Using Player Loyalty Data to Detect Risk for Problem Gambling

Developing and Testing Risk Identification Models for Use in the UK Casino Market

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Overview

As part of the National Casino Forum's (NCF's) Playing Safe initiative, four of its member casino operators assisted Focal Research in an international collaborative research project. We examined the potential for using gaming machine data routinely gathered by UK casinos to detect behaviour patterns associated with a high probability of high risk for problem gambling. The project, conducted from June 2014 to February 2015, was the first step in assessing the feasibility of a new prototype designed by Focal Research to automate the customization process for building risk-identification models for gaming operators in diverse markets.

Overall, 1,498 eligible, regular UK casino gamblers voluntarily completed a player survey measuring their risk for problem gambling using the Problem Gambling Severity Index (PGSI), as well as the Focal Adult Gambling Screen (FLAGS©). This overall sample was then used to build and test how well resulting models performed in identifying risk using a training and validation sample. Study results were promising; the prototype produced preliminary models achieving pre-set standards for success with models produced in other markets. The current research provides strong proof of concept for the model automation process, although variations in data characteristics and small sample sizes did not permit model optimization at the UK operator level during this initial phase of study.

Based on the results, the next steps for this research are now underway. We will increase sample sizes at an individual casino level to build operator-specific models, resulting in improved model sensitivity (recall) and precision (accuracy). Resulting models will be tested over a 12-month trial to assess model performance over time. During the trial phase, there is an opportunity to use an evidence-based approach in linking risk identification to appropriate customer interactions to evaluate the value of the technology as a tool in assisting operators and customers in reducing or preventing development of risk and gambling harm. Additionally, NCF and its members will be collaborating in new co-funded international research by Focal Research exploring risk identification using "uncarded" data among those who gamble without using a player membership or loyalty card. This new research also includes development of algorithms for detecting money laundering (AML models) and gambling with misappropriated funds.

This research continues to position Focal Research and our collaborators, such as NCF, at the forefront of risk identification using player data and behavioural analytics, providing leadership in advancing the global understanding of the technology as a practical tool for risk assessment and management.

The following report summarizes key findings emerging from the UK research process.

Introduction

For millions of people around the world, gambling is a readily available and enjoyable source of entertainment. As a consequence, the revenue generated by gambling continues to rise. For example, in the previous year in the UK (2013–14) regulated gambling generated almost £7 billion in gross gambling yield (Gambling Commission 2014–15 Annual Report, p. 12). Unfortunately, some individuals are unable to control their gambling activity and their behaviour may lead to negative financial, emotional, and social consequences (Williams, Volberg & Stevens, 2012).

The team at Focal Research have been examining the behaviour of gamblers for the past 29 years, completing the first comprehensive study demonstrating at-risk gamblers could be identified using behavioural measures alone (Schellinck & Schrans, 1998; Schrans, Schellinck & Walsh, 2000 www.focalresearch.com). Much of our early work in this area involved the design and administration of groundbreaking surveys with regular and at-risk gambling patrons that consequently enabled us to identify their specific patterns of behaviour (Schellinck & Schrans, 2003, 2004, 2007). At the same time, the Focal Research team was working with large transactional and loyalty databases, using data-mining techniques and behavioural analytics for marketing and customer relationship management (CRM) in retail, finance, and insurance sectors.

In 1998, Focal Research started to apply these data-mining techniques to model gambling behaviours and outcomes to inform responsible gambling and social policy development primarily for electronic gambling machines and devices (e.g., slots, video lottery, pokies, EGMs) in casinos and other wide-area gaming networks in Canada, Europe, and the Australasian market. In 2005, we used casino loyalty data to build the first bespoke models for detecting behavioural patterns associated with a high probability of risk for problem gambling to accurately identify high-risk customers for Saskatchewan Gaming Corporation's and iView System's iCare program (proprietary data, Casino Regina and Casino Moose Jaw, Saskatchewan, Canada). This was the first customized commercial system developed for such a purpose. Since then Focal Research has designed and implemented various predictive models for use in multiple gambling environments around the world.

While such models are helpful in targeting and evaluating operator resources, the development process is costly and time consuming, and resulting models need to be updated to remain relevant over time. Therefore, despite the value of this technology to gaming end-users, it has remained expensive, complex, and beyond the reach of many operators as an effective responsible gaming and risk management tool. Focal Research theorized that it is possible to automate the modelling process to help streamline market customization, making the technology more practical, less expensive, easy to use, and, hence, more accessible to gaming operators. With support and co-funding from government and industry sponsors, from October 2013 to February 2014, we developed a prototype as part of an Algorithmic Risk Tracking System (ALeRT™) using predictive variables and algorithms from three different countries to automate the model development and customization process. To assess the replicability and validity of the system, the resulting automation program needed to be applied to data from a new market.

Based on a review of the NatCen Social Research, "Scoping the use of industry data on category B gaming machines" Final Report (Wardle et al., 2013), we concluded UK casino industry data was suitable for our proposed purposes. For the next phase of model testing, we invited the UK National Casino Forum (NCF) and its members to participate in our research study. Four member casino operators took part in this collaborative project from June 2014 to February 2015. In this summary, we briefly explain our model creation process prior to describing the UK component of the research with NCF.

Model Development

Focal Research uses gamblers' loyalty data to create an inventory of variables or defined behaviours that, when combined with survey data from these same gamblers, can be used to develop an algorithm (i.e., predictive model) to identify high-risk and problem gamblers. Loyalty or player tracking data is available from individuals who use a unique membership card (or other identifier) when they gamble.

Problem Gambling Severity Index (PGSI)

Categories	PGSI Score
No Risk	0
Low Risk	1–2
Moderate Risk	3–7
Problem Gambling	8+

To collect survey data, gamblers are administered the Problem Gambling Severity Index (PGSI) (Ferris & Wynne, 2001), a nine-question screen, as well as FLAGS©-EGM (Focal Adult Gambling Screen for Electronic Gambling Machines) (Schellinck, Schrans, Bliemel, & Schellinck, 2015a, 2015b), a 57-question screen.

The PGSI is the standard measure used in most gambling prevalence studies around the world, including the British Gambling Prevalence Survey in 2010, measuring the probability that someone is a problem gambler.

FLAGS©-EGM Risk Indicators

FLAGS Constructs	
Pre-Harm Risk Indicators	Risky Cognitions Beliefs
	Risky Cognitions Motives
	Preoccupation Desire
	Impaired Control (During Play)
	Risky Practices Early
	Risky Practices Later
	Impaired Control (Before Play)
	Preoccupation Obsession
Harm Indicators	Negative Consequences
	Persistence

In contrast, FLAGS-EGM is a new instrument specifically designed by Focal Research to identify risk and harm among those playing slots and other electronic gambling machines (EGMs[1]). Although both instruments accurately identify problem gamblers, FLAGS-EGM provides additional information about levels of risk for problem gambling before customers are experiencing any negative consequences, thereby offering greater versatility in developing and targeting models for prevention applications as well as identification of harm.

The results for the risk survey are linked to the player's loyalty data. It is important to note that through a sophisticated number-generating system used to label and link the loyalty and survey data, the individual customers providing the data remain anonymous throughout the research process.

1 FLAGS General was developed for testing risk among the wider population of gamblers in 2011–12 through funding from the Ontario Problem Gambling Research Centre and Ontario Ministry of Health and Long-Term Care (Schellinck et al, 2011b).

Generally, the following information is included in loyalty data sets in one form or another: player identification number; machine identification information; date and time play started and ended; total amount bet during the session; and total amount won or lost during the session. Using the available data and data-mining techniques, we have created an inventory of over 700 potential variables that can be assessed for their role in predicting problem gambling. Our goal is to identify a broad array of behavioural patterns and sets of behavioural cues that are strongly associated with the occurrence of problem gambling in order to pick up high-risk gambling patterns that vary by individual and by the random action of the games. For example, chasing losses – behaviour closely associated with high-risk gambling – may be examined by creating a number of complex variables to capture the full range of potential cues that signal chasing, ranging from chasing within one session of play or over multiple sessions. In order to detect high risk among high- and low-spending segments, variables must be included to detect risk despite frequency of play (or how often a player used their player card when they gambled) or how much a gambler spends.

Following the variable creation process, the ALeRT™ prototype then automatically selects appropriate variables from the inventory to assess risk for each specific market and/or operator, taking into account the data available in the system, as well as any unique market/operator characteristics that can influence individual playing patterns. The goal is to automatically produce customized algorithms that will predict an individual's gambling status with a measurable and similar degree of accuracy regardless of the type of data retained in the system or other differences across venues or operators.

By comparing the algorithm results with an individual's actual PGSI and/or FLAGS score, we are able to evaluate our level of success in correctly predicting levels of risk using both a training and validation sample. As a result of these extra steps, we can generate detailed performance metrics about how the models perform not only in theory, but when applied to the real market – an advantage over approaches that do not include a model-evaluation component as part of the risk-identification process.

Research Objectives

The primary objective of the UK component of the study was to determine if it was possible, using standard player data from different casinos operating in the UK gaming market, to use Focal Research's automation prototype to develop models identifying UK customers at high risk for problem gambling with reasonable sensitivity (i.e., recall) and accuracy (i.e., precision) as defined below.

Data Collection

The four participating NCF casino operators provided player data as well as funding for conducting the player risk survey portion of the project. Our principal investigators met with management at the participating casinos in London, UK, to examine current data systems and practices. All four venues differed in terms of the type of data systems used to manage and store the raw data and the type of information gathered by each system.

From June 2014 to October 2014, we worked with the information technology and marketing teams of the operators to obtain the player loyalty data samples. A survey invitation was sent out to 14,803 eligible gamblers that had an available email address. The survey was voluntary and consisted of two parts: Part 1: PGSI completed by about 10 per cent of gamblers (n =1,498), and Part 2: FLAGS completed by 8 per cent (n=1,114) with the survey information then linked to their player data.

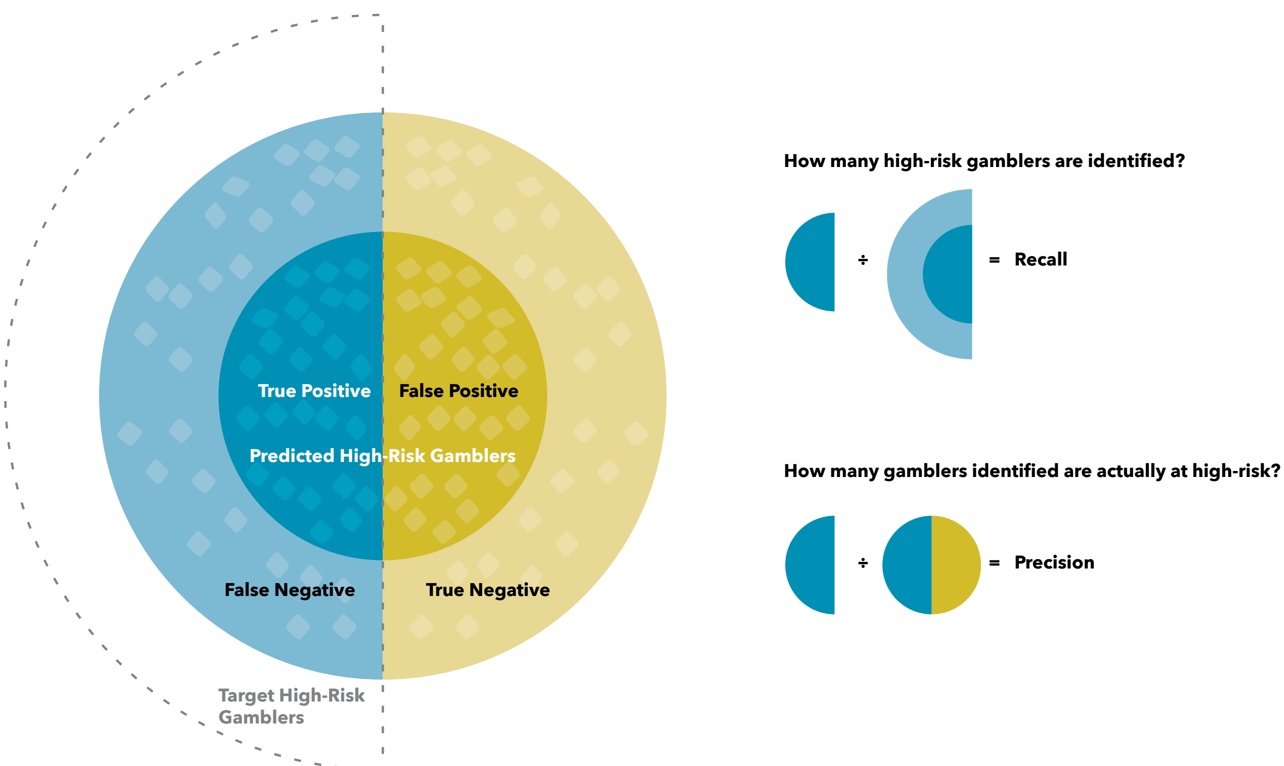
The final data set (n =1,498) was randomly partitioned into two groups: a 60 per cent training set used to build the predictive models, and a 40 per cent validation set to test how well the model performed (i.e., assessment of model performance when implemented in the gaming population at large). This process is essential to assess the accuracy of the algorithms produced as it ensures that the variables determined to predict high risk do not simply reflect the characteristics of the specific sample used to build the model, but will continue to perform at claimed levels once the algorithm is put into commercial use (Schellinck & Schrans, 2011a).

Results

It is important to keep in mind that the following analysis **does not identify the number of customers that are problem gamblers** or at risk for developing gambling problems in the participating casinos' customer bases. Rather, the analysis assesses how well the models perform in identifying high-risk gamblers in the high-risk gambler population only.

While there are many complex outcomes for assessing model performance, our results in this summary document are reported in terms of two critical metrics, per cent sensitivity (i.e., model recall) and per cent accuracy (i.e., model precision). In the illustration below, the circle represents players identified by the model; blue represents the target population (e.g., high-risk gamblers), and gold represents the non-targets (e.g., no-risk gamblers).

Model Performance Matrix – Recall[2] & Precision



2 Walber. (2014). Precision and recall, Retrieved from https://commons.wikimedia.org/wiki/File:Precisionrecall.svg. Adapted from Wikimedia Commons, licensed under the Creative Commons Attribution-Share Alike 4.0 Intern'al.

- **Sensitivity – Model Recall (True Positives)** refers to the percentage of individuals in the target group (e.g., high-risk gamblers) that are identified by the model (True Positive versus False Negatives) (that is, how many of the total high-risk gamblers in the sample are identified by the model versus how many are missed)

- **Accuracy – Model Precision (True Positive Rate)** refers to the percentage of individuals correctly identified as part of the target group versus those incorrectly identified by the model who are not part of the target group (e.g., non-risk gamblers) (True Positives versus False Positives) (that is, of all those identified by the model, how many will be at-risk gamblers versus non-risk gamblers)

It is important to note, that there is a trade-off between making sure you are reaching as many high-risk gamblers as possible without needlessly disturbing low-risk customers. As model sensitivity improves, the chance of including low-risk gamblers also increases, meaning that accuracy, as defined above, usually declines. In other words, the model identifies a larger proportion of the target group (e.g., high-risk gamblers), but, at the same time, includes a greater proportion of non-targets (e.g., low-risk gamblers).

Model performance was assessed in the current study by selecting the top 5 per cent, 10 per cent, and 15 per cent of players predicted to be at high risk for problem gambling.

Risk Categories Using PGSI Scores[3]
Problem Gambling Severity Index (PGSI)

Categories for Model Testing	Adapted Scoring
No Risk	0
Any Risk	1+
Moderate Risk	3-7
High Risk	5+
Severe Risk/ Problem	8+

Readers are cautioned that not all high-risk gamblers can be identified by distinctive playing patterns. Therefore, our objective for the prototype during this preliminary stage of testing was to build models that, at any given time, identified at least 20 per cent of those individuals scoring at high risk (e.g., PGSI 5+ Moderate to Severe PG; FLAGS Advanced Risk & Harmed) with an overall model accuracy of at least 80 per cent, meaning that 80 per cent or more of those identified by the model will be at some level of risk for developing problems, with the majority falling in the moderate-to-severe range.

3 The PGSI categories were based on the original classifications specified by Ferris & Wynne (2001) and adapted by Wiebe et al in Measuring Gambling and Problem Gambling in Ontario. Toronto: Canadian Centre on Substance Abuse and Responsible Gaming Council (Ontario). (www.responsiblegambling.org).

As shown in Table 1 below, when using the validation sample, the automated prototype was found to produce models that achieved the preset outcomes with 80 per cent or more of those identified as scoring at some level of risk on the PGSI (e.g., PGSI≥1) and 60 per cent to 71 per cent scoring as higher-risk gamblers (PGSI≥3).

Table 1 Automated Model Performance (Validation Sample Results)

Players	Model Sensitivity (PGSI = 5+)	Model Accuracy (PGSI = 1+)	Model Accuracy (PGSI = 3+)
Top 5%	11.2 ± 0.4%	86.2 ± 1.5%	70.8 ± 2.0%
Top 10%	19.3 ± 0.7%	84.5 ± 1.0%	65.1 ± 1.2%
Top 15%	26.5 ± 0.8%	83.2 ± 0.9%	61.4 ± 0.9%

When we broaden the scope to the top 15 per cent of those players scoring at high risk, model performance clearly indicates a higher sensitivity (26.5 per cent of all high-risk gamblers were identified by the model) with slightly reduced accuracy (83 per cent of those identified by the model scored at any risk; 61 per cent at high risk). These results suggest there is some versatility in how the models can be applied. For example, when it is more important to reach as many high-risk players as possible, even if some lower-risk customers are targeted at the same time, the threshold can be lowered to include more coverage of high-risk players. This might be useful when an operator is offering information or tools to customers for setting gambling budgets or wants to exclude any high-risk gamblers from being targeted by an advertising campaign (i.e., gambling inducement). However, in other cases, such as for initiation of a customer interaction, a higher threshold can be set for model identification; while the operator may reach fewer high-risk and problem gamblers (e.g., ≈1 in every 10 high-risk customers) there is greater certainty that the vast majority of those identified by such a model will be at risk for developing problems with their gambling (e.g., almost 9 out of every 10 customers identified will be at some level of risk).

To assess the degree to which no-risk players would be targeted by the model, we examined the model misclassification rate, that is the percentage of customers scoring at no risk for problem gambling that would be identified by the model. As shown in Table 2 below, as we increased our reach in detecting high-risk players we also increased the inclusion of no-risk gamblers, although 8 per cent or fewer were being picked up by the preliminary algorithms.

Table 2 Model Misclassification of No-Risk Players (Validation Sample Results)

High-Risk Players	Model Sensitivity (PGSI = 5+)	Model Misclassification Rate (PGSI = 0)
Top 5%	11.2 ± 0.4%	2.3 ± 0.2%
Top 10%	19.3 ± 0.7%	5.1 ± 0.3%
Top 15%	26.5 ± 0.8%	8.3 ± 0.4%

The overall model, as described above, was created using combined data from all four participating operators in order to have large enough sample sizes during this early stage of testing. However, at this early stage it was also useful to know how the model performed when applied to each individual operator (Table 3). The overall model was applied to the validation set and assessed for each operator.

Table 3 Automated Model Performance by Casino (Top 15% Prediction) (Validation Sample Results)

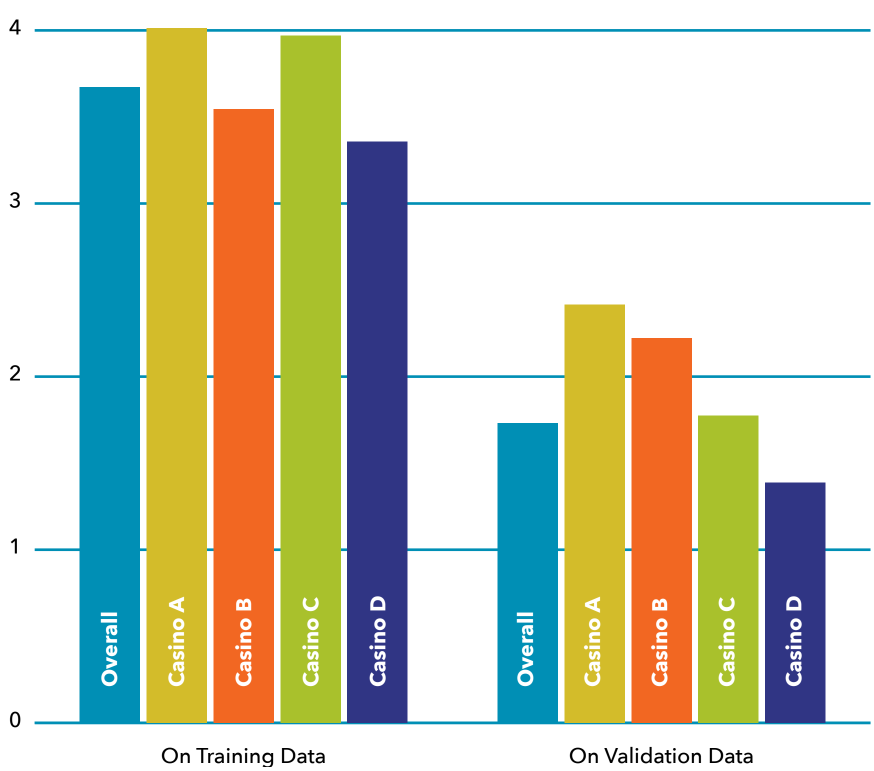
Casinos	Model Sensitivity (PGSI = 5+)	Model Accuracy (PGSI = 1+)
Overall Model	26.5 ± 0.8%	83.2 ± 0.9%
Casino A	38.2 ± 1.9%	89.0 ± 2.0%
Casino B	36.4 ± 2.3%	75.4 ± 4.8%
Casino C	27.4 ± 1.2%	78.8 ± 1.7%
Casino D	21.8 ± 1.4%	87.1 ± 1.3%

When targeting the top 15 per cent, the model reaches from 21.8 per cent to 38.2 per cent of the high-risk players in the validation samples; Casinos A and D reach the criterion for accuracy. Casino C meets the criterion for sensitivity but is slightly below 80 per cent in terms of accuracy. Casino B achieves excellent sensitivity but falls short in terms of accuracy.

Another measure of the success of the model can be determined by assessing its "lift." **Lift refers to the ability to identify at-risk and problem gamblers by using an algorithm when compared to drawing from a random sample of gamblers.** For example, a lift of 1.5 for Casino A means that when the model is applied to the validation sample it identifies 50 per cent more of the target group of gamblers than a random sample would (Figure 1 below).

These results also underscore the importance of using a validation sample to judge the effectiveness of the model because lift values for the sample used to build the models will decline substantially when applied to the validation sample as compared to results for the sample used to build the models (Casino A lift = 4.0 in the training sample versus a lift of 2.4 on the validation sample). When the model is applied to the total population of eligible customers, results will reflect those observed for the validation sample.

Figure 1 Model Lift by Casino (Top 15% Prediction)



Discussion

The results of the current project indicate that Focal Research's automation algorithm process is suitable for use in developing customized models to detect individuals at risk for problem gambling.

Increasingly, operators are moving away from off-the-shelf solutions for risk identification and management. A key reason for this low demand is mounting evidence that such solutions are not directly transferable and need to be customized to meet the unique needs and data configurations of specific markets and operators. Operators typically have made large investments in customer relationship management and data management systems and are seeking to integrate risk-identification functionality within existing infrastructure to optimize resources. However, most data vendors have limited understanding of high-risk gambling and may have a conflict of interest in balancing maximization of ROI with mitigation of high-risk gambling, suggesting there may be a role for an independent Risk ID component within operators' various systems.

We have demonstrated that the use of a common variable pool across diverse operators and data systems created algorithms that met our preliminary targets of 20 per cent sensitivity and 80 per cent accuracy; at any given time, the model identifies approximately 1 in 5 customers at high risk for problem gambling with 8 out of 10 found to be at some level of risk using a gold standard comparison (Problem Gambling Severity Index) and at least 6 in 10 scoring for moderate to severe problems. It is not possible to detect all problem- and high-risk gamblers using loyalty data; some will not exhibit distinctive playing patterns or use their membership card often enough. However, an advantage in using a broad array of sophisticated multi-cue variables is that the rate of identification can be expected to increase overtime as customers trigger on certain risk indicators during the course of their play experience. To ensure relevance and consistency of the final outputs at an individual operator level, we are now focusing on model optimization whereby the automation algorithm would be self-tuning for selection of the best models using techniques such as genetic algorithms.

While the combined sample size in the current UK casino operator study satisfied the minimum requirement for creating and testing the model automation process, it is associated with several limitations:

- First, a larger sample size, e.g., 3,000, will increase the likelihood of collecting a wider range of playing patterns with greater confidence that the full range of behaviours are included in the training and validation samples. It would permit us to improve model precision resulting in higher accuracy rates and a reduction in false positive identification. Every customer is different and can encounter many different situations while gambling, so the models need to cover many different types of risk indicators or cues so that customers do not fall through the cracks. The models also need to be accurate so resources are targeting the right customers. If the rate of false positive identification is too high, that is, the people identified by the model are not actually at-risk, then neither staff nor customers will trust the outcomes and the system will ultimately have no value to users.

- Second, the use of a shared sample over the four operators meant that we did not have enough information to build and test specific models for each of the participating UK operators.

- Third, the loyalty data from participating casinos was not always complete as some systems were undergoing change. We expect to overcome these issues in the next phase of the project currently underway (commenced December 2015).

In summary, the automation algorithm Focal Research created in this project phase performed well. Model development tasks that previously were labour intensive and expensive were carried out automatically while still maintaining acceptable model performance. Although the accuracy levels are slightly lower than for operator custom-built models, by adding a model optimization layer to the system, we expect greater precision arising from this design. Moreover, the results of the study are promising from a practical perspective. Through this collaborative research, NCF now has compelling evidence that the data routinely gathered by UK casino operators can be used to produce reasonably accurate models to identify player risk. Preliminary UK models produced by the prototype achieved pre-set standards for success comparable to custom-built models in other markets, suggesting value to members in continuing to invest in such research.

NCF and its member casinos agreed to take part in the next phase of this collaborative project (December 2015 to December 2016) including assessment of uncarded data for identifying risk among the majority of customers who do not use a membership or loyalty card at the gambling venues. The goal will be to develop operator-specific models for testing in a 12-month trial to confirm model consistency and stability over time, as well as sensitivity in detecting changes in playing patterns over time. Adopting an evidence-based, staged approach positions all NCF stakeholders for success in creating the necessary knowledge, infrastructure, and motivation to act with confidence in achieving desired outcomes.

Additionally, NCF will be cooperating in research using player data to identify other high-risk gaming patterns including algorithms to detect money laundering (AML models) or other suspicious gambling activity such as gambling with misappropriated funds (MF models).

For additional information, refer to Focal Research's technical report to be released March 2016 (www.focalresearch.com).

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