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Using account data to identify online problem gambling

What this research is about

Online gambling has become popular over recent years. It is also associated with more problematic gambling behaviours, as it is easily accessible and private. At the same time, online gambling provides opportunities for researchers to study “actual” (as opposed to self-reported) gambling behaviour. This can be achieved by examining the account data of people who gamble online.

The researchers of this study were interested in using the account data of people who gamble online to better understand online gambling behaviour and problem gambling. The researchers applied machine learning algorithms to online gambling account data to identify people with gambling problems.

What you need to know

The researchers used online gambling account data to develop models that could identify problem gambling. They used survey data and account data provided by two French authorities, the ARJEL and the FDJ. The researchers developed two models to predict problem gambling in skill-based and chance-based games, respectively. The first model produced good results and was best at identifying non-problem and problem gambling, but performed poorly at identifying low-risk and moderate-risk gambling. The second model produced moderate results, but was also better at identifying non-problem and problem gambling over low-risk and moderate-risk gambling.

What the researchers did

Four types of online gambling are legalized in France: poker, horse race betting, sports betting, and lotteries. Online lotteries are managed by the Française des Jeux (FDJ). The other types of online gambling are managed by the Autorité de Régulation des Jeux En Ligne (ARJEL). The researchers requested account-based data from the ARJEL and FDJ. Both organizations emailed a random selection of their customers to participate in a survey.

The survey consisted of several questionnaires. The Problem Gambling Severity Index (PGSI) was used to assess problem gambling behaviour in the past 12 months and in the last 30 days (the latter being used to determine the current problem gambling status).

The past 12 months of gambling tracking data were also provided for the customers who responded to the survey. In addition, the researchers calculated three types of potential indicators of problem gambling behaviour from the gambling tracking data. The first type was chasing behaviour, which is when someone gambles more or continues to gamble after losing multiple times. The researchers used two proxies of chasing behaviour: making three deposits in less than 12 hours, or making a deposit in less than 1 hour after placing a bet. Another indicator was breadth of involvement. Breadth of involvement referred to the number of different games a participant placed at least one bet on. The third indicator was the extent to which a participant varied their gambling behaviour from their “usual” (previous three months) behaviour.

The researchers used the participants’ account data from the previous four months to predict their current problem gambling status. The ARJEL dataset included 7,359 participants. The FDJ dataset included 5,079 participants. These participants all had created their accounts for more than four months and had gambled in the 30 days before the survey.

What the researchers found

From the ARJEL dataset, the prediction model correctly identified 71% of participants with non-problem gambling according to their PGSI scores (score 0). It also correctly identified 18% of participants with low-risk gambling (score 1–4); 7% of those with moderate-risk gambling (score 5–7); and 75% of those with problem gambling (score 8+).

After examining the responses for causes of misclassification, 308 participants were excluded. The reasons for exclusion included possible gambling offline; differences in PGSI status in the past 12 months versus the past 30 days; and not citing any forms of online gambling in the datasets as the source of problem. The prediction model improved in its prediction, with 84% of non-problem gambling, 24% of low-risk gambling, 12% of moderate-risk gambling, and 85% of problem gambling cases being correctly identified.

For the FDJ dataset, the prediction model correctly identified 68% of participants with non-problem gambling; 23% of participants with low-risk gambling; 0% of participants with moderate-risk gambling; and 55% of participants with problem gambling. A total of 134 participants were excluded when the reasons for misclassification were considered. The prediction model then correctly identified 73% of non-problem gambling; 27% of low-risk gambling; 0% of moderate-risk gambling; and 67% of problem gambling cases.

These results showed that the prediction models worked well at identifying non-problem and problem gambling. The models performed poorly at identifying low-risk and moderate-risk gambling. For the ARJEL dataset, the most important predictors of moderate-risk and problem gambling were related to deposits. The most important predictors of low-risk gambling were related to money wagered and number of bets made. For the FDJ dataset, money wagered was the most important predictor.

How you can use this research

The authors suggested that this research could be used by online gambling operators to identify people who are at risk of problem gambling and offer them self-exclusion or other help services. This research could also be useful to researchers.

About the researchers

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Citation

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