Deposit Patterns as Early Gambling Risk Indicators

1st Edition

APRIL 2026

playtech
SOURCE OF SUCCESS

Deposit Activity Patterns as Early Indicators of Gambling Risk

What is the topic?

Can the pattern of deposit activities during the very early days of a player's journey help to identify players on a path towards problem gambling?

The core topic centres on whether specific deposit metrics, including deposit amount, deposit frequency, number of deposits per gaming day, and count of declined deposit events, can effectively predict which players are at risk of experiencing gambling issues and might benefit from early safer gambling engagement/support.

Why is it important?

Identifying gambling risk as early as possible increases opportunities for operators to intervene and support players, reducing the rates and severity of problem gambling.

What did the research do?

The research was designed to determine if the first five days of a player's journey provide enough behavioural evidence to predict long-term risk. To ensure the findings were robust across the industry, the study used data from three distinct online gambling environments over a two-year period (2022 to 2023). This approach allowed the study to account for how different product types, ranging from slots only platforms (Brand 1) and dual product sites (Brand 2) to complex multi-platform ecosystems (Brand 3), influence the visibility of at-risk behaviour. To maintain data integrity, outliers were removed based on deposit amount per deposit day using the Interquartile Range (IQR) method, where data points more than 3 times the IQR above the third quartile or below the first quartile have been removed. The target sample was players who played at least 20 active gambling days.

14 behavioural features wereengineered using deposit data from players' first five active gambling days following registration.Thesefeatures were designed to identify early indicators of impaired control, focusing on metricssuchasdeposit velocity, which captures how frequently and quickly a player tops up their account,andfinancial friction, which reflects real time signs of distress including declined depositsorfailedtransaction. Further details on these features can be found in Table 1, Table 2, and Table3.

Table1: Brand 1 Features Descriptive Statistics

	Number of deposit days		Avg. deposit amount per deposit day(€)		Avg. number of deposit events per deposit day		Number of decline deposits	
	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group
Count	14,261	2,988	14,261	2,988	14,261	2,988	14,261	2,988
Minimum	1.00	1.00	5.00	5.00	1.00	1.00	-	-
Average	2.75	3.50	27.68	40.04	1.93	2.57	0.76	0.96
Std. Deviation	1.54	1.48	29.65	35.85	1.58	1.92	2.49	2.49
Median	3.00	4.00	15.00	26.00	1.25	2.00	-	-
Maximum	13.00	7.00	161.00	160.00	27.60	16.00	83.00	54.00

Table 2: Brand 2 Features Descriptive Statistics

	Number of deposit days		Avg. deposit amount per deposit day(€)		Avg. number of deposit events per deposit day		Number of decline deposits	
	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group
Count	16,753	5,614	16,753	5,614	16,753	5,614	16,753	5,614
Minimum	1.00	1.00	5.00	5.00	1.00	1.00	-	-
Average	3.08	3.72	63.12	84.82	2.58	3.27	0.93	1.17
Std. Deviation	1.55	1.40	87.98	94.17	2.43	2.58	2.68	2.69
Median	3.00	4.00	23.75	46.67	1.75	2.50	-	-
Maximum	14.00	7.00	440.80	440.25	40.00	26.75	137.00	52.00

Table 3: Brand 3 Features Descriptive Statistics

	Number of deposit days		Avg. deposit amount per deposit day(€)		Avg. number of deposit events per deposit day		Number of decline deposits	
	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group	Lower Risk Player Group	Higher Risk Player Group
Count	35,491	7,924	35,491	7,924	35,491	7,924	35,491	7,924
Minimum	1.00	1.00	10.00	10.00	1.00	1.00	-	-
Average	3.49	4.14	80.15	88.65	1.71	2.08	0.63	0.86
Std. Deviation	1.52	1.23	77.04	79.28	1.11	1.39	1.62	2.13
Median	4.00	5.00	50.00	60.00	1.33	1.67	-	-
Maximum	14.00	10.00	396.00	396.00	24.20	23.40	77.00	60.00

These features served as inputs into two Random Forest classification algorithms. The first model was based on the Table 4 sample and aimed to classify players based on whether they subsequently self-excluded for at least six months from the gambling platform, which is often (but not always) an indicator that the players feel they may be experiencing, or be at risk of experiencing harm from their gambling. The second model, based on Table 5, identified at-risk players based on those who had multiple declined deposit events within their first five active gambling days (i.e. 2+ declined deposits), compared to players with zero or one declined deposit events. In many cases, multiple declined deposits is a sign that players are struggling to monitor their spend or over-spending relative to their bank balances.

Model performance was validated through a suite of metrics applied to a hold-out test set, including precision, F1 score, and True Positive Rate (TPR), examining how well the model identified players who actually had high declined deposit rates or went onto self-exclude, based solely on their early deposit behaviour.

Table 4: SE Sample Distribution

Self-Exclusion Modelling Sample			
	Brand 1	**Brand 2**	**Brand 3**
Postive class sample numbers:	3,930	2,092	5,547
Negative class sample numbers:	11,726	9,982	24,843
Postive class percentage:	25.1%	17.33%	18.25%

Table 5: DD Sample Distribution

Declined Deposit Modelling Sample			
	Brand 1	**Brand 2**	**Brand 3**
Postive class sample numbers:	5,813	3,279	3,916
Negative class sample numbers:	25,916	19,072	25,201
Postive class percentage:	18.32%	14.67%	13.45%

What did the research find?

Overall model performance and classification accuracy

The research demonstrated that predictive modelling can effectively identify at-risk players using only the first five days of data, achieving an initial classification accuracy of 65% to 70%. (see Exhibits 1 & 2). True positive rates varied between 62% and 76%, suggesting that a significant proportion of players at risk can be identified. Since this approach is based on the first 5 AGD of players who eventually reach 20 AGD, we observed that performance improved even further when applying the BetBuddy models to players with 20 or more Active Gambling Days. Under this criterion, accuracy increased to around 80%, and the true positive rate rose to approximately 85%.

With such early stage metrics, it is common for accuracy-optimising models to identify a significant proportion of false positives. Across these models, the false positive rates average 33% in all but one analysis. This elevated rate is partly due to relying on only the first five AGDs, where some high spenders resemble those who feature risky patterns such as elevated declined deposits and self-exclusion. Nonetheless, these players may still be acceptably included in a given intervention, depending on the overall safer gambling strategy. For instance, a light touch intervention might be reasonably applied to players even with only a moderate chance of being at risk (tolerating higher false positive rates), whereas a more intensive intervention might be applied only to those with the highest chance of being at risk (accepting that some at-risk players might be missed from that particular intervention, being addressed instead through broader player support initiatives).

Exhibit 1: Self-Exclusion (SE) Model Performance

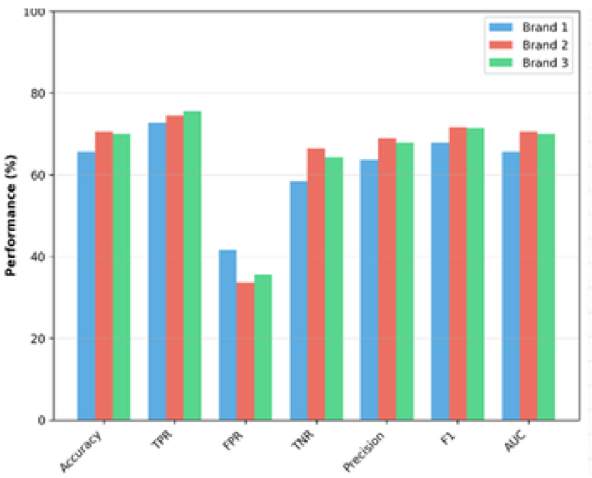
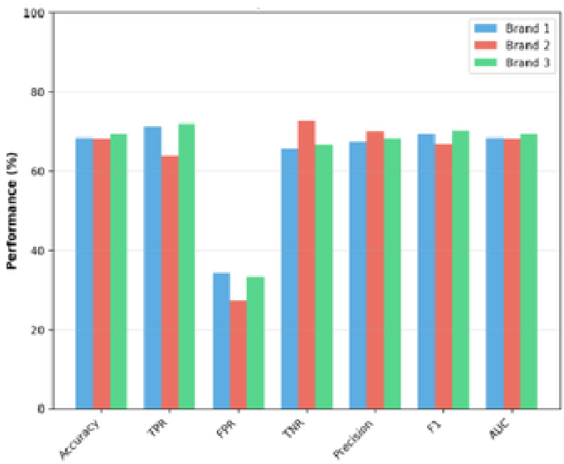


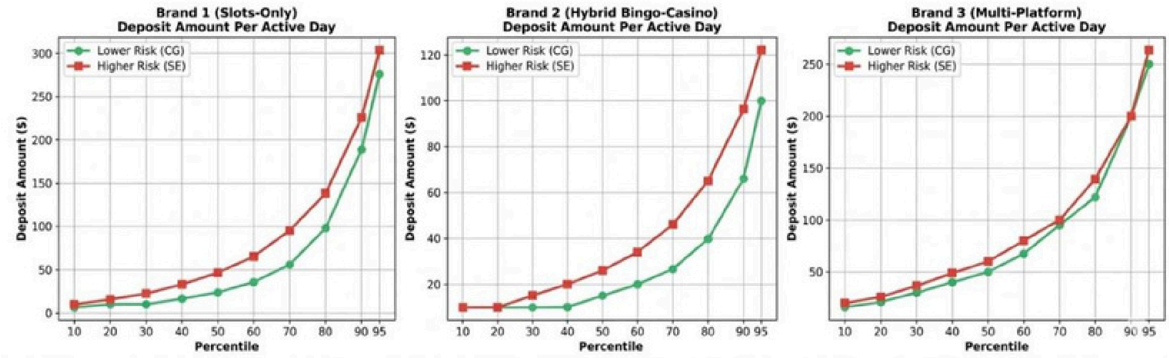
Exhibit 2: Declined Deposit Model Performance



Individual feature analysis for the self-excluder cohort

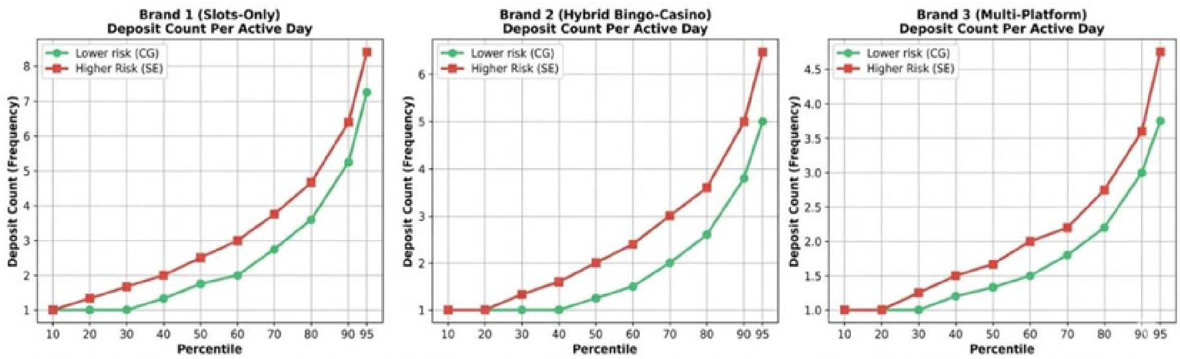
Examining individual features illustrates the potential for deposit-related markers to differentiate higher risk groups. For instance, mean deposit amounts were higher among at-risk cohorts across all operators (Exhibit 3). At-risk players recorded average deposits of €85 for Brand 1, €40 for Brand 2, and €88 for Brand 3, all above the equivalent metrics for the lower-risk group. Greater financial variability was also observed within at-risk groups, as shown by standard deviation patterns, particularly around the median percentiles where at-risk group deposit values (€33-65) diverged sharply from levels in the lower-risk group (€17-36)

Exhibit 3: Percentile chart of Deposit Amount per active day



Deposit frequency, measured as the number of deposits per active day, was likewise higher for at-risk players, reaching mean values of 3.3, 2.6, and 2.1 across the three brands (Exhibit 4). Behavioural separation between the two groups was evident from the 20th percentile through the 60th percentile; however, convergence emerged at the upper extremes (80th to 95th percentiles), suggesting that the most intensive spending patterns become increasingly similar regardless of risk status.

Exhibit 4: Percentile chart of Deposit Count per active day



Individual feature analysis for the multiple declined deposits cohort

Similar patterns were identified for the cohort defined as at risk due to having multiple declined deposits. For this at-risk cohort, mean deposits were recorded at €96 for Brand 1, €51 for Brand 2, and €92 for Brand 3, while averages for the lower risk group remained lower at €71, €33, and €83 respectively. Standard deviation values also showed greater spending volatility within the at-risk groups. Mean deposit counts reached 2.5, 2.3, and 1.8 across the three brands for the at-risk group, exceeding the lower-risk group baselines of 2.2, 1.8, and 1.6. Increased variability was also evident in the at-risk groups across all brands based on standard deviation patterns.

The analysis of three diverse brands revealed that platform complexity influences how risk is detected. In simpler environments like slots-only sites, behavioural signals are initially strong but fade over time, whereas multi-platform environments produce subtler signals that remain remarkably stable

What are the implications for industry and policy?

Early deposit indicators contain useful information about player risk. While behavioural algorithms are imperfect – missing some players at risk and over-classifying others – they nonetheless play a powerful role in personalising interventions as part of a comprehensive player protection strategy. This research suggests that there is no need to wait to gather multiple weeks of data on play behaviour. Five gambling days of deposits already provides enough information to take initial actions, provided the data are engineered into suitable features and analysed with machine learning. These early warning indicators, specifically deposit amount per active day and deposit frequency, are objective and quantifiable measures of player behaviour, supporting non-judgemental interactions with players to promote more sustainable play. Deposit-related features can also be analysed in real-time, supporting timely engagement and reaching players at moments when they are most active and most likely to benefit from safer gambling support.