




Using Artificial Intelligence Algorithms to Predict Self-Reported Problem Gambling Among Online Casino Gamblers from Different Countries Using Account-Based Player Data

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Abstract

The prevalence of online gambling and the potential for related harm necessitate predictive models for early detection of problem gambling. The present study expands upon prior research by incorporating a cross-country approach to predict self-reported problem gambling using player-tracking data in an online casino setting. Utilizing a secondary dataset comprising 1743 British, Canadian, and Spanish online casino gamblers (39% female; mean age=42.4 years; 27.4% scoring 8+ on the Problem Gambling Severity Index), the present study examined the association between demographic, behavioral, and monetary intensity variables with self-reported problem gambling, employing a hierarchical logistic regression model. The study also tested the efficacy of five different machine learning models to predict self-reported problem gambling among online casino gamblers from different countries. The findings indicated that behavioral variables, such as taking self-exclusions, frequent in-session monetary depositing, and account depletion, were paramount in predicting self-reported problem gambling over monetary intensity variables. The study also demonstrated that while machine learning models can effectively predict problem gambling across different countries without country-specific training data, incorporating such data improved the overall model performance. This suggests that specific behavioral patterns are universal, yet nuanced differences across countries exist that can improve prediction models.

Keywords Responsible gambling · Responsible gambling tools · Problem gambling · Problem Gambling Severity Index · PGSI · Machine learning · Artificial intelligence

Introduction

Online gambling involves an activity where money is wagered on the internet and can involve a wide variety of games (e.g., sports betting, poker, slots, and lotto). Such gambling can take place on personal computers, smartphones, or any other device which is connected to the internet. Over the past decade, online gambling has become more popular and widespread, leading to diverse regulatory landscapes across different countries (Selin,

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2019). For example, in the United States, the regulatory framework differentiates between online sports betting and online casino gambling, commonly known as iGaming (Holden & Edelman, 2020). These frameworks are crucial not only for regulating the industry, but also for monitoring how the increasing accessibility of online gambling affects the prevalence of problem gambling.

Prevalence of Problem Gambling Among Online Gamblers

As the present study investigated self-reported problem gambling of online gamblers across different countries, this section highlights recent research regarding the prevalence of problem gambling among these populations. Several studies have reported a higher risk prevalence of problem gambling among online gamblers (e.g., Chóliz, 2016; Elton-Marshall et al., 2016; Hing et al., 2017). Hing et al. (2022) compared land-based-only gamblers (LBOGs), online-only gamblers (OOGs), and mixed-mode gamblers (MMGs), using data from a 2019 Australian national telephone survey ($N=15,000$). MMGs had the highest gambling involvement, gambling problems, and gambling-related harm. Relative risk of gambling problems for MMGs exceeded that of both LBOGs and OOGs. The study found that engaging in more gambling forms, being male, being single, being less educated, being indigenous, and speaking a non-English language increased the risk of problem gambling. Gambling on the internet (OOGs and MMGs combined) was associated with a higher problem gambling severity than land-based-only gambling.

Mora-Salgueiro et al. (2021) conducted a meta-study of prevalence, comorbidities, and/or demographics of online disordered gambling using studies in the *Medline* database. There was a large variation in the prevalence of problem gambling (2.7% to 20.3%) reported by the selected studies. Prevalence rates of at-risk and disordered gambling among adolescents ranged from 5.7% to 57.52%. Being male and single were the most common risk factors among online gamblers with disordered gambling.

Tomei et al. (2022) collected survey responses from 1869 young males in Switzerland about offline and online gambling behaviors, as well as the severity of problem gambling. Compared to a previous study (Tomei et al., 2015), which reported that 16% of the participants gambled online during the past 12 months, Tomei et al. (2022) reported that 24% of participants gambled online. Moreover, 70% of online gamblers reported using the smartphone to access internet gambling sites. The study also found that compared to those without gambling problems, those at-risk and those with gambling problems had higher prevalence rates of online gambling. The proportion of those at-risk or with gambling problems was approximately twice of those without problems among online-only gamblers.

The Use of Account-Based Data in Problem Gambling Research

Online gambling operators record every bet, win, deposit, and withdrawal, and therefore have objective data concerning each player's money and time expenditure, as well as data on every game played. For two decades, researchers have emphasized the potential of player tracking as a method of detecting problematic gambling in online gambling settings (Catania & Griffiths, 2021; Finkenwirth et al., 2021; Griffiths & Parke, 2002; Haeusler, 2016; Hancock et al., 2008). One way of assessing problem gambling among online gamblers is for operators to collect responses to a problem gambling screen from a sample of their gamblers. However, this involves substantial effort. Therefore, researchers frequently

use voluntary self-exclusion as a proxy measure for problem gambling as it is always recorded and readily available for analysis.

A number of studies have used voluntary self-exclusion as a proxy measure for problem gambling (Hopfgartner et al., 2023; Nower & Blaszczynski, 2006a; Percy et al., 2016). The underlying assumption is that gamblers who voluntarily self-exclude are problem gamblers. An algorithm that detects gambling patterns which precede voluntary self-exclusion could then be used to identify problem gamblers. This would then allow gambling operators to interact with these players. Self-exclusion is a very common responsible gaming tool, and most regulated markets require licensed online gambling operators to offer voluntary self-exclusion (Catania & Griffiths, 2023). This might also be a reason for the relatively large number of studies which have used voluntary self-exclusion as a proxy measure for problem gambling. Moreover, a few studies have used machine learning algorithms to analyze correlations between voluntary self-exclusion and preceding gambling behavior using player-tracking data (e.g., Finkenwirth et al., 2021; Hopfgartner et al., 2023).

Finkenwirth et al. (2021) used 20 variables, including gambling frequency, intensity, and variability to predict self-exclusion using player-tracking data. The study found that the variability in the amount of money wagered per session was the most important predictor of self-exclusion. This variable captured betting patterns with significant fluctuations in bet amounts, indicative of problematic gambling behaviors (e.g., loss chasing). The second most important predictor was the number of bets per day. The performance of the machine learning models varied between 65% and 76%, demonstrating the efficacy of player-tracking data in identifying individuals who might experience problem gambling.

Hopfgartner et al. (2023) applied hierarchical regressions using behavioral and monetary metrics. In the first step, behavioral variables, such as the type of payment method, frequency of deposits, session length, and number of game types, were used. In the second step, monetary metrics, such as the amount of money lost, deposited, or withdrawn, were added. Interestingly, very few of the monetary metrics significantly improved the model quality. The same study also reported that the number of voluntary limit changes, previous voluntary self-exclusions, number of deposits per session, number of different payment methods, and playing multiple types of games were predictive of future voluntary self-exclusion. The fact that the monetary variables were less important could reflect differences in the financial backgrounds of individual gamblers. For some gamblers, spending \$1000 a month might be easily affordable whereas for others, spending just \$100 per month might not be affordable.

Griffiths and Auer (2016) have argued that there can be some issues when voluntary self-exclusion is used as a proxy measure for problem gambling in player tracking studies. This is because not all gamblers who self-exclude are problem gamblers and not all problem gamblers self-exclude. After analyzing a sample of 7732 gamblers who voluntarily self-excluded in a 90-day period, Catania and Griffiths (2021) concluded that this group was heterogeneous and therefore not a reliable proxy measure for problem gambling. More specifically, 19% of the gamblers played for less than 24 h before self-excluding and 50% of the gamblers played for less than a week before self-excluding. These findings suggested that gamblers were self-excluding for reasons other than problem gambling.

Combining Self-Reported Problem Gambling and Player-Tracking Data

Given that voluntary self-exclusion among online gamblers is a sub-optimal proxy measure of problem gambling, responses to standardized questionnaires on problem gambling have to be collected. The correlation between actual player-tracking data and self-reported

gambling behavior can provide insight into the behavioral predictors of self-reported problem gambling. Five player tracking studies have used self-reported problem gambling to predict problem gambling using player-tracking data (Auer & Griffiths, 2023a; Louderback et al., 2021; Luquiens et al., 2016; Murch et al., 2023; Perrot et al., 2022). All five studies collected self-reported problem gambling data using a problem gambling screen (e.g., PGSI, Ferris & Wynne, 2001) and correlated the self-report results with objective player tracking data. The resulting statistical models predicted the likelihood of a player being a self-reported problem gambler.

Murch et al. (2023) had access to the responses of the PGSI from 9145 adults (aged 18+ years) who played on *lotoquebec.com*. The website offers lottery, casino, and sports-betting products. The player-tracking data included time and money expenditure as well as responsible gambling (RG) tool use for the 12 months preceding the completion of the PGSI (using a 5+ score to indicate at-risk gambling and 8+ to indicate problem gambling). The final model retained 10 explanatory variables, including younger age and repeated depositing over a weekly period following a bet. The other significant variables were based on the amount of money bet and amount withdrawn. However, they did not examine any session explanatory variables which were based on gambling sessions. Their overall model had an area under the curve (AUC) of 84%. Although this was an impressive finding, it could also have been the result of a large number of inactive players in the final sample. More specifically, gamblers only needed to have at least one bet in the 12 months preceding the completion of the PGSI. Players with high PGSI scores most likely gambled shortly before answering questions on the PGSI, and players with low PGSI scores most likely gambled very little or not at all in the weeks before completing the PGSI. This means that any activity before completing the PGSI most likely contributed largely to the high model accuracy.

Perrot et al. (2022) collected PGSI responses from 8172 French online sports bettors and poker players, as well as 5404 online scratch-card and lottery players. Like Murch et al. (2023), they used the same PGSI scoring. The AUC values which reflect model quality were 83% and 74% for the two samples. Player-tracking features (e.g., amount of money lost, deposited, wagered, gambling days, and number of bets) were computed for the 4 months preceding the PGSI completion, and only participants who showed any gambling activity in the 30 days before were included. Chasing losses was operationalized as “*making three deposits in less than 12 h*” or “*making a deposit less than 1 h after placing a bet*” (Perrot et al., 2022, p. 3). Perrot et al. argued that a repeated sequence of deposits or a deposit that quickly followed a bet may reflect cases where gamblers lose all the remaining money on their account, and then try to recover the losses by depositing money. However, Perrot et al.’s study did not include online casino gamblers because it was limited to sports bettors, poker players, and lottery players. Casino games typically possess a much higher event frequency, which influences amount of money wagered, amount of money won, as well as the amount of time spent gambling (Auer & Griffiths, 2023d). Therefore, the results cannot be generalized to online casino gamblers.

Luquiens et al. (2016) developed predictive machine learning models based on PGSI responses from 14,261 online poker players. Explanatory variables were computed for the 30 days preceding the completion of the PGSI (using a PGSI score of 5+ for problem gambling). The risk factors of problem gambling reported by the predictive model were being male, being “compulsive” (i.e., defined by having at least three deposits in a 12-h period), being younger than 28 years, making a monetary deposit in the 30 days before completing the PGSI, having a mean loss per gambling session > €1.7, losing a total of > €45 in the last 30 days, having a total stake > €298 in the 30 days before completing the PGSI, having > 60 gambling sessions in the past 30 days, and multi-tabling.

The model quality using the AUC was 72%. However, Luquiens et al.'s study was based on data from online poker players. Given that poker possesses different structural characteristics to other forms of gambling, the findings might not be valid for online casino gamblers (Auer & Griffiths, 2023d).

Louderback et al. (2021) identified low-risk gambling thresholds based on a sample of 1772 online casino gamblers who completed the Brief Biosocial Gambling Screen (BBGS; Gebauer et al., 2010). The BBGS comprises three items which can be answered "yes" or "no." Answering any item 'yes' was considered as an indication for problem gambling. They concluded that a high likelihood of self-reported problem gambling was indicated by wagering €167.97 or more each month, spending more than 6.71% of annual income on online gambling wagers, losing €26.11 or more per month, and demonstrating variability (i.e., standard deviation) in daily amount wagered of €35.14 or more over a 1-month period. In contrast to Murch et al. (2023), Perrot et al. (2022), and Luquiens et al. (2016), Louderback et al. used the BBGS to assess problem gambling among a sample of online gamblers. Dowling et al. (2018) reported that the BBGS adequately detects both problem and moderate-risk, but not low-risk, gambling. Moreover, Auer and Griffiths (2023e) did not find significant correlations between responses to the BBGS and player-tracking data in a sample of 1000 online slot gamblers.

Auer and Griffiths (2023a) were given access to the raw data of 1287 players from a European online gambling casino who answered questions on the PGSI. They used the player tracking data 30 days before completion of the PGSI (using 8+ for problem gambling) to train machine learning models. They found that self-reported problem gamblers lost less money, deposited less money, and bet on fewer days compared to non-problem gamblers in the 30 days before answering the PGSI. However, self-reported problem gamblers self-excluded more often than non-problem gamblers during the 30 days before, which might explain the lower overall activity. Self-reported problem gamblers lost more money per gambling day, lost more money per gambling session, and deposited money more frequently per gambling session. Problem gamblers also tended to deplete their gambling accounts more frequently compared to non-problem gamblers. Auer and Griffiths (2023a) also recommended that online gambling operators should make depositing more than once per day more difficult to prevent players from chasing their losses. However, Auer and Griffiths did not analyze country-specific differences regarding the association between self-reported problem gambling and player-tracking data.

The Present Study

Several European countries (e.g., UK, Germany, Spain, Sweden, Denmark) as well as the province of Ontario in Canada require online gambling operators to assess the risk of problem gambling among their players. However, as aforementioned, the body of research which has correlated self-reported problem gambling with objective gambling behavior is limited (i.e., Auer & Griffiths, 2023a; Louderback et al., 2021; Luquiens et al., 2016; Murch et al., 2023; Perrot et al., 2022). Therefore, the present study attempted to increase the knowledge concerning the association between gambling behavior at an online casino and self-reported problem gambling. To do so, the study utilized a secondary dataset with gamblers from three different countries (i.e., Canada, Great Britain, and Spain). The present study investigated the following three research questions (RQs):

1. What type of account-based tracking behavior correlates with self-reported problem gambling? (RQ1)
2. Can self-reported problem gambling be explained by behavioral variables independent of the actual amount of money spent? (RQ2)
3. Can machine learning models predict self-reported problem gambling across gamblers from three countries? (RQ3)

These research questions aimed to evaluate whether behavioral variables such as the number of deposits per session, the number of payment accounts, or the number of failed deposits were sufficient to predict self-reported problem gambling across online casino gamblers from different countries. This reasoning is because Auer and Griffiths (2023b) predicted high-risk gambling based on the first 7 days of behavior after registration, and found that behavioral variables were responsible for a larger part of model accuracy compared to monetary intensity variables. Therefore, the present study extended previous lines of research by comparing player-tracking data with self-reported problem gambling among players from three different countries to assess the importance of monetary features in identifying self-reported problem gambling. The advantage of using behavioral variables to predict problem gambling is their greater generalizability. Income levels vary across countries, which lead to deviations in monetary measures such as amount of money bet, won, deposited, and withdrawn, impairing the accuracy of prediction models. On the other hand, metrics such as the number of deposits, the number of gambling days, and gambling during the night are independent of income levels, leading to more robust and generalizable statistical models.

Additionally, the present study tested the generalizability of machine learning models to predict self-reported problem gambling among players from different countries. It is important to understand whether such models developed in specific countries can be effectively applied to players from other countries. Such data would likely provide valuable insights into the development of universally applicable responsible gambling tools and policies.

Method

The authors were given access to a secondary dataset comprising British, Canadian, and Spanish online casino gamblers playing a variety of casino games (e.g., slots, roulette, and blackjack) who completed the nine PGSI questions between January 2022 and November 2023. If the PGSI was completed more than once, only the most recent answers were used. The nine PGSI questions are listed in Appendix 1. For each gambler, the raw data 30 days before completing the PGSI were available. Every bet, win, deposit, withdrawal, the type of game played, depositing method, and withdrawal method were included in the data. Additionally, the monetary balance before and after each bet, win, deposit, and withdrawal was recorded. Session length was computed in line with previous research (e.g., Auer & Griffiths, 2023a, 2023b; Hopfgartner et al., 2023). More specifically, if two bets were placed within a 15-min period, the time between was counted as within session. If more than 15 min elapsed between two bets, they were counted as belonging to separate sessions.

Study Design

Each of the nine PGSI items could be answered with “never” (0), “sometimes” (1), “most of the time” (2), and “almost always” (3). Therefore, the maximum score was 27, and the minimum score was 0. Player-tracking features were computed for the 30 days prior to completing the PGSI (mirroring the studies by Auer and Griffiths [2023a] and Luquiens et al. [2016]). The player-tracking features examined are listed in Appendix 2 and are largely in line with those of Auer and Griffiths (2023a). Apart from the demographics (i.e., country, gender, and age in years), the player-tracking features included the total amount of money bet, lost, withdrawn, and deposited 30 days prior to PGSI completion. Monetary aspects can be a crucial aspect in the development of problem gambling (Tabri et al., 2022; Blaszczynski and Nower, 2010). Previous studies have also emphasized the importance of time spent gambling in the development of problem gambling (Lin et al., 2010; Williams et al., 2006). The player-tracking features also included behavioral aspects such as the number of monetary deposits per session and the number of failed deposits (e.g., due to insufficient funds). The number of voluntary limit changes, as well as the number of voluntary temporary self-exclusions, was also included in the data collected. Two metrics (i.e., regular account depletion and frequent depositing) were specifically designed to assess impulsivity as it is a crucial aspect of problem gambling (Nower & Blaszczynski, 2006b).

1. *Regular account depletion*: This was assessed using the percentage of sessions ending with low account balance for each gambler. The authors had access to the account balance before and after each monetary bet, win, deposit, and withdrawal. The authors assumed that individuals with disordered gambling only stop gambling when their online gambling account is depleted. This metric indicates if less than €5 was left in the online gambling account at the end of a session. Furthermore, regular account depletion was identified by Auer and Griffiths (2023c) as a significant indicator of chasing losses.
2. *Frequent deposits*: This was assessed using the average number of monetary deposits per session for each gambler. This metric was also highlighted as a significant indicator of chasing losses by Auer and Griffiths (2023c).

Statistical Analysis

A hierarchical logistic regression was conducted to test the importance of three categories of independent variables, as proposed by Hopfgartner et al. (2023). These were age and gender (i.e., control variables), behavioral variables, and monetary intensity variables. These are listed in Appendix 2. First, three control models were fitted, one for each country, utilizing the control variables and a subsequent stepwise backward elimination process. Given the limited number of groups (i.e., three countries), individual regression models for each country (i.e., no pooling approach) were opted for as opposed to a mixed effects or a multilevel model (i.e., partial pooling approach) as recommended by Gelman and Hill (2006). During the backward elimination, variables with the highest collective p -value (Zaykin, 2011) were sequentially excluded until only variables significant in at least one country remained.

To address RQ1, the authors employed the same methodology, conducting three regressions that included both control and behavioral variables. These models (model RQ1) were then evaluated against the initial control models. To address RQ2, monetary intensity

variables were also added to the models (model RQ2), and comparisons were made with the previous models (model RQ1). A likelihood ratio chi-squared test was used to validate the significance of each feature category and with Akaike's information criteria (AIC) providing additional information concerning potential improvements of the models.

To mitigate potential multicollinearity within the variables, a threshold was set to include only those variables with a variance inflation factor (VIF) below 10 (James et al., 2013). Standardization of all independent variables was performed to facilitate the comparison between models. Coefficients are reported for each model, where negative coefficients indicate a decrease (and positive coefficients an increase) in the probability of self-reported problem gambling. To assess the fit of all models, Nagelkerke's (1991) R^2 is reported, quantifying the explained variance within the models.

To address RQ3, five different machine learning models were trained: AdaBoost, decision trees, extra-trees (extremely randomized trees), gradient boosting, and random forests. To test whether machine learning models generalized to other countries in predicting self-reported problem gambling, each model was trained using data from two countries while reserving the third country for testing. This process allowed every country to function as a test set once to assess how well the models could be applied across countries.

For comparability, the authors also included a baseline model, which used the gamblers' total amount of money deposited within the past 30 days as a direct score for self-reported problem gambling. The rationale for this baseline was to evaluate how such a simple model, which only relied on the total monetary deposits, would compare to a model including more complex behavioral variables. Therefore, the baseline model established a direct correlation, where higher deposits indicated a stronger tendency towards problem gambling. To further evaluate whether incorporating country-specific data during model training improved the overall performance of the prediction, an additional model was trained which included the data of all three countries and performed a 70/30 train-test split on it.

The optimization of hyperparameters for each tree-based model was conducted through a randomized cross-validation search, using a unified parameter space. For parameters such as maximum tree depth and the minimum percentage of samples per leaf, a range was pre-defined, specifically from 2 to 10 for tree depth, and 0% to 10% samples per leaf. The learning rates for gradient boosting and AdaBoost were set within a 0 to 0.5 range. Default parameters from the scikit-learn library (Pedregosa et al., 2011) were applied for any remaining parameters. The performance of all models was reported using the receiver operating characteristic area under the curve (ROC-AUC) values, which indicate the extent to which the models can distinguish between individuals with and without self-reported problem gambling.

Participants

A total of 6352 players completed the nine PGSI questions between January 2022 and November 2023. Figure 1 displays the PGSI score distribution before and after data cleaning. The PGSI score and the respective frequency were negatively correlated (i.e., most gamblers had low PGSI scores). However, before data cleaning, there was strong increase in scoring 27 (the maximum score) on the PGSI. In line with Auer and Griffiths (2023a), it was assumed that this spike was caused by gamblers who did not take enough time and simply rushed through the scale items. Therefore, participants who completed the PGSI in less than 1 min were excluded from the analysis to ensure the reliability of the data, leaving 1743 participants.

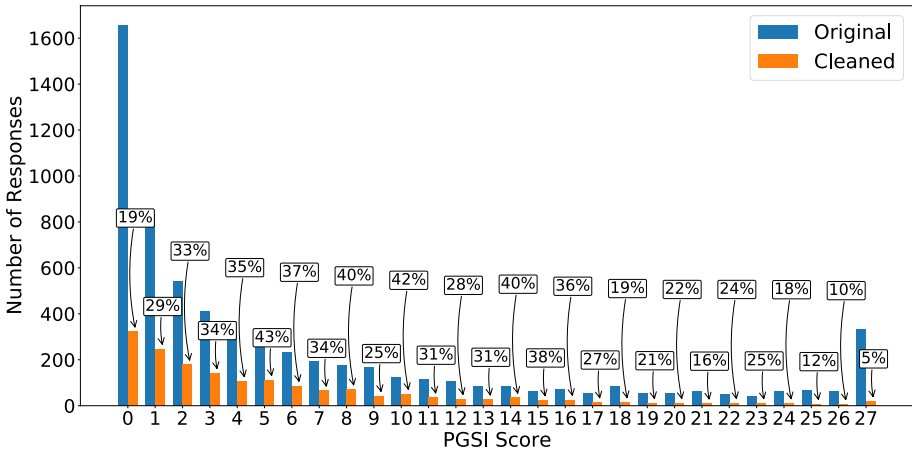


Fig. 1 Distribution of PGSI responses before and after removing participants who completed the PGSI in under a minute. The percentages above the orange bars indicate the percentage of participants which were retained after removing short response times

Less strict variations to this exclusion criterion (e.g., only excluding participants who completed the PGSI in less than 40 s or 50 s) yielded significant, but not practically relevant differences. The 1-min threshold was also empirically supported by the observed data pattern for participants who scored 27 out of 27 on the PGSI. A visible natural gap in completion times around the 1-min mark, as shown in Fig. 2, indicated a difference between participants who engaged thoughtfully with the PGSI survey questions and those who did not. This pattern confirmed the use of this threshold and suggested that responses completed in less than 1 min were unlikely to reflect genuine self-assessment and therefore

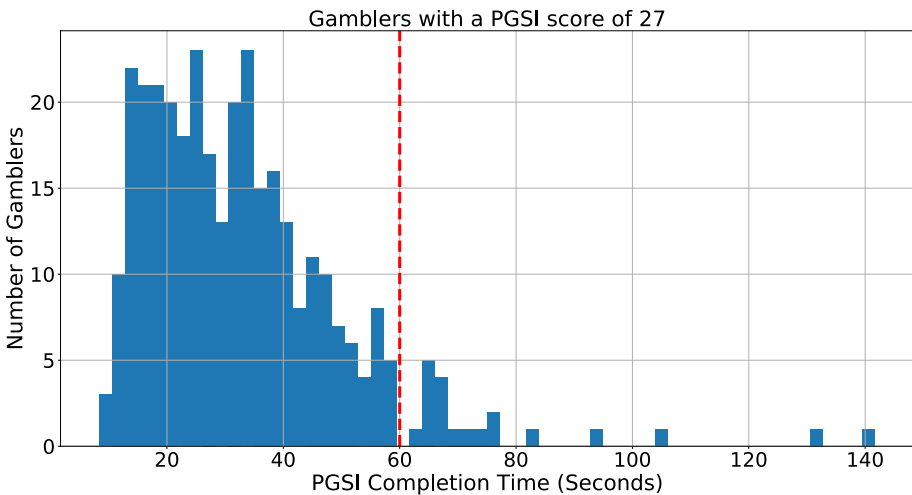


Fig. 2 Distribution of PGSI completion times for gamblers who scored 27 out of 27. A natural gap in completion times around the 1-min mark indicates a separation between gamblers who thoughtfully engaged with the PGSI items and those who likely rushed their responses

indicated a lack of engagement with the PGSI survey questions. Notably, the distribution of scores after this cleaning process shows a stronger reduction in the proportion of participants with extreme scores of 0 and 27, supporting the hypothesis that these responses were likely hasty and uniformly answered with the same response, indicating a potential bias in the validity of their data.

Table 1 presents a comparative overview of gambling statistics by the participants across the three countries (Canada, Spain, GB) in the dataset. Canadian gamblers comprised 6.0% of the sample, with a mean PGSI score of 7.11, and 35.2% having a PGSI score equal or above 8 (indicating problem gambling). The mean age of Canadian gamblers was 45.9 years, and the proportion of female gamblers was 40.0%. British gamblers comprised 73.7% of the sample, with a mean PGSI score of 5.47, and 26.4% having a PGSI score of equal or above 8. The mean age of British gamblers was 43.5 years, and the proportion of female gamblers was 41.8%. Spanish gamblers comprised 20.3% of the sample, with an average PGSI score of 5.67, and 28.9% having a PGSI score of equal or above 8. The mean age of Spanish gamblers was 37.3 years, and the proportion of female gamblers was 28.3%. Overall, the mean PGSI score across the total sample of gamblers was 5.61, and 27.4% having a PGSI score of equal or above 8. The mean age of the total sample was 42.4 years, and the proportion of female gamblers was 39.0%. These results highlight the cross-national variations in the demographic and risk profile of the gamblers from the three different countries.

The cross-national variations in gambling behaviors, as indicated by the PGSI scores among participants from Canada, GB, and Spain, were further evident in the post hoc analysis shown in Table 2. This analysis showed statistically significant differences in PGSI scores between the gamblers from the three countries (Kruskal–Wallis test: $H=18.3$, $p<0.001$). Notably, the difference between Canadian and British gamblers, as well as between Canadian and Spanish gamblers, was significant ($U=51,348$, $p<0.001$ and $U=14,996$, $p=0.0014$, respectively), indicating that Canadian gamblers had a significantly higher PGSI score compared to their British and Spanish counterparts. The difference between the PGSI scores from Spanish and British gamblers ($U=213,829$, $p=0.0486$) was

Table 1 Descriptive statistics of the dataset per country

Country	Number of players	Mean PGSI score	Players with PGSI 8+	Mean age	Female gamblers
Canada	105 (6.0%)	7.11	37 (35.2%)	45.9 years	40%
Great Britain	1285 (73.7%)	5.47	339 (26.4%)	43.5 years	41.8%
Spain	353 (20.3%)	5.67	102 (28.9%)	37.3 years	28.3%
	1743 (100%)	5.61	478 (27.4%)	42.4 years	39.0%

not significant after Bonferroni correction for multiple testing (i.e., corrected alpha level

Table 2 Post hoc tests for differences in the countries' PGSI scores. Significant p -values highlighted in bold according to the Bonferroni corrected alpha level of $0.05/3=0.016$

	Canada	Great Britain
Great Britain	< 0.001	-
Spain	0.0014	0.0486

of 0.016). These findings align with the initial observations from Table 1, which suggested notable variations in the gambling risk profiles across these nations.

Ethics

The study adhered to the guidelines set forth in the Declaration of Helsinki and received approval from the research team's university ethics committees.

Results

Table 3 highlights descriptive statistics distinguishing problem gamblers (PGs, PGSI score 8+) from non-problem gamblers (NPGs, PGSI score < 8). PGs had a lower mean amount of money deposited in the 30 days before completing the PGSI (€524), as compared to the average of €708 deposited by NPGs. However, a Mann–Whitney *U* test showed no significant difference between PGs and NPGs in the amount of money deposited ($U=290,854.5$, $p=0.2207$). A significant difference in age was observed between PGs and NPGs. As a Shapiro–Wilk test reported that the age was not normally distributed ($S=0.98$, $p<0.001$), a Mann–Whitney *U* test indicated that PGs were significantly younger than NPGs ($U=235,128$, $p<0.001$). The proportion of female gamblers did not significantly differ between PGs (36.2%) and NPGs (40.0%; $Z=1.45$, $p=0.146$).

Associating Player-Tracking Data with Self-Reported Problem Gambling (RQ1 and RQ2)

Figure 3 shows the findings from hierarchical regression analyses focusing on the predictors of self-reported problem gambling. The control models (Fig. 3a) explored the impact of demographics after backward elimination, showing that in Great Britain and Spain, younger gamblers were more likely to be self-reported problem gamblers, with a visible but non-significant trend in Canada suggesting the same direction. A solid dot indicates statistical significance and a cross that the variable is not statistically significant in that country.

The models addressing RQ1 in Fig. 3b incorporated behavioral variables to assess their influence on self-reported problem gambling. The results suggested that specific behaviors, such as taking self-exclusions, gambling for a shorter average session length, frequent in-session depositing, and frequent depletion of the gambling balance, were indicators of a higher likelihood towards self-reported problem gambling. Frequent in-session depositing

Table 3 Descriptive statistics for problem gamblers (PG, i.e., PGSI score 8+) and non-problem gamblers (NPG; PGSI score < 8)

Self-reported problem gambler	Number of players	Mean amount of money deposited (€)	Mean number of active gambling days	Mean age	Female gamblers
No	1265 (72.6%)	708	8	43.7 years	40.0%
Yes	478 (27.4%)	524	7	39.2 years	36.2%
	1743 (100.0%)	657	8	42.4 years	39.0%

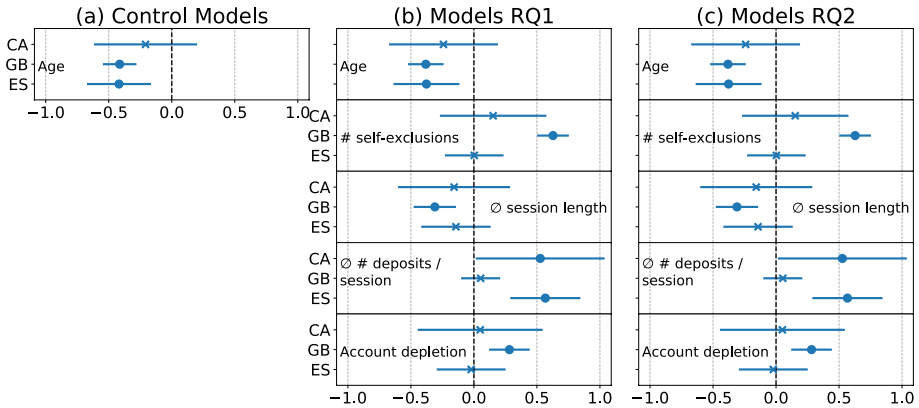


Fig. 3 Coefficients including 95% confidence intervals for the hierarchical regression analyses. Each model consisted of three separate regressions (i.e., one for each country) and included only those variables that were significant in at least one country. Solid dots indicate statistical significance

was significantly associated with self-reported problem gambling in two countries (i.e., Canada and Spain). The other behavioral variables were only significantly associated with self-reported problem gambling in one of the three countries. Overall, adding behavioral features to the models significantly increased the Nagelkerke R^2 (see likelihood ratio chi-square tests in Table 4 for RQ1) and reduced the AIC compared to the model which only contained the control variables. Only in Canada did the inclusion of behavioral variables not significantly improve the model performance ($\chi^2 = 6.2, df = 4, p = 0.184$).

RQ2, illustrated in Fig. 3c, adds monetary gambling intensity variables to the aforementioned demographics and behavioral features. The results suggested that monetary variables did not significantly improve the models' performance, given the inclusion of demographics and behavioral features. Therefore, the backward elimination resulted in the same models as for RQ1, suggesting that beyond behavioral patterns, the intensity of monetary

Table 4 Likelihood ratio chi-squared test (LRT), Nagelkerke- R^2 (NK- R^2), and AIC values for the hierarchical regression analyses. Significant p -values highlighted in bold according to the Bonferroni corrected alpha level of $0.05/3 = 0.016$. Note that the values of the Nagelkerke- R^2 and the AIC are the same for RQ2, as the final models were the same. Therefore, also no LRT for RQ2 was calculated

		Canada (CA)	Great Britain (GB)	Spain (ES)
LRT (RQ1)	$\chi^2(df)$	6.2 (4)	145.5 (4)	19.1 (4)
	p -value	0.184	< 0.001	< 0.001
LRT (RQ2)	$\chi^2(df)$	-	-	-
	p -value	-	-	-
NK- R^2	Model control	0.013	0.044	0.045
	Model RQ1	0.091	0.196	0.118
	Model RQ2	0.091	0.196	0.118
AIC	Model control	139.3	1447.5	417.2
	Model RQ1	141.0	1310.0	406.0
	Model RQ2	141.0	1310.0	406.0

gambling does not significantly contribute to the likelihood of self-reported problem gambling.

Overall, the regression analyses emphasized the significance of behavioral factors over monetary ones when associating player-tracking data with self-reported problem gambling. The models showed that age and specific gambling behaviors, like self-exclusions, in-session depositing, and account depletion were more important predictors than the amount of money gambled.

Predicting Self-Reported Problem Gambling (RQ3)

Table 5 shows the performance (ROC-AUC values) of various machine learning models in predicting self-reported problem gambling. In the first approach, data from one country was reserved for testing, and the other two countries provided the training data. This approach enabled the testing of whether the models generalized across countries in predicting self-reported problem gambling. For the second approach, a standard 70/30 train-test split on the entire data was utilized, and the performance was reported by country. With this approach, each country's data were included in the training dataset, which provided country-specific patterns to the models.

The results from Table 5 indicated the machine learning models, which are trained on data from all three countries, outperformed those that were trained on two countries only. For Canada, the random forest model, which was trained including Canadian players, had a ROC-AUC score of 0.717, while the extra-trees model which was only trained on data from GB and Spain had a score of 0.662. In Great Britain, the extra-trees model with which was trained including British players had a ROC-AUC of 0.699, compared to 0.644 (random forest) which was only trained on Canadian and Spanish players. In Spain, the highest score for the model, which was trained including Spanish players, was 0.654 (gradient boosting), while the decision tree, which was only trained on British and Canadian players, had a ROC-AUC of 0.609.

The baseline model's performance, utilizing the total amount of money deposited as a stand-alone predictor, had an ROC-AUC value of approximately 0.5. Therefore,

Table 5 ROC-AUC values of the five machine learning models for each country. In the first approach, one country was left out during training and was used as test set. In the second approach, a global model trained on all data was used and a 70/30 split into training and test data was applied

	Canada		Great Britain		Spain	
	Canada data left out	Entire dataset	GB data left out	Entire dataset	Spain data left out	Entire dataset
Baseline	0.518	0.518	0.476	0.476	0.548	0.548
AdaBoost	0.575	0.515	0.597	0.606	0.572	0.631
Decision tree	0.592	0.475	0.585	0.598	0.609	0.519
Extra-trees	0.662	0.613	0.617	0.699	0.541	0.598
Gradient boosting	0.588	0.570	0.577	0.653	0.585	0.654
Random forest	0.600	0.717	0.644	0.653	0.597	0.647

its performance was similar to a random guess, emphasizing the limitations of relying solely on a monetary metric. This result again highlighted the importance of behavioral variables in the detection of self-reported problem gambling. Overall, the results indicated that including country-specific patterns generally enhanced the models' predictive power. However, the variance in ROC-AUC scores across different models and countries also emphasized the importance of model selection based on the data characteristics.

Discussion

The present study analyzed the correlation between self-reported PGSI responses and actual gambling behavior in a secondary dataset of 6352 Spanish, British, and Canadian (from the Canadian province Ontario only) online casino gamblers. Out of the 6352 gamblers, 1743 spent at least 1 min responding to the nine items. These were retained for further analysis. In line with Auer and Griffiths (2023a), the minimum answering time was seen as an indication responding to the items seriously. Taking a very short amount of time to respond to all the items assumes that the gamblers did not properly read the questions, and therefore, the responses would not accurately reflect their problem gambling status. The data cleaning process removed the majority of the gamblers reaching the highest score (27/27) as they chose the highest answer category for each of the nine items. The same effect was observed on the lowest end of the score range (0/27) as these gamblers always chose the lowest answer category for the nine items.

Out of the 1743 gamblers, 478 had a PGSI score of 8 or more out of 27 (27.4%). A score of 8+ is considered as indicating problem gambling (Holtgraves, 2008). Several other studies have collected PGSI responses from online gambling cohorts. Auer and Griffiths (2023a) reported that among a sample of European online casino players, 26% reported a PGSI score of 8 or more. Murch et al. (2023) reported 12% problem gambling among a sample of Canadian online casino gamblers. However, the Canadian online gambling site also offered lottery games, which are less likely to cause gambling problems which may have explained the lower prevalence of problem gambling. Among a sample of French online gamblers (engaging in horse betting, sports betting, poker), 26% of gamblers reported problem gambling based on a PGSI score of 8+ (Perrot et al., 2022). Therefore, the present study's prevalence of problem gambling is in line with previous research using similar methodologies.

In the present study, the largest prevalence of problem gambling was observed among Canadian gamblers (35.2%). Online gambling in the Canadian province of Ontario was introduced in 2022, whereas Spain legalized the online gambling market in 2011. To the best of the authors' knowledge, legal online gambling has been available in Great Britain for over 20 years. The long availability of legal online gambling is also related to a longer history of regulation, which could have resulted in safer gambling practices and therefore lower problem gambling rates. Additionally, the UK Gambling Commission frequently fines operators for player safety violations (e.g., Andrade et al., 2023; Gambling Commission, 2022a, 2022b), which could also have led to improved player protection.

Demographics and Behaviors Associated with Self-Reported Problem Gambling

Age was negatively associated with self-reported problem gambling, and the effect was significant among online casino gamblers in Great Britain and Spain. Although there was a visible effect in Canada, it was not statistically significant. Many prevalence studies have reported a higher prevalence of problem gambling among younger individuals (e.g., Abbott et al., 2014; Ekholm et al., 2014; 2015; Kun et al., 2012). Impulsivity (i.e., acting without thinking and the inability to delay gratification and sensation seeking) and depression have been reported as key risk factors for problem gambling among adolescents (e.g., Gupta et al., 2013; Secades-Villa et al., 2016; Turner et al., 2008). Although online gambling is only legal from the age of 18 years in most countries, the adolescent brain does not fully mature until around the mid-20s (Andrews et al., 2021; Icenogle et al., 2019).

After adding behavioral metrics to the regression model, only taking self-exclusions, gambling for shorter session lengths, frequent monetary depositing per session, and regular account depletion significantly contributed to self-reported problem gambling. These independent variables were significant in at least one of the three countries. Frequent monetary depositing within sessions has previously been reported as a behavior that is indicative of chasing losses (Auer & Griffiths, 2023c). Chasing losses is a crucial aspect of impulsivity, and online gambling among vulnerable individuals can have negative impacts on self-control (Siemens and Kopp, 2011). Depositing frequently within sessions and regular account depletion also significantly contributed to the prediction of self-reported problem gambling in a previous study (Auer & Griffiths, 2023b). Moreover, Perrot et al. (2022) and Murch et al. (2023) also identified frequent depositing (although not within sessions) to be significant predictors of self-reported problem gambling.

Several previous studies predicting self-reported problem gambling have reported a significant association with self-exclusion. Perrot et al. (2022) reported that 31% of those with problem gambling had taken at least one temporary self-exclusion since they started gambling online. In contrast, only 4% of non-problem gamblers had done so. The respective percentages reported by Auer and Griffiths (2023a) in their study were 46% among those with problem gambling and 12% among those with no problems.

Among the behavioral variables, the average time spent gambling per session over the past 30 days was also significant. However, the association between self-reported problem gambling and average time spent gambling was negative. This means that self-reported problem gamblers average session length was lower compared to non-problem gamblers. Time devoted to gambling has been reported as a predictive factor of online gambling (Barrault & Varescon, 2013; Hopley & Nicki, 2010). Luquiens et al. (2016) reported a significantly longer gambling time for problematic online poker playing compared to non-problematic online poker playing. Considering previous research, the negative association in the present study between average gambling duration and self-reported problem gambling appears contradictory. However, one explanation could be that those with self-reported problem gambling might already have attempted to control their gambling, and therefore had shorter average gambling sessions in the 30 days prior to completing the PGSI. This hypothesis is also supported by the higher percentage of self-exclusions among those self-reporting problem gambling, which is indicative of attempts to control or stop gambling.

None of the monetary intensity variables contributed significantly to the model, which included demographic and behavioral metrics. This means that the total amount of money bet, lost, withdrawn, and deposited did not improve the prediction of self-reported problem gambling. To the best of the authors knowledge, the present study is the first that has predicted self-reported problem gambling using a hierarchical modeling approach. Only one previous study (Hopfgartner et al., 2023) applied hierarchical logistic regressions to investigate behavioral patterns associated with voluntary self-exclusions. In their study, the authors also reported that monetary intensity variables did not significantly contribute to the model's performance in most countries. The fact that the amount of money gambled did not significantly contribute to the prediction of self-reported problem gambling in the present study also supports the generalizability of the statistical model across jurisdictions. Income levels (and therefore expenditure) vary across countries, but a purely behavioral model is not affected by these variations.

Applying Machine Learning Models to Predict Self-Reported Problem Gambling

Despite the improved performance of the models, which were trained on all three countries's data, the models trained without one country's data still showed a good performance indicating a weak generalization across countries. The slightly lower AUC values can be partly attributed to the nature of the target variable, which is self-reported and was determined using a threshold (i.e., considering a score of 8 or more as problem gambling), leading to skewness in the data. This aspect, coupled with the smaller number of Canadian participants in the dataset and its distinct characteristics compared to the other two countries (i.e., higher PGSI scores in Canada), emphasizes the challenges in achieving higher ROC AUC values in such varied settings. Despite these constraints, the ability of these models to (weakly) generalize across countries and identify patterns of self-reported problem gambling is promising. This means that models which were not trained with data from a specific country still identified some of the patterns of self-reported problem gambling in the player-tracking data of that country. This robustness suggests that while country-specific patterns enhance model performance, the underlying behavioral patterns captured by the machine learning models were sufficient to weakly generalize across countries to predict self-reported problem gambling. This is, for example, important regarding newly regulated jurisdictions, which might introduce legalized online gambling in the future. The general predictors of self-reported problem gambling, which were identified in the present study, appeared to be valid in all three jurisdictions. Nevertheless, future research can explore these possibilities on larger datasets and information from additional countries to isolate the common as well as diverging behavioral patterns across those countries.

Applications and Implications

The present study is important because it is one of the very few studies to integrate subjective self-report data with objective account-based tracking data. Such a methodological approach will help move the gambling study field given the robustness of the combined datasets. Such an approach can be used by both researchers and practitioners in the field, as well as by the gambling industry who often do their own internal approach. Importantly, the present study also (i) highlighted the benefits of using artificial intelligence in the study of both gambling and problem gambling, (ii) identified behavioral markers of gambling harm (e.g., frequent monetary depositing within session, regular account depletion) which can be utilized by gambling operators (and enforced by regulators) to help them identify

risky gambling and potential problem gamblers, and (iii) provided important implications for the development of responsible gambling tools and interventions. By highlighting the significance of behavioral patterns, such as frequent in-session monetary depositing and account depletion, the study contributes to the body of knowledge required for designing tailored responsible gambling strategies that can be adapted to diverse regulatory contexts. The comprehensive approach used in the present study could serve as a foundation for future research in newly regulated or evolving online gambling markets.

Limitations and Future Research

While contributing valuable insights into the predictors of self-reported problem gambling, the present study is subject to specific limitations that must be acknowledged. One specific limitation arises from the self-selection bias inherent in the dataset (Tripepi et al., 2010) because it only included data from gamblers who had voluntarily completed the PGSI. This self-selection bias is also visible in the disproportionately high rate of problem gamblers within the present sample compared to the rates reported in prevalence studies. More specifically, the present study identified self-reported problem gambling rates of 35.2% in Canada, 26.4% in Great Britain, and 28.9% in Spain, using the PGSI with a threshold of 8 or more for problem gambling. These rates were significantly higher than those reported in the respective national prevalence studies: 0.6% in Canada (Williams et al., 2021), between 2.5% and 2.8% in Great Britain (Gambling Commission, 2023; Gunstone et al., 2022), and 0.72% in Spain (Chóliz et al., 2021). Individuals who choose to assess their gambling behaviors through the PGSI may already have concerns about their gambling habits, thereby skewing the sample towards higher rates of problem gambling compared to a randomized or representative sample of the general gambling population. This bias must be considered when interpreting the results because it may influence the predictive accuracy of the machine learning models used. Future studies would benefit from analyzing a more representative sample to provide a more comprehensive picture.

Secondly, the reliance on self-reported data in determining problem gambling severity presents another limitation, given the potential discrepancies between self-perceptions and actual gambling behaviors. The accuracy of self-reported data can be compromised by a variety of factors, including memory recall, social desirability bias, and the subjective nature of self-assessment tools (Auer et al., 2023; Schell et al., 2021). While the present study provides insights to the predictive factors of self-reported problem gambling, these limitations must be considered.

Third, another limitation to consider is the relatively small sample size of this study in comparison to other player-tracking studies. The reduction in sample size, primarily due to the data cleaning process where participants completing the PGSI in less than 1 min were excluded, can limit the statistical power of the study. This, in turn, can potentially affect the robustness and reliability of the findings (Button et al., 2013). However, it is equally important to emphasize that the integrity and reliability of the data are of paramount importance. Including data from gamblers who were unlikely to have engaged seriously with the PGSI survey questions could have led to confounding and potentially misleading results, which could affect the validity of the study's findings. The significant reduction in sample size is therefore considered a limitation, but this decision was made to ensure the quality and reliability of the data. Furthermore, the imbalance between the proportions of gamblers in each country presents another limitation. Gambling behaviors can vary significantly across different regions and cultures, influenced by various factors such as legal regulations, societal norms, and economic conditions (Raylu & Oei, 2004; Selin, 2019). Therefore, the

overrepresentation or underrepresentation of gamblers from specific countries can impact the study's ability to generalize its findings.

Next, the use of a 30-day period for calculating gambling behavior prior to completing the PGSI represented a methodological decision that may have affected the results of the study. One advantage of this time frame is that it captured the current gambling behavior that is likely to most influence participants' responses to the PGSI, which is intended as an instrument to reflect gambling behavior over the past year. On the other hand, a shorter period does not account for long-term behavioral trends and fluctuations in gambling that can be captured by a 12-month period, such as episodic gambling. However, a 12-month observation period can also lead to biases. For example, it is possible that players who scored high on the PGSI may have participated in gambling shortly before completing the PGSI, while players with lower scores may not have gambled recently. This temporal proximity could lead to an overestimation of problem gambling behavior among active gamblers and an underestimation among less active gamblers, which in turn affects the accuracy of the model. The present study's choice to rely on a 30-day observation period is therefore a compromise between the temporal relevance of the behavioral data and the risk of biasing the model by including less recent gambling activity. This trade-off should be considered in future research to match the observation period to the temporal scope of the PGSI.

Finally, several behavioral variables in the present study were not significantly associated with self-reported problem gambling. This highlights the multifaceted nature of gambling disorder, which encompasses not only behavioral aspects, but also psychological aspects. The PGSI incorporates indicators such as experiencing health problems and feelings of guilt, which are reflective of the psychological state of individuals with gambling disorders. These characteristics relate to cognitive aspects and the consequences of gambling, factors that are cannot be captured in player tracking data. Given this difference in the items of the PGSI between measurable behaviors and less measurable psychological criteria, this may be one explanation why only specific behaviors were significantly associated with self-reported problem gambling in the present study.

Future research should aim to mitigate these limitations and explore the utility of the findings across a wider and more balanced array of gambling platforms and jurisdictions to improve the development of effective responsible gambling tools and interventions. Moreover, the machine learning models' performance in predicting self-reported problem gambling across countries highlighted the potential for future research to refine and enhance these predictive capabilities. Finally, replication studies with various operators and across different countries are needed. Such studies would provide greater insight into the generalizability of the present findings and could potentially identify unique behavioral patterns that are specific to specific regions or gambling platforms.

Conclusions

The present study provided a nuanced understanding of the predictors of self-reported problem gambling, emphasizing the importance of behavioral variables over monetary variables. The findings support the hypothesis that self-reported problem gambling can be predicted using player-tracking data, independent of monetary expenditure, across different countries. Applying machine learning models to predict self-reported problem demonstrated that the inclusion of country-specific data enhanced the predictive performance. Nevertheless, the robustness of the models without country-specific training data suggested the existence of universal behavioral patterns that cross cultural and regulatory boundaries.

Appendices

Appendix 1 Problem Gambling Severity Index items. Individuals can answer: never (0), sometimes (1), most of the time (2), and almost always (3). A score of 8 + indicates problem gambling

Item number and question

- (1) Have you bet more than you could really afford to lose?
 - (2) Have you needed to gamble with larger amounts of money to get the same excitement?
 - (3) Have you gone back to try to win to back the money you'd lost?
 - (4) Have you borrowed money or sold anything to get money to gamble?
 - (5) Have you felt that you might have a problem with gambling?
 - (6) Have you felt that gambling has caused you any health problems, including stress or anxiety?
 - (7) Have people criticized your betting, or told you that you have a gambling problem, whether or not you thought it is true?
 - (8) Have you felt your gambling has caused financial problems for you or your household?
 - (9) Have you felt guilty about the way you gamble or what happens when you gamble?
-

Appendix 2 Player tracking features based on the thirty days before answering the PGSI

Demographics	Behavioral features	Monetary features
Country	Number of self-exclusions	Amount of money bet
Age (in years)	Number of voluntary limit changes	Amount of money deposited
Gender	Number of withdrawals	Amount of money lost
	Standard deviation of withdrawals	Amount of money withdrawn
	Number of failed deposits	
	Standard deviation of bets	
	Number of different game types played	
	Number of different payment methods	
	Average session length (in minutes)	
	Average number of deposits per session	
	Percent of bet at night	
	Percent of sessions at night	
	Percent of sessions on weekends	
	Percent of bet on weekends	
	Percent of sessions ending with low account balance (Account depletion)	
	Percent of loss at night	

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Data Availability The data for this study are not available due to commercial sensitivity.

Declarations

Ethics This study was performed in line with the principles of the Declaration of Helsinki and was approved by the research team's university ethic committees.

Conflict of Interest The last author has received research funding from *Norsk Tipping* (the gambling operator owned by the Norwegian government). The last author has also received funding for a number of research projects in the area of gambling education for young people, social responsibility in gambling and gambling treatment from *Gamble Aware* (formerly the *Responsibility in Gambling Trust*), a charitable body which funds its research program based on donations from the gambling industry. The first, second and last authors undertake consultancy for various gaming companies in the area of social responsibility in gambling.

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