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BRIEF REPORT

Measurement invariance of the Problem Gambling Severity Index across sociodemographics and gambling modalities

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ABSTRACT

The Problem Gambling Severity Index (PGSI) has been extensively used to identify the severity of problematic gambling behaviors in the general population; however, presently there is a lack of research that ensures that the PGSI measures the same latent construct in a consistent way across different socio-demographic groups (age, gender, income, education, and race) and gambling modalities (online, sports, and casino gamblers). This concept, known as measurement invariance (MI), is important as it reinforces the validity of the scale as well as survey research conclusions in the field of problem gambling. A sample of nationally representative respondents in the United States was used to test the measurement invariance of the PGSI ($n = 2{,}972$). Measurement invariance was tested using multiple group confirmatory factor analysis across the various comparison groups. Analysis supported the measurement invariance of the PGSI across demographic groups (sex, age, race, income, and education) as well as gambling modalities (online gambling, sports wagering, and casino gambling). Differences in latent means demonstrated that younger adults, sports wagerers, and online gamblers reported higher problem gambling severity. As the global gambling industry continues to grow and expand into new jurisdictions, this study has implications for both scientific and clinical use of the PGSI as an instrument to diagnose gambling disorder.

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1. Introduction

With the addition of the fifth edition of the Diagnostic and Statistical Manual of Mental Disorder (DSM-5), pathological or problem gambling (formerly an impulse control disorder) was reclassified as an addictive behavior as gambling disorder (GD; American Psychiatric Association, 2013). To aid in the identification of at-risk individuals, researchers developed the Problem Gambling Severity Index (PGSI) which assesses nine indicators of problematic gambling behavior (Ferris & Wynne, 2001). While the PGSI was not developed directly based on DSM criteria, it

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demonstrates high internal consistency, sensitivity, specificity, and correlations with other problem gambling severity measures (Holtgraves, 2009). Since its initial development over 20 years ago, the PGSI has been used to assess both demographic (James et al., 2016) and activity-based (Forrest & McHale, 2012) risk factors for problem gambling in populations around the world.

The PGSI measures nine different aspects of problem gambling – loss chasing, self and other perceptions of gambling problems, health, tolerance, over-betting, guilt, financial problems, and borrowing money to gamble. Each item is measured on a 4-point scale ranging from 0 to 3 (0 = *Never*, 1 = *Sometimes*, 2 = *Most of the time*, 3 = *Almost always*). The score for each item is then summed up, resulting in a score between 0 and 27. This sum is used to classify respondents to one of four risk categories for problem gambling – non-problem gambling (0), low risk (1–2), moderate risk (3–7), or high risk (8 or more).

Today, the PGSI is frequently used by researchers and practitioners in experimental (Newall et al., 2022), observational (Nower et al., 2022), and clinical (Roberts et al., 2022) research settings, as the PGSI has been found to have high reliability with respect to test-retest reliability and internal consistency (Ferris & Wynne, 2001; Lopez-Gonzalez et al., 2018; So et al., 2019). In fact, it has been referred to as the 'gold standard' when it comes to assessing gambling disorder (Caler et al., 2016; Cooper & Marmurek, 2023).

Latent constructs, such as problem gambling, are often assessed by measurement scales. It is essential that scales operate consistently across different groups of people, as it assures the comparability, validity, and generalizability of a scale (Edgren et al., 2016). If the scale does not measure the same construct in the same way across different groups, the instrument is considered measurement variant or biased (OtbiÇer) Acar, 2021; Thissen, 2024). Lack of measurement invariance (MI) in scales could lead to invalid results when making inference, difficulties in identifying groups at risk of harm, and comparing different groups. In other words, for a scale to be a tool with high validity, it must be measurement invariant (Van De Schoot et al., 2012). Although the PGSI is frequently used to assess problem gambling, the measurement properties of the scale have not been rigorously tested across various demographic groups (Public Health England, 2020).

While there has been some research on the MI of the PGSI across groupings of various demographic variables (e.g. gender, income, education) (Gorenko et al., 2022; Hitcham et al., 2023), there has been no research evaluating MI as it relates to different gambling modalities. This study builds upon previous literature by rigorously testing the PGSI for MI using a census-matched sample of gamblers from the United States (US), both to confirm invariance over different levels of demographic variables and to investigate the MI across gambling modalities. Specifically, this work seeks to test MI over levels of five demographic variables (i.e. gender, age, education, income, and race) and three gambling modality-related variables (sports gambling, online gambling, and casino gambling).

This study builds upon previous MI studies of the PGSI by validating previous demographic results and providing new gambling modality related results. Establishing MI across these groups ensures that researchers and practitioners have a valid and reliable tool for diagnosing problem gambling, comparing prevalence rates, and analyzing risk factors in different populations.

1.1. Measurement invariance in gambling literature

Despite its importance, the testing of MI has historically been limited in problem gambling literature. In recent years, however, there has been an increased awareness of the importance of establishing invariance in scales that measure gambling disorder. A variety of scales have been assessed for MI, such as the Short Gambling Harms Scale (SGHS; Browne et al., 2018), the Diagnostic Screen for Gambling Problems (NODS; Richard & King, 2023), and the Gambling Outcome Expectancies Scale (GOES; Flack & Morris, 2016; Richardson et al., 2024). In most studies, though, the focus has been on MI across gender, with limited research on invariance over other factors such as time points (Flack & Morris, 2016) or age groups (Molander et al., 2023).

A small number of studies have examined the MI of the PGSI specifically. Maitland and Adams (2007) found the PGSI to be measurement invariant across a binary categorization of gender (but did not specify their estimation method), a result that Boldero and Bell (2012) confirmed with a sample of college students using Bayesian estimation. Smith et al. (2015) also established MI across gender among adults seeking treatment for gambling disorder. Gorenko et al. (2022) established PGSI MI across gender among older adults. Yet, Smith et al. (2015) and Gorenko et al. (2022) both used maximum likelihood estimation (MLE), but due to the skewed indicators of the PGSI, MLE is not suitable for testing MI (Wu & Estabrook, 2016).

Other groups have also been assessed. Additionally, Miller et al. (2013) validated MI among electronic gambling machine or casino gamblers and other gamblers by solely inspecting the loadings via factor analysis and differential item functioning analysis (DIF). They found that the PGSI likely underestimates the severity of the 'borrowing money' item across casino game types. Recently, Hitcham et al. (2023) performed a rigorous assessment of the PGSI, confirming its MI across gender, age, income, and education level using a large, representative sample of United Kingdom (UK) gamblers using robust estimation techniques. They found measurement invariance to hold across all tested age, gender, education, and income groups. However, there has yet to be a study that analyzes the MI of the PGSI across race and given the racial topography within the US, this remains a critical future aim for research.

Evidently, additional research investigating the validity of the PGSI is sorely needed. There are three significant gaps that need to be addressed regarding the MI of the PGSI. Firstly, MI must be tested rigorously using robust methods that can properly account for the often-skewed distribution of problem gamblers in the sample. Secondly, while gambling literature has used the PGSI to analyze how the risk factors for gambling disorder vary across groups, it has not been evaluated whether the PGSI consistently measures problem gambling across differing groups of people. These groups are generally constructed based on socio-demographic variables such as marriage status, race, and income, as well as different types or segments of gamblers. Finally, there is a general lack of invariance studies that use representative samples, particularly census-matched samples.

Accordingly, we used a large census-matched sample of US adults to examine the MI of the PGSI across demographic groups (e.g. gender, age, income, education, and race) and gambling modalities (e.g. online gambling, sports betting, casino players). Assessing MI is foundational for any future research that uses the PSGI, as it is imperative that a survey functions consistently across different groups of people. Without the establishment of MI, valid comparisons between individuals belonging to different groups cannot be made (Schmitt & Ali, 2014).

1.2. The present study

The present study aims to rigorously test the measurement invariance of the PGSI across a range of demographic and gambling-related variables. Specifically, we assessed measurement invariance across sex, age, race, income, and education level, as well as online gambling, sports gambling, and casino gambling status. Then, we compared the latent mean scores across the different groups to determine which groups had higher problem gambling severities.

1.2.1. Demographic variables

Some groups have higher risks of problem gambling than others. When considering demographic variables, Moreira et al. (2023) found that key risk factors for problem gambling vary across gender, age, race, income, and education level, which are consistent with previous literature (Cookman & Weatherly, 2016; Fluharty et al., 2022; Hing et al., 2016; Shead et al., 2010; Williams et al., 2021). We will test the measurement invariance across these demographic groups, as it is essential for measurement tools to be invariant across groups to ensure the validity and reliability of intergroup comparisons. Given the results in the extant literature, we expect to see that the latent means are higher for younger individuals, males, minorities, low income earners, and low educational level.

1.2.2. Gambling modalities

Similar to the various demographic-related risk factors, evidence indicates increased risks for problem gambling as it relates to different segments of gamblers, particularly online, casino, and sports gamblers. Much of the literature concerning problem gambling in online settings suggests that online gamblers have higher problem gambling severity and prevalence rates when compared to other groups of gamblers (Gainsbury, 2015; Wardle et al., 2011). This is also the case with sports bettors, which have been found to have significantly higher problem gambling prevalence rates than the general population (Grubbs & Kraus, 2023; Lopez-Gonzalez et al., 2020; Winters & Derevensky, 2019). In fact, in a survey study conducted using data collected from Bwin, 27% of the sports bettors were classified as having gambling-related problems (LaPlante et al., 2014). Casino gamblers have higher problem gambling severity and prevalence rates (Fisher, 2000; Welte et al., 2007, 2009), likely due to the large number of different gambling opportunities as well as the structural characteristics of the casino that induce gambling (Thomas et al., 2011). With the continued growth of the online, sports, and casino gambling industries (Moreira et al., 2023; Polaris Market Research, 2022; US Census Bureau, 2020), it is imperative that researchers have validated and reliable instruments when conducting research in these new frontiers. For this reason, we tested the measurement invariance of the PGSI across the different gambling modalities. Furthermore, based on previous literature, we expect online gamblers, sports gamblers, and casino gamblers to have higher latent mean scores of problem gambling severity.

2. Material and methods

2.1. Sample

This study was preregistered online with the Center for Open Science in line with best practices for preregistrations (Nosek et al., 2018). The preregistration documentation can be found at: https://osf.io/jszkt/?view_only=fc68e5f3b8514f22bf0ea14938906379.

We used two samples from a previous study conducted by Grubbs and Kraus (2022, 2023). Both samples were drawn based on a random hypothetical sample from the 2019 American Community Survey and were census-matched and weighted to the sampling frame using propensity scores. The first sample of US adults was of 2,806 respondents (response rate = 87.6%), and the second sample of sports-wagering adults was of 1,557 respondents (response rate = 78.7%).

Each sample contained demographic information (age, income, gender, education, race, etc.), modalities of gambling played (sports, online, casino), and responses to the nine questions of the PGSI. When collecting the data, the PGSI was only administered to the participants that had gambled before, so respondents who were not gamblers were excluded from the dataset. After exclusion of non-gamblers, there were no missing values.

2.2. Measurement groups

We tested MI across different groups of five demographic variables and three variables related to gambling modalities. The demographic variables tested were gender, age, income, education level, and race due to the increased risk for members of certain groups – for example, men, younger adults, less educated, lower income, and non-Whites (Williams et al., 2021). Similarly, MI was tested over different types of gambling modalities: mixed vs. offline gambling, sports gamblers vs. non-sports gamblers, and casino goers vs. non-casino goers. Like the demographic variables, these variables have been associated with increased risks of problem gambling (Allami et al., 2021; Jenkinson et al., 2018; Welte et al., 2007).

As displayed in Table 1, the dataset consisted of $n = 2{,}972$ gamblers, which was made up of 1,712 (57.6%) men and 1,260 (42.4%) women. The original survey captured participant's birth year, which was used to calculate the age of the participant on 31 December 2019. Following Hitcham et al. (2023), age was then binned into three groups: younger adults (18–34 years old), middle-aged adults (35–59 years old), and older adults (60+). Income was categorized into low-income or non-low income based on whether or not the income was below the second quintile of US household income (Kochhar & Sechopoulos, 2022). Education data was categorized into three groups: high school or less, some college, and college graduate or post-graduate. Race was re-categorized from eight different race categories into white and nonwhite.

The demographic variables were modified from their original form of measurement and condensed into groups to increase model convergence rates. The issue could have been addressed in two ways: (1) condensing the variables into less subgroups (e.g. less categories for age) or (2) condensing the Likert scale of the survey for one of the questions that does not have an extreme response (e.g. merging items 4 and 5 into one on a 1–5 Likert scale). Because the approaches to

Table 1. Sample characteristics.

	Characteristic	Count	Percent
Gender			
	Male	1712	57.6
	Female	1260	42.4
Age			
	18–34	572	19.25
	35–59	1378	46.37
	60+	1022	34.39
Race			
	White	2048	68.91
	Non-white	924	31.09
Education			
	High school or less	801	26.95
	Some college	894	30.08
	College grad or Post-grad	1277	42.97
Income			
	Lower class	968	32.57
	Not lower class	1789	60.2
Online Gambling			
	Mixed	1335	44.92
	Offline	1637	55.08
Sports Gambling			
	Sports gambler	1492	50.2
	Non-sports gambler	1480	49.8
Casino Gambling			
	Casino gambler	2480	83.45
	Non-casino gambler	492	16.55
PGSI			
	Non-problem gambling (0)	1418	47.71
	Low Risk (1–2)	626	21.06
	Moderate Risk (3–7)	370	12.45
	High Risk (8+)	558	18.78

testing MI across many groups are subject to scalability issues, groups are often condensed such that less groups are studied (Muthén & Asparouhov, 2018). Condensing the Likert scale comes at a loss of information but is advantageous in the case of skewed and/or sparse data when it comes to estimation of the model through Weighted Least Squares Mean Variance (WLSMV) as well as model convergence rates (DiStefano et al., 2021). For this study, the groups were condensed in such a way that is consistent with the way that risk factors are studied in the general population (e.g. young-, middle-, and older-age). The Likert scale was not modified in any way.

2.3. Instrument

To assess the degree and prevalence of problem gambling, respondents were administered the PGSI. Respondents were asked to answer each of the nine items on the PGSI on a 4-point scale ranging from 0 to 3 (0 = *Never*, 1 = *Sometimes*, 2 = *Most of the time*, 3 = *Almost always*) and were categorized into the following four groups based on the sum of their responses: non-problem gambling (0), low risk of problem gambling (1–2), moderate risk of problem gambling (3–7), or high risk of problem gambling (8 or more). The sample in this study had a high internal consistency ($\alpha = 0.945$) with respect to the PGSI.

2.4. Data analysis

All data analysis and MI testing was conducted in R using the lavaan (Rosseel, 2012) and SEMTools (Jorgensen et al., 2025) packages. Then, to confirm the structure and assess the MI, factor analyses were conducted on the PGSI data. All nine of the PGSI items were loaded onto a single factor in the CFA models. Additionally, estimation was done using the theta parameterization, robust maximum likelihood estimation based on WLSMV, and freely estimated error variance. The theta parameterization was used instead of the delta parameterization in order to test residual invariance (Muthén & Asparouhov, 2002). WLSMV was used as it yields more accurate fit indices and factor loading estimates, better accounts for non-normality, and performs better with small and uneven sample sizes (Beauducel & Herzberg, 2006).

First, the unidimensional models were fit without any restriction for the full sample and for each subgroup to assess goodness-of-fit of the measurement model for each group individually (see supplementary materials). Then, MG-CFA was conducted with different levels of restrictions to test for measurement invariance.

The tests for different invariance types were done in the order of least to most restrictive, such that configural invariance was evaluated first, then threshold and metric invariance, and finally residual invariance. Four levels of invariance are tested: (1) *configural*, equivalence of model form, (2) *threshold*, equivalence of thresholds, (3) *metric*, equivalence of factor loadings, and (4) *residual* equivalence of the residuals of the items (Putnick & Bornstein, 2016). We did not test scalar invariance, as scalar invariance is automatically satisfied under the theta parameterization after threshold and metric invariance are established (Wu & Estabrook, 2016).

Non-invariance at the configural level indicates that the groups conceptualize problem gambling differently, which would render any comparisons of means or variance invalid. At the metric level, non-invariance means that the PGSI items used to measure problem gambling do not have the same level of importance or meaning across groups. In the case of threshold invariance, non-invariance implies that the ordinal response categories of the PGSI items do not correspond to the same level of the problem gambling trait across groups. Finally, non-invariance at the residual level suggests that the amount of measurement error associated with the items differs across groups (Pendergast et al., 2017). While residual invariance has been considered an optional step for testing measurement invariance since it does not have any direct consequences for latent mean comparisons (Leitgöb et al., 2023), we tested it because violations of measurement invariance can be masked by unequal residual variances across groups (Lubke & Dolan, 2003).

2.5. Evaluation criteria

To evaluate the performance of the multiple-group confirmatory factor analysis (MG-CFA) fit measures, we followed the operational procedure of Hitcham et al. (2023). Invariance was tested in the following order: configural, threshold, metric, and finally residual. The fit indices were then compared between the models with differing constraints to determine whether each degree of restriction increased misfit.

CFA model fit is often evaluated by chi-squared tests, where a significant result indicates poor fit. But because larger sample sizes often inflate chi-square statistics

(Bollen, 1989), we followed the guidelines for other means of evaluation. Following Chen (2007) and Sass et al. (2014), we considered changes in Comparative Fit Index (CFI; Bentler, 1990) less than or equal to 0.010 and changes in root mean square error of approximation (RMSEA; Steiger, 1980) less than or equal to .015 as reasonable evidence of invariance. Additionally, the CFI and the Tucker-Lewis Index (TLI) should be no smaller than .950, RMSEA should be no larger than .050, and square root mean residual (SRMR; Bentler, 1995) should be no larger than .080 (Chen, 2007; Sass et al., 2014). Due to the potential for inconsistency in type I error rates in using the change in TLI and SRMR as cutoffs, we followed the recommendations of Sass et al. (2014) and chose smaller-than-normal cutoff thresholds for their deltas, using .01 as the cutoff for the change in the metric across measurement models.

2.6. Ethics statement

This work involved secondary analysis of existing, de-identified data and did not meet the criteria for human subjects research. It was therefore exempt from IRB review.

3. Results

3.1. Confirmatory factor analysis (CFA)

In general, the results established strong MI in the PGSI across the various groups measured. As shown in Table 2, there was strong support for MI across the different levels of each variable. CFI and RMSEA were below their respective thresholds and showed very little change across the different measurement models. Similarly, TLI and SRMR showed miniscule differences across all levels of model restrictions. None of these metrics exceeded their respective thresholds when considering the demographic or gambling modality variables. This indicates that there is strong support for MI across all categories of the tested groups, both for demographic and gambling modality variables.

3.1.1. Latent means analysis

Since measurement invariance was established across the groups of interest, latent mean differences were examined using the metric invariant models. The results, presented in Table 3, show variations in problem gambling severity across demographics and gambling modalities. In terms of demographic differences, latent means were relatively similar between men and women, with males (1.4206) and females (1.4363) reporting nearly identical levels of problem gambling severity. However, more pronounced differences emerged across age groups, with younger adults (18–34) exhibiting higher latent means (1.4245) compared to middle-aged adults (35–59; 1.2084), while older adults (60 +) had the highest latent mean (1.8374). Racial differences were also evident, with nonwhite gamblers reporting a higher latent mean (1.6483) than white gamblers (1.3311). In contrast, income and education levels showed minimal variation, with latent means remaining relatively stable across different socioeconomic groups. Among gambling modality groups, online gamblers (1.6996) and sports gamblers (1.5818) had notably higher latent means than their non-online (1.2095) and non-sports (1.2764)

Table 2. Measurement invariance testing results.

Invariance Test	CFI	△ CFI	TLI	△ TLI	RMSEA	△ RMSEA	SRMR	△ SRMR
Gender								
Configural	0.9992		0.9989		0.0319		0.0101	
Threshold	0.9991	0.0001	0.999	0.0001	0.0307	0.0012	0.0101	-
Metric	0.9993	0.0002	0.9993	0.0003	0.0266	0.0041	0.0101	-
Residual	0.9991	0.0002	0.9993	-	0.0263	0.0003	0.0116	0.0015
Age								
Configural	0.9986		0.9982		0.0366		0.0152	
Threshold	0.9973	0.0013	0.9971	0.0011	0.0463	0.0097	0.0152	-
Metric	0.9975	0.0002	0.9977	0.0006	0.0413	0.0050	0.0153	0.0001
Residual	0.9963	0.0012	0.9973	0.0004	0.0445	0.0032	0.0216	0.0063
Race								
Configural	0.9991		0.9988		0.0323		0.0102	
Threshold	0.9987	0.0004	0.9985	0.0003	0.036	0.0037	0.0102	-
Metric	0.9988	0.0001	0.9988	0.0003	0.0325	0.0035	0.0103	0.0001
Residual	0.9987	0.0001	0.999	0.0002	0.0301	0.0024	0.0122	0.0019
Income								
Configural	0.9989		0.9986		0.0374		0.0115	
Threshold	0.9987	0.0002	0.9985	0.0001	0.0382	0.0008	0.0115	-
Metric	0.9988	0.0001	0.9988	0.0003	0.0345	0.0037	0.0115	-
Residual	0.9991	0.0003	0.9993	0.0005	0.0262	0.0083	0.0128	0.0013
Education								
Configural	0.9991		0.9988		0.0346		0.0121	
Threshold	0.9991	-	0.999	0.0002	0.0312	0.0034	0.0121	-
Metric	0.9992	0.0001	0.9992	0.0002	0.0277	0.0035	0.0122	0.0001
Residual	0.9993	0.0001	0.9995	0.0003	0.0222	0.0055	0.0146	0.0024
Online Gambling								
Configural	0.9987		0.9983		0.0338		0.0141	
Threshold	0.9983	0.0004	0.9981	0.0002	0.0356	0.0018	0.0141	-
Metric	0.9983	-	0.9983	0.0002	0.0335	0.0021	0.0142	0.0001
Residual	0.9974	0.0009	0.9978	0.0005	0.0379	0.0044	0.0214	0.0072
Sports Gambling								
Configural	0.9989		0.9986		0.0343		0.0112	
Threshold	0.9988	0.0001	0.9986	-	0.0335	0.0008	0.0112	-
Metric	0.9987	0.0001	0.9986	-	0.0332	0.0003	0.0112	-
Residual	0.9985	0.0002	0.9987	0.0001	0.032	0.0012	0.0157	0.0045
Casino Gambling								
Configural	0.9991		0.9988		0.0342		0.0109	
Threshold	0.9992	0.0001	0.9991	0.0003	0.0305	0.0037	0.0109	-
Metric	0.9992	-	0.9991	-	0.0295	0.0010	0.0109	-
Residual	0.9992	-	0.9993	0.0002	0.0265	0.0030	0.013	0.0021

The table shows the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the root mean squared error of approximation (RMSEA), the square root mean residual (SRMR) and the respective change in each across measurement models. The differences in the fit measures with each restriction on the model should be less than their respective threshold.

counterparts, while casino gamblers (1.3963) and non-casino gamblers (1.4363) had comparable latent means.

To assess these differences further, latent mean comparisons were conducted for each variable by fixing the thresholds of the first PGSI item at 1, and freely estimating the intercept for the latent mean. There were no significant differences in problem gambling severity between men and women (b = −0.0157, se = 0.0295, Z = −0.5326, p = 0.5943), nor between individuals with different income levels (b = −0.0063, se = 0.0319, Z = −0.1983, p = 0.8428) or educational backgrounds (all p-values >0.05). In contrast, younger adults (18–-34) had significantly higher problem gambling severity than middle-aged adults (35–59; b = 0.2161, se = 0.0266, Z = 8.1242, $p < 0.001$), while those 60 and older reported significantly lower levels than both younger groups (b = −0.6290, se = 0.0459, Z = −13.6892, $p < 0.001$ for

Table 3. Latent means analysis results.

	Variable	Estimate	Std. Error	Z-score	P-value
Gender					
	Male	1.42	0.02	63.80	0.0000
	Female	1.43	0.02	74.37	0.0000
	diff: Male - Female	−0.01	0.03	−0.53	0.5943
Age					
	18–34	1.42	0.02	66.83	0.0000
	35–59	1.21	0.02	75.92	0.0000
	60–120	1.84	0.04	42.63	0.0000
	diff: 18–34–35–59	0.22	0.03	8.12	0.0000
	diff: 35–59–60+	−0.63	0.05	−13.69	0.0000
	diff: 18–34–60+	−0.41	0.05	−8.59	0.0000
Race					
	White	1.33	0.01	86.66	0.0000
	Non white	1.65	0.03	52.97	0.0000
	diff: White - non white	−0.32	0.03	−9.14	0.0000
Income					
	Non low income	1.44	0.02	57.41	0.0000
	Low income	1.45	0.02	74.21	0.0000
	diff: Non low income - low income	−0.01	0.03	−0.20	0.8428
Education					
	High school or less	1.42	0.02	62.73	0.0000
	Some college	1.43	0.03	55.01	0.0000
	College grad or more	1.44	0.03	51.53	0.0000
	diff: High school or less - Some College	−0.01	0.03	−0.14	0.8902
	diff: High school or less - College grad +	−0.02	0.04	−0.48	0.6358
	diff: Some college - College grad +	−0.01	0.04	−0.32	0.7474
Online Gambling					
	Non online	1.21	0.01	88.63	0.0000
	Online	1.70	0.03	65.38	0.0000
	diff: Non online - online	−0.49	0.03	−16.69	0.0000
Sports Gambling					
	Non sports gamblers	1.28	0.02	78.57	0.0000
	Sports gamblers	1.58	0.02	67.21	0.0000
	diff: Non sports gambler - sports gambler	−0.31	0.03	−10.68	0.0000
Casino Gambling					
	Non casino gambler	1.44	0.02	90.07	0.0000
	Casino gambler	1.39	0.04	38.66	0.0000
	diff: Non casino gambler - casino gambler	0.05	0.02	1.01	0.3116

The table shows the latent means of the different groups of each variable as well as the mean difference comparisons between different groups.

35–59 vs. 60+). Non-white gamblers had significantly higher problem gambling severity compared to white gamblers (b = −0.3172, se = 0.0347, Z = −9.1412, $p < 0.001$). Gambling modality differences were also notable, with online gamblers reporting significantly higher problem gambling severity than non-online gamblers (b = −0.4901, se = 0.0294, Z = −16.6915, $p < 0.001$), and sports gamblers having significantly higher severity compared to non-sports gamblers (b = −0.3054, se = 0.0286, Z = −10.6802, $p < 0.001$). However, casino gambling did not significantly differentiate problem gambling severity (b = 0.0399, se = 0.0395, Z = 1.0119, $p = 0.3116$). Overall, the results suggest that younger adults, minorities, online gamblers, and sports gamblers show higher problem gambling severity.

4. Discussion

The current study evaluated the MI of the nine-item PGSI with a census-matched sample of 2,972 US adults to determine the validity and reliability of the PGSI when making comparisons between different population segments. The results indicate that the PGSI was measurement invariant among the measurement groups at all four levels of MI (configural, threshold, metric, and residual).

The MI of the PGSI across the various demographic variables is consistent with previous MI studies. Specifically, the results were consistent with those of previous studies on MI across gender, age, income, and education level (Boldero & Bell, 2012; Hitcham et al., 2023; Maitland & Adams, 2007; Miller et al., 2013). Additionally, this study is the first to demonstrate MI across race (i.e. Whites and non-Whites), providing assurance of the validity of past and future PGSI studies that consider race in the context of GD. The lack of significant variance in the factor structure between demographic groups suggests that the construct of problem gambling is consistently measured across all groups, which supports the use of the PGSI to compare prevalence and severity rates between populations.

This study also extended the PGSI MI literature by analyzing MI across different gambling modalities. Most extant research has focused on demographic variables for testing MI, except for Miller et al. (2013), who tested MI across those who played EGMs or casino games and those who did not. This study further validated the MI of the PGSI among casino gamblers and non-casino gamblers, while also extending the literature to validate the PGSI's MI for other gambler types (e.g. sports bettors and online gamblers). MI was also confirmed for the PGSI across online gamblers and non-online gamblers as well as between sports bettors and non-sports bettors. Problem gambling will remain a key focus of research efforts as the online gambling and sports wagering industries continue to expand, particularly since online gamblers and sports bettors have higher prevalence rates for problem gambling (Etuk et al., 2022). The results also support the claim that the PGSI remains the gold standard for assessing problem gambling and ensures that it is reliable when comparing prevalence rates, risk factors, and other characteristics of respective populations.

The results of the latent means analysis partially align with previous findings. As expected, younger individuals and nonwhite participants exhibited higher problem gambling severity, reinforcing prior research on demographic risk factors (Moreira et al., 2023). However, contrary to expectations, differences based on gender, income, and education were not significant, suggesting that their influence on problem gambling severity may be more nuanced than previously assumed (Shead et al., 2010; Williams et al., 2021). Findings on gambling modalities were consistent with previous studies, with online gamblers and sports bettors exhibiting significantly higher problem gambling severity (Gainsbury, 2015; Grubbs & Kraus, 2023; Wardle et al., 2011). In contrast, no significant difference was found between casino and non-casino gamblers, diverging from studies suggesting higher problem gambling severity associated with casino play (Welte et al., 2007, 2009). These findings emphasize the need for continued validation and assessment of problem gambling measures as gambling behaviors evolve.

4.1. Limitations and future research

This study is not without its limitations, which should be considered when interpreting the current findings. First, the study does not test the MI of standalone games (e.g. lottery vs. table games vs. EGMs). This stemmed from two challenges: convergence rates in the

CFA model and limitations due to the secondary analysis. The convergence issues with the confirmatory factor analysis arose from low numbers of participants with greater PGSI scores, meaning that it was not possible to separate out more precise groups to analyze without combining Likert scale categories. This would have resulted in a loss of information. Because the study relied on secondary analysis of survey data, the variables and items were not always specific enough to create independent groups. For example, some questions were too vague and did not isolate single gambling modalities with some of the questions asked (playing EGMs, playing table games, playing at casinos). As outlined by Hitcham et al. (2023), an area of future research could be to test the MI of the PGSI over specific types of gambling.

While this is the first study that evaluates the PGSI across different racial groups and gambling modalities, one of the limitations is that this study lacks evaluation across specific subgroups. Despite minorities having a higher risk of GD (Okuda et al., 2016), this study did not look at the MI of the PSGI across specific races, solely across white and nonwhite populations. Future research could add more granularity to our results by assessing the MI of the PGSI across specific racial groups. Similarly, this study only evaluated the MI of the PGSI across those who participated in a particular gambling modality and those that did not, meaning that specific subgroups were not tested. Future research may seek to test the MI of the PGSI across bettors of different sports (e.g.: e-sports vs. traditional sports), different online gaming platforms, or different casino types.

This study evaluates the single factor version of the PGSI, yet there has been novel research that suggests the use of a two-factor structure for the PGSI (Cooper & Marmurek, 2023; James et al., 2024; Tseng et al., 2023). Although the two-factor model of the PGSI has been found to have a superior fit over the one-factor model, there is no consensus as to which is better as the two-factor model yielded divergent factor validity (Tseng et al., 2023). Future research could psychometrically evaluate the two-factor model or compare the fits between the models for gambling modality variables.

Another limitation to this study was that the results were from one-way comparisons of the indicators. Other than the study done by Gorenko et al. (2022) that proved the MI of the PGSI across different genders among older adults, there are no studies that look at two-way interactions of indicators for MI (e.g. male sports bettors and female sports bettors). Further research to understand the intersectionality of high-risk groups or activities would be extremely valuable. Similarly, it may be interesting to study the MI of the PGSI over time and/or over groups interacted with time. There has been no study to date that tests the MI of the PGSI over time, which would be critical for longitudinal studies on problem gambling. Finally, it would be interesting to perform a latent mean analysis to quantitatively measure differences in problematic gambling behavior across the different groups.

5. Conclusions

In this study, we evaluated the MI of the PGSI for its use across different sub-populations using a nationally representative sample of the United States population. We established strict MI across demographic (age, gender, income, education, and race) and gambling-modality related variables (online, sports, casino gambling). Latent differences within these groups were partially consistent with previous studies in the sense that problem gambling severity was associated with young adults, minorities, online gambling, and sports gambling. However, these latent differences differed from the literature in not picking up any significant difference in problem gambling severity across gender, income level, education level, and casino gambling. Based on the findings of the study, we maintain that the PGSI has the same psychometric properties across different populations, ensuring its reliability and validity for studying problem gambling.

Disclosure statement

Over the past three years, Mana Azizsoltani has either worked on projects funded by or has personally recieved funding, honoraria, travel reimbursement, or consulting fees from AXES.ai, Walker Digital Table Systems, Melco Resorts, Crown Melbourne, Inspire Resort, Bally's Resorts, the Nevada Council on Problem Gambling, and the Nevada Department of Health and Human Services. None of these entities had any role in the design, analysis, or interpretation of the present study and imposed no constraints on its publication.

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Data availability statement

The data used in this study would be made available upon reasonable request.

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