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Player Risk in the Sports Vertical:

Is player risk more accurately flagged with a vertical-specific approach?

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What is the topic?

Player risk algorithms seek to estimate the probability that a player is at risk of harm from their gambling, typically based primarily on behavioural data about how they gamble and interact with a gambling service provider. The central question is whether a vertical-specific approach, such as developing a player risk model specifically for sports betting or specifically for bingo play, results in more accurate risk identification and more effective interventions. This study provides a first look at risk identification accuracy in the sports vertical.

Why is it important?

Problem gambling prevalence data identify that player risk typically varies by gambling vertical, with in-person betting on non-sports events and online slots often featuring higher risk players than in-person bingo and national lottery draws.[1] Recent research with players and player data further reveals that different verticals have particular features such that certain risk markers used in predictive models might usefully be adapted by vertical.[2] Some metrics also apply differently across verticals. For instance, 'time spent betting' is easier to construct for continuous games, such as slots, than for delayed outcome bets, such as pre-play sports betting or lottery draws. As a result, operators and regulators have increased ambitions for vertical-tailored algorithms.

What did the research do?

We used a structured academic literature view and iterative consultative approach with sector experts to develop a taxonomy of new markers and analytical approaches tailored to the sports vertical. New techniques included adjustments for seasonality and big match days, markers for micro-event and in-play betting, re-staked cash-outs, bet type and league variety, among others.

A number of high priority markers were calculated for a population of online sports bettors, alongside traditional holistic behavioural markers. We tested the accuracy gain from using these additional markers and the key accuracy drivers in identifying bettors estimated to be at higher risk, via serious self-exclusion as a proxy for one of several types of risk that players might face. Serious self-exclusion requires players to self-exclude for at least 180 days and to have previously been at least semi-regular gamblers (e.g. at least 20 active gambling days within a year).

Data are sourced from a large, integrated operator, with an analytical sample of 1,334 players with a serious self-exclusion from Jan-Nov 2023 and a comparison group of 5,336 players who did not self-exclude in the period but met the same minimum play requirements. The comparison group is chosen via stratified random sampling to match the distribution of sports wager share as the self-exclusion group (84% of both groups have zero sports play in the research period).

A simple modelling and evaluation approach was chosen to support a rapid initial study, noting that our purpose was to compare across models rather than to optimise a single model for deployment. The risk estimation algorithm was trained using a random forest classifier (500 trees, up to 200 depth per tree, using 12 features randomly chosen at each split). Performance was evaluated on a 20% hold-out sample, with the same 4:1 distribution as the training sample.

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[1] https://www.gamblingcommission.gov.uk/report/gambling-survey-for-great-britain-annual-report-2023-official-statistics/gsgb-annual-report-problem-gambling-severity-index

[2] E.g. Cooper, A., Olfert, K., & Marmurek, H.H.C. (2022). Predictors of Problem Gambling for Sports and Non-sports Gamblers: A Stochastic Search Variable Selection Analysis. Journal of Gambling Studies.

What did the research find?

Including sports variables alongside basic behavioural markers improved accuracy among sports-focused gamblers

Models performed better if allowed to train on all players, perhaps unsurprising given the modest sample size with non-zero sports gambling in the sample. Nonetheless, within the 'all players' model, including sports variables alongside basic behavioural markers improved accuracy among the more sports-focused gamblers (see chart), e.g. with accuracy improving from 85% to 88% among those wagering over 15% of their real money wagers on sportsbook and from 80% to 87% for pure sportsbook players (there are very few pure sports players in the holdout sample, so the latter findings should only be interpreted in the context of the full analysis). Overall, including the extra variables decreases performance on non-sports players from 88% to 87%, although we would expect model optimisation to address this in a deployed model version.

Accuracy comparison [%]

Holdout dataset performance by sports-wager intensity

Model	**Baseline**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Trained on?	All players			Players with non-zero sports gambling		
Input features	Basic	Initial sport	All	Basic	Initial sport	All
All players	88.0%	77.5%	87.6%			
Non-zero sports bets	88.6%	84.1%	88.6%	86.4%	83.6%	85.9%
1. No sports (0% of real money wagers on sports)	88%	76%	87%			
2. Min sports (0% to 0.5%]	90%	82%	89%	89%	82%	86%
3. Little sports (0.5% to 15%]	91%	82%	89%	88%	82%	83%
4. Partial sports (15% to 100%)	85%	93%	88%	80%	93%	90%
5. Pure sports *(100%; v. small N)*	80%	87%	87%	80%	80%	87%

Accuracy = (correctly identified SE players + correctly identified CG players) / all players
NB. sample is 4:1 CG:SE in all strata by sports wagering intensity; n=14 SE in pure sports group so 3 in holdout – best interpreted only in context with other groups, not as standalone evidence

Sports-only markers should also be considered a supplement to baseline holistic behavioural markers, rather than a replacement for them, as models trained using sports-only markers performed poorly (e.g. models (1) and (4) compared to the other four models in the chart above).

The additional sports markers are particularly valuable for reducing 'missed positives'

In a public health context, it is often more important to be confident we are identifying as many players at risk as we can, even if that means a modest increase in false positives. In this context, the additional sports markers are particularly valuable (see chart overleaf).

For instance, in the model trained with all players, the missed positive rate improves from 48% to 34% with the inclusion of the additional sports markers. The improvement is particularly notable for more intense sports players, e.g. with missed positives improving from 50% to 13% among those wagering over 15% of their real money wagers on sports book and from 100% to 67% for pure sports players. In analysing these non-optimised models, we focus on comparisons between them, rather than overall performance. For instance, in these cases, the classification threshold was set to maximise accuracy, driving the high missed positive rate. In a deployed model, it is possible to set the threshold to place greater weight on reducing missed positives.

Missed positives comparison [%]

Holdout dataset performance by sports-wager intensity

Model	Baseline	(1)	(2)	(3)	(4)	(5)
Trained on?	All players			Players with non-zero sports gambling		
Input features	Basic	Initial sport	All	Basic	Initial sport	All
All players	52.8%	65.5%	48.3%			
Non-zero sports bets	47.7%	47.7%	34.1%	52.2%	47.7%	38.6%
1. No sports	54%	69%	51%			
2. Min sports	40%	70%	40%	45%	70%	55%
3. Little sports	46%	46%	31%	54%	46%	38%
4. Partial sports	50%	0%	13%	50%	0%	0%
5. Pure sports *(v. small N caveat)*	100%	33%	67%	100%	33%	33%

Missed positives = (SE players incorrectly identified as CG) / all SE players

Feature importance analysis points towards metrics to capture intensity by vertical and cash-outs

As can be inferred from the charts above, the basic behavioural markers are the key drivers of model performance, at least at the current level of R&D investment into marker optimisation. Within sports betting, as with gambling in general, the key factors include wagering volumes and frequency. Nonetheless, developing such volume and frequency metrics specifically for the sports vertical adds incremental value, even when combined with cross-vertical volume and frequency metrics. Within the new types of sports metrics, cash-outs had highest importance, but some in-play intensity and seasonality-adjusted factors remained in the top half of features analysed.

What are the implications for industry and policy?

At a high level, the baseline model performs similarly overall with similar feature rankings when trained on just core holistic gambling metrics or additional sports metrics. In other words, status quo modelling based on holistic metrics is a reasonable baseline. However, literature reviews and sector discussions identified the potential for sports-tailored models – and this potential is directionally supported by this initial study. Initial sports-tailored models already show some improvement on baseline models, especially in terms of missing fewer at-risk players among more sports-intense players (e.g., players with 15%+ wager share on sports book).

This work-in-progress R&D is subject to a number of limitations which point the way to future work. The small sample size in a single jurisdiction, especially for sports-intensive players with a serious self-exclusion, the partial set of potential sports markers analysed so far, and a simplified model development process are the key limitations to address first. For instance, the sample size can be increased and diversified by including other proxies for risk (such as self-report and subsequent month prevalence in declined deposits and spike play) and analysing other jurisdictions. Additional sports markers can also be constructed (see options in the Appendix) and optimised as part of an extended model development process.

Overall, we assess that operators can pursue worthwhile incremental model improvements (and reduced model blindspots) through vertical-optimised approaches. There is significant scope to refine our initial study as part of work to produce models that make full use of novel insights by vertical, aiming both to enhance overall performance and to ensure that no verticals are overlooked in a risk estimation algorithm.

Appendix: Behavioural markers

Potential new metrics for sports models

Engaged operators in 3 areas + structured academic lit review of 869 papers 2018-2023

Sports-specific risk factors

- In-play bets
- Micro-event bets & outcome type diversity
- Early cash-outs at a loss *(excl. if lowered loss vs waiting, e.g. skill factor?)*
- Cash-outs re-staked in play (*excl. favourable re-bets?)*
- More complex bets *(e.g. big accumulators, but if operator wraps up for you?)*
- …

Extending existing risk factors

- Track trends per vertical *(e.g. sports vs casino trajectory, loss-chasing, play-till-depletion)*
- Number of distinct sports/leagues or distinct outcome types bet on
- Number of unusual sports/leagues bet on (relative to self/market)
- Perhaps bets by channel *(but evidence on smartphone gambling might be temporary?)*
- Bonus play / targeted promotion uptake by vertical
- …

Seasonality & big match days

- New features derived via wager/win levels relative to norm group for that sport/event
- Needs care to define norm group – different sports/ leagues have different calendars
- Aggregate thin sports?
- Or annual calendars remade each year?
- Or manual business rules?
- …