-being, though we cannot be sure of the directionality of the effects. For all well-being measures, people classified as 'problem gamblers' (8+) on the PGSI had the worst well-being outcome scores, which were typically substantially higher than those who had a moderate risk of problem gambling. Indeed, over 40% of people classified as 'problem gamblers' lived in deprived areas, the average number of disability related conditions reported by people was 44% and the average number of mental health related conditions reported was 25%.

'Moderate risk gamblers' (3-7+) also reported more psychological distress, had more disabilities and mental health issues than people identified as 'low-risk gamblers' and were more likely to live in a deprived area.

Similarly, 'low-risk gamblers' (1-2) tended to have worse outcomes than 'people with gambling experience who were not at risk. However, differences between people with no gambling experience and people who gambled but who were not at risk were mixed. People with no gambling experience reported more psychological distress and slightly higher numbers of mental health issues than people with gambling experience who were not at risk.

Table 3.12: Mean outcome scores by traditional PGSI severity risk group

PGSI Group	K-10 score	Audit-C score	Bottom 30% IMD deciles	Number diagnosed disabilities	Number mental health issues
Non-gambler	20.0	2.9	.26	.22	.10
No Risk	17.9	3.6	.27	.22	.08
1-2	20.7	4.0	.31	.25	.11
3-7	23.3	4.1	.36	.31	.17
8+	28.7	5.1	.43	.44	.25
Total	19.4	3.4	.27	.23	.10

Note: statistics produced on weighted data. All outcomes are significant (P<0.05) using a one-way ANOVA test.

Gambling and severity of psychological distress

Collapsing the K-10 score into the traditional K-10 groupings clearly emphasises the link between the severity of gambling risk and psychological distress. Nearly half (47%) of the 'problem gamblers' were classified as severe on the K-10 score, with another 28% classified as moderate distress on K-10. In other words, around seven in ten of 'problem gamblers' experience at least moderate or severe distress, which compares to around 15% of the overall population experiencing severe distress, i.e., a rate of over three times the rate among 'problem gamblers' compared to the overall population.

Table 3.13: K-10 psychological distress risk by PGSI risk

		PGSI risk group					
		Non gambler	0	1-2	3-7	8+	Total
K-10 risk group	Well	56.8%	67.4%	53.4%	39.4%	10.8%	59.7%
	Mild	16.1%	13.3%	16.3%	18.8%	13.9%	14.8%
	Mod	11.2%	8.8%	12.8%	17.3%	28.2%	10.8%
	Severe	15.9%	10.6%	17.6%	24.5%	47.1%	14.7%
Total		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

One quarter (25%) of moderate risk gamblers were also likely to experience severe distress, with another 17% experiencing moderate distress. Low-risk gamblers were only just slightly more likely than people with no gambling experience to experience severe distress, whereas severe distress was least likely to be experienced by low-risk gamblers.

Gambling and alcohol consumption

The overall prevalence of 'dependence' alcohol intake was relatively low at 2% among people who gamble (Table 3.14). Consequently, the 3.9% prevalence rate of alcohol 'dependence' amongst PGSI 'problem gamblers' was almost double the population average. Moderate and low-risk gamblers also showed elevated rates of dependence (around 3%) above the population average but lower than for the 'problem gambler' group. People with no gambling experience were least likely (1.5%) to show dependence and non-problem gamblers were around the population average at 2.1%. For the 'problem gambler' group, their prevalence rates were higher in each of the ascending Audit-C classifications beyond the low alcohol score. The low and moderate-risk PGSI groups had similar profiles in terms of alcohol consumption risk, which tended to be more negative than the profile of no-risk gamblers. Non-gamblers were most likely to fall into the low alcohol risk group and less likely than gamblers to be at increasing, higher or dependence alcohol risk.

Table 3.14: Audit-C risk by PGSI risk

		PGSI risk group					
		Non gambler	No risk	Low risk	Mod risk	High risk	Total
Audit-C group	Low	74.3%	66.3%	59.2%	58.9%	41.2%	68.4%
	Increasing	17.6%	22.0%	24.4%	22.7%	35.6%	20.7%
	Higher	6.5%	9.6%	13.2%	15.1%	19.2%	8.9%
	Dependence	1.5%	2.1%	3.2%	3.3%	3.9%	2.0%
Total		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

4 Conclusions and Recommendations

1. Items in the PGSI scale should not be treated equally; individually they make a different contribution to assessments of risk.

Previous studies have suggested that some of the nine PGSI items are more likely indicate a more severe risk of gambling than are other items (e.g., Miller et al., 2013[50]). Consequently, treating each item as equivalent to other items when summing the scores of each to create the PGSI score would not be appropriate. The evidence found in our study concurs with these findings and so suggests that not all the PGSI items should contribute equally to the index nor to higher PGSI groups. The items Borrowing Money, Financial Problems and Tolerance (Table 1) appeared to measure a higher severity level, whereas Guilt Feelings and Chasing Losses appeared to be indicative of less severity[51]. In other words, someone scoring a maximum of nine through summing the items scores from Borrowing Money, Financial Problems and Tolerance would be at greater risk than someone scoring nine across a different three PGSI items.

For example, whilst only four per cent of people who had gambled in our study had borrowed money or sold something to get money to gamble ('Borrowing Money'), of those who did, 83% were in the PGSI 'problem gambler' (8+) group. Similarly, only five per cent said gambling had caused them financial problems ('Financial Problem') but of these, 73% were in the PGSI 'problem gambler' (8+) group. Of the six per cent who reported they need to gamble with greater amounts of money (Tolerance), 63% were in the 8+ group. At the other extreme, 13% said they felt guilty about the way they gamble ('Feeling Guilty'), but just under one-third of these were in the PGSI 1-2 group with just under a third in PGSI 8+ and PGSI 3-7 groups. Similarly, 12% of people who gambled said they chased losses (Chasing), but of those who did, 38% were classed as PGSI 1-2, 29% PGSI 3-7 and 34% PGSI 8+.

Analysis also considered the extent to which items 'co-occurred' (selected by the same individual [shown in the network analysis]). This showed that Problem Recognition ('have you felt you have a problem with gambling') may have acted as a pathway for many other items to connect to each other.

Our findings concur with previous studies in this respect,[52] and challenge the notion that each PGSI item measures the severity of gambling risk to the same extent as all other items. Care is therefore needed to use PGSI as a clinical or screening tool. For example, selecting 'sometimes' to financial difficulty may be more illustrative of a need for help and support than an individual declaring they 'almost always' feel guilty.

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[50] https://pubmed.ncbi.nlm.nih.gov/24014164/

[51] These findings were also apparent in cognitive interviews. It was common for participants to comment that feeling 'guilty' was less severe than feeling that there was 'a problem'. Some participants also placed greater importance on financial items which were seen as more likely to be accurate and a pre-curser to other outcomes.

[52] For example, Miller et al. (2013)[52] using survey data provided by Canadian adults found similar results, though 'Tolerance' was not as a high an indicator of severity in their study.

2. Despite its limitations, the PGSI scale should continue to be used as a general instrument to estimate potential risk of 'problem gambling' among larger groups.

Notwithstanding the findings above, overall, the PGSI items hold together as a composite single measure using standard statistical techniques. The statistical analysis showed evidence that the items worked together to form a single scale and that responses across the items were consistent, showing that the scale had good reliability.[53] Additionally, use of a specialised statistical grouping technique[54] did reproduce three groupings of classification to a high degree of separation, which were distinguished by their PGSI summary total scores – this indicates that there is merit in making broad distinctions between summary groups within the PGSI summary scale[55].

3. There is a clear link between PGSI scores and psychological distress, it is therefore appropriate to continue to use PGSI as an indicator of likely harm

One indicator of harm available through the Treatment and Support Survey dataset is wellbeing. There is strong evidence shown within the analysis that higher PGSI scores equate to worse wellbeing outcomes. For example, nearly half (47%) of those PGSI 8+ (problem gamblers) were classified as 'severe' on K-10 scale[56], with another 28% classified as 'moderate' distress.

We do not know to what extent people in a poor state of wellbeing have a higher propensity for involvement in 'problem gambling' or vice-versa. However, the general trend is apparent and suggests that there is value in using PGSI as a tool by which to consider interventions or plan prevention activity.

As the PGSI score increases, the K-10 score increases in line, until around a PGSI score of 20, when sample sizes are too small for this level of resolution. The cut-off point for a severe disorder classification on the K-10 scale is 30, which tends to occur at around a score of 16 and above on the PGSI.

This relationship between the PGSI and K-10 scales suggests that whilst the PGSI does not intrinsically measure harm, inference of the probability of harm in the form of psychological wellbeing can be inferred from the PGSI score. Whilst not everybody with a PGSI score of 16+ will necessarily be severely distressed, a majority will be. However, lower PGSI scores will result in fewer instances of severe distress. For example, of the PGSI 8+ group, 47% are classified as in severe distress.

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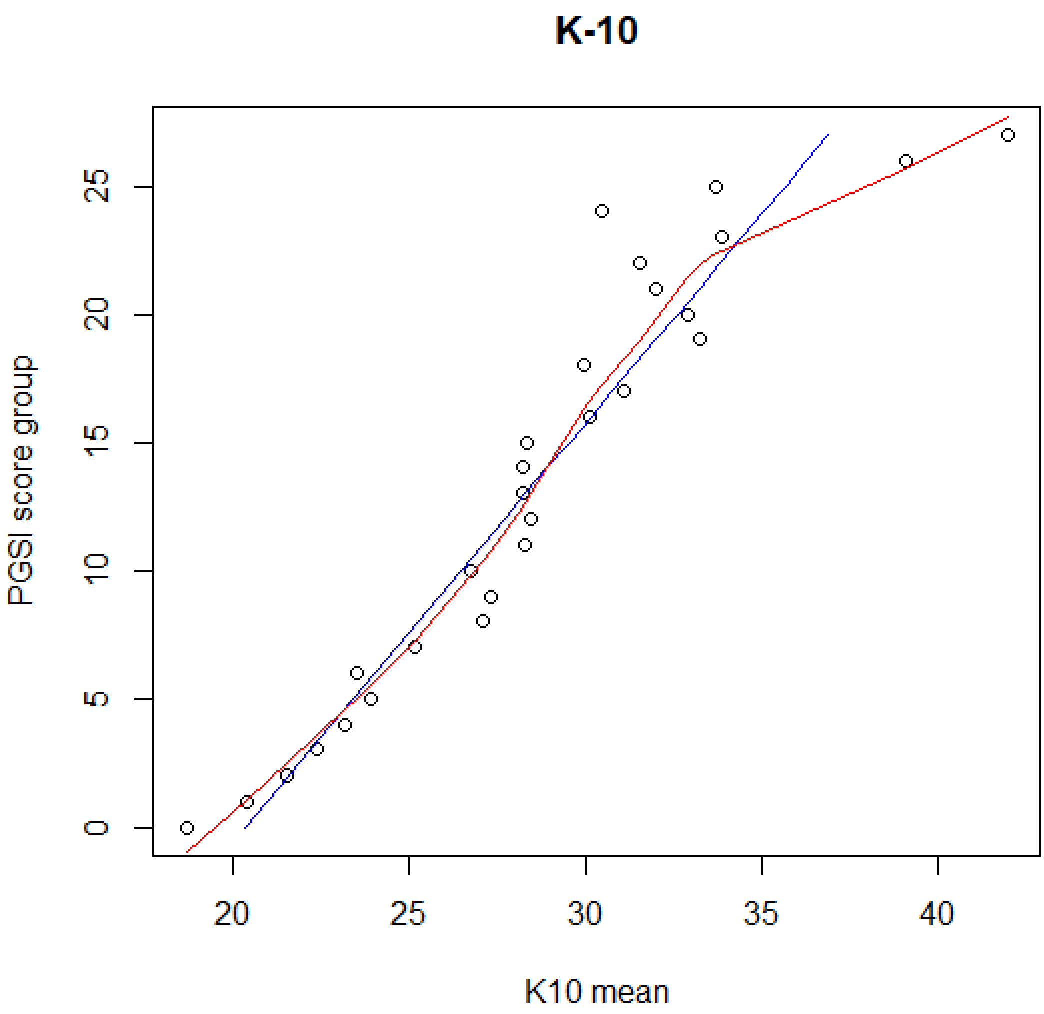
[53] Factor analysis indicated a strong association between items and all other items. All items show solid correlations with the overall scale score and a high Cronbach's alpha score (0.94).

[54] Latent class analysis was used to identify different groupings across all scores of 1+; this helped identify different patterns of co-occurrence between the variables.

[55] The current PGSI classifications group individuals into one of three categories: PGSI = 1-2, PGSI = 3-7; PGSI = 8+

[56] The K-10 scale is also known as the Kessler Psychological Distress Scale and ranges between 10 and 50.

Figure 1: Scatterplot of K-10 average scores against PGSI score



4. There is merit in revisiting the traditional PGSI classifications; however, this should be traded against pragmatic considerations to identify, target and track groups over time

Analysis also shows that the current PGSI groupings of 1-2, 3-7 and 8+ may not be optimal in making clear distinctions between different sub-populations. For example, when comparing current PGSI classifications to three groups created separately by analysis for this study, the findings identified a poor degree of correspondence (or overlap) between the two models[57]. Initial analytics conducted for this study suggests that groupings of 1-4, 5-10 and 11+ offer an alternative to the traditional groupings and are directly based on the relationships between the nine items. Further research is required to test if this grouping is more reliable and appropriate.[58] Testing which groupings are most appropriate requires an external reference point against which to judge the scale, either on the basis of what it is measuring, i.e.,

[57] The Latent Class Analysis produced three groups (or 'classes'). PGSI 8 + comprised all but one of the Class 1 cases, but also around half of the Class 3 cases. Class 2 cases were predominantly aligned to PGSI 1-2 but a substantial minority were also classed as PGSI 3-7.
[58] A Discriminant Function Analysis (DFA) was used to predict allocation to different classification models. The DFA was able to predict the 1-4, 5-10, 11+ classifications to a higher degree of accuracy (95%) than it was able to predict to traditional 1-2, 3-7, 8+ classifications (87%)

‘at risk of problem gambling’ or against an associated concept (e.g., harm). Subsequent analysis in this study examining the link between the PGSI summary score and the K-10 distress score showed good separation using a different grouping of PGSI 0-7, 8-15 and 16+. However, this is but one potential validation scale out of many, and different validation scales may suggest different PGSI groupings.

Currently, it is not clear which breakdown is most appropriate and if any one breakdown is suitable for all purposes. At the population estimate level, analysis suggests that there may be some value to revisiting notion that a threshold of PGSI 8+ justifies the label of ‘problem gambling'. For example, increasing the cut-off threshold from 8 to 11 would result in being more sure that those classified at PGSI 11+ were more likely to experience harm than those at 8+. However, the PGSI 8-10 group would still include some people who were harmed but were no longer being classified in the 11+ ‘problem gambling’ group.[59] Additionally, it should be noted that a highest category of PGSI 11+ would reduce the total number of cases in this group by around a third, thus making it more difficult to identify and monitor over time, i.e., social surveys would require comparatively large sample sizes to measure the 11+ group with precision.

In designing treatment and support services, it seems that the 8+ group does capture many in psychological distress; however, distress does not flatline at PGSI 8+. A more stringent cut-off higher up the PGSI scale (16+) will certainly identify a group who are even more distressed than the 8+ group, and will likely require different scale or nature of support.

5. Overall, there is a risk that that PGSI underreports the proportion of individuals who are at risk of harm from gambling; where possible, additional survey measures should therefore be explored that ask people to self-refer as experiencing harm

The cognitive interviews identified a risk that some individuals may not want to or be unable to answer PGSI accurately. This was particularly relevant to items which consider personal consequence, and whether an individual feels guilty or that they may have a ‘problem’. Participants felt it was likely that someone who is experiencing significant impact from gambling may be inclined to answer ‘sometimes’ if they are unable or unwilling to acknowledge the true significant impact on their lives or want to ‘play down’ the impact. It was further suggested that an individual may genuinely not feel guilty or perceive there to be a problem, even if they were experiencing harm. This would in turn underestimate the prevalence of those scoring 3-7 and 8+ because respondents may be underreporting the frequency of occurrence when responding to individual items and lowering their overall PGSI score.

Wider research further indicates that there is a gap between those who self-identify as suffering harm from gambling and those who score 8+ on PGSI. We therefore recommend further research to develop a validated pairing of PGSI with a secondary question which assess self-reported harm (regardless of gambling activity) may help identify a separate pool of individuals who require tailored support to help raise self-awareness.

6. Careful consideration should be given to the use of PGSI 1+ as a threshold at which ‘harm’ begins

Using the K-10 psychological distress score, analysis shows that people with a PGSI score of 1-2 have some wellbeing scores that are more similar to people who do not gamble and people with a PGSI score of zero, than they do to PGSI 3-7 and PGSI 8+. For example, the average K-10 score for those in PGSI

[59] Thus, we would decrease the number of false positives but at the expense of increasing the number of false negatives

1-2 group was 20.7 compared to a score of 20.0 among people who do not gamble and 17.9 among those with PGSI = 0. Where people in the 3-7 group had an average K-10 score of 23.3 and those in the 8+ group had a K-10 average score of 28.7. Consequently, levels of psychological distress in the 1-2 group are more similar to those of people who do not gamble than they are to people with a score of 3-7 or 8+. Therefore, these results suggest that treating all those who have a PGSI score of 1+ as similar in terms of harm is inappropriate.

Taken alongside findings above that suggest not all PGSI items are equivalent, further analysis could explore the extent to which all scores of PGSI 1+ are equivalent in association with wellbeing and other gambling harms (for example comparing outcomes for individual with score of 1 for 'feeling guilty' vs score of 1 for 'financial problems'), and whether there would be any benefit to differentiating further within PGSI classifications.

7. Avoid use of the short forms PGSI measure unless there is extremely limited opportunity to interact with individuals

Analysis shows that the short form PGSI measure tends to underpredict the PGSI 8+ group, reducing the prevalence of 'problem gambling' from 4.5% to 3%. Using the nine-item form as the 'true' measure, the short-form predicts 634 cases as 8+ equivalent, of which 595 are accurate predictions, i.e., only 6% are false positive predictions. However, the short form misses 355 of the 950 true positives, a false negative rate of 37%. The predictive performance of the short form measure for the long-form 1-2 and 3-7 groups is worse than for the 8+ group.

The further work suggested under Recommendation 1 should take the severity of items into account with reference to the construction of the short form. This suggests that the short form should not be used as a tool for population estimates of potential risk of gambling harms and has limited value as a tool for self-assessment or in service delivery. However, it may still have some value in identifying those most likely to be PGSI 8+ where collection across all 9 PGSI items may be impractical or not appropriate.

Implications

The PGSI is based on responses to nine question items which cover both behavioural situations and consequences of gambling. Using standard procedures, responses to each of these items are treated as equally important in contributing to the total summary score created through adding up the response to each item. This summary score approach appears to work well as a general indicator of potential risk of problem gambling among the general population. As such, it can be used to monitor trends in potential levels of gambling harm, identify groups of people who are potentially at higher risk and be used to monitor the impact of policies aimed at reducing harm. However, it is unlikely to work as well on its own as a diagnostic instrument for individuals or for such screening purposes. Further work is recommended to explore PGSI items which appear more and less severe and their relationship to the wellbeing outcomes. The tendency of the more severe items to co-occur, as well as the less severe items also to co-occur might be indicative of different experiences of risk and harm, which would require further work to assess.

There is a need for PGSI users and practitioners to distinguish between the risk of problem gambling and the binary problematic or not problematic classification using the classification grouping. Not all people within a PGSI classification group are at the same risk of harm on wellbeing measures. Again, this consideration is especially important when considering using the PGSI for treatment screening purposes and reinforces the need for supporting measures of harm.

This study has considered the PGSI as an existing instrument. It has not considered the extent to which other relevant questions might extend the classification of risk. The cognitive interviews suggested that further work in this regard might be useful to test for people whose risk is currently hidden from view of the PGSI. The work comparing the short-form measure to the nine-item PGSI illustrates the risk of missing hidden harms because not all appropriate items were included in the short-form measure. Extending the nine item PGSI could reveal a hidden sub-group at risk of harm. However, extension of the PGSI should be done with care. Any additional items should be justified on both theoretical and statistical grounds.

Changes to the PGSI, whether this be through increasing the number of items or changing the classification score groupings, will disrupt ongoing statistical series and comparability with other countries using the same scale and groupings. Consideration should be given to reporting any changes and ensuring either continuing to report comparable measures over time (where possible) alongside any new measures. Alternatively, adjustment factors between old and new measures should be derived to enable switching between new and old statistical series.

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