

Schellinck, T., Schrans, T., and Zou, Y., (2009). Informing the Debate: Specifications for an Effective Gambling Risk Assessment System Based on Loyalty Tracking Data, the 6th International Conference on Gaming Industry and Public Welfare, pg. 149-168, Macau China, December 2009.

Informing the Debate: Specifications for an Effective Gambling Risk Assessment System Based On Loyalty Tracking Data

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Abstract

Player tracking data through customer loyalty programs, online systems, smart cards and other technology is fundamentally changing the gambling industry and how it operates. Traditionally this information has been used for marketing purposes. However, there is increasing pressure and controversy in trying to adapt these systems as tools for managing risk within the gaming industry. One such important and potentially contentious area is the use of player tracking data for prevention and corporate social responsibility (CSR) purposes, such as identifying and helping at-risk and/or problem gamblers. While the prospect of successful identification and intervention is vastly improved by the use of such a system, there are still legitimate concerns surrounding how to implement and evaluate the use of player data for these purposes. Opinions on the issue are ubiquitous despite the fact that there are few individuals or stakeholders, including regulators, researchers, and operators that have any experience or expertise in using such database information for CSR applications, defining policy and practices and informing the decision making process.

To inform on-going debate the paper will provide an overview of lessons learned through our substantive work in this important area of inquiry. This paper will present the fundamentals of working with player tracking data as well as common errors to look out for and pitfalls to avoid.

Introduction

Use of player tracking systems in gathering and analyzing player behavioural data is an established practice in the gambling industry. The original purpose of collecting gaming data for individual players was to understand their gaming patterns, and then to facilitate

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special promotional offers to those high-value patrons. However, with growing awareness of potential harms associated with gambling and the concept of corporate social responsibility (CSR), the idea of using player tracking technology for responsible gaming purposes has been addressed and implemented by various gaming stakeholders (Hancock et al 2008). In the context of legislation, some jurisdictions have enforced gaming operators' legal responsibilities for preventing and minimizing harms through the Gambling Act, regulations and licence conditions (New Zealand Gambling Act 2003, Great Britain, the 2005 Gambling Act and Code of Practice). As one of the key requirements for gambling providers is to develop a program or policy for identifying problematic gambling behaviour within venues, the use of loyalty data and player tracking has been noted by both researchers and regulators as an important and feasible approach to screen for At-Risk and/or Problem Gamblers (SkyCity Auckland Host Responsibility Programme, 2007). In addition, several gaming operators have also undertaken initiatives to utilize player tracking data for assessing players' risk level and mitigating related harms and problems through host intervention programs (iView and Saskatchewan Gaming Corporation 2006; Svenska Spel 2007).

While past research has indicated that player tracking data may be applied to develop models for identifying Problem Gamblers, there is lack of discussion on the typical procedures of model development as well as criteria for evaluating the identification results and model performance. This paper assembles authors' past research experiences in relation to player tracking, identification of problem gambling as well as loyalty data analysis. The purpose is to address the fundamentals of working with player tracking data as well as common errors to look out for and pitfalls to avoid. Based on the outcomes of past and recent projects, the authors also present an overview of the applications and limitations of current systems, as well as a discussion of the development of standards and other issues impacting future development.

Why consider a Gambler Risk Assessment System (GRAS)

Few Problem Gamblers seek professional assistance (Shaffer & Korn 2002; Schrans, Schellinck and Walsh 2003). The estimated 5 – 15 % who do get help are likely the most extreme cases and may have been referred for treatment by other agencies. The remaining Problem Gamblers include those who seek assistance from informal sources such as spouses, who find themselves being harmed by their gambling activity, but are not motivated to seek assistance or are those who simply do not recognize that they are at risk. It seems likely that the latter group, in particular, would benefit if made aware of their status. The Transtheoretical Model of Change (TTM) proposed by Prochaska and Diclemente (1992) suggests that recognition by a gambler that they have a problem is a major step toward recovery¹. Research studies have also shown that gamblers are likely

¹ The five stages of change are as follows: 1. precontemplation when the person has no intention of changing their behaviour in the foreseeable future; 2. contemplation where people are aware they have a problem but have not yet made a commitment to change their behaviour; 3. preparation when the person

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to benefit from assistance in recognizing they have a problem (Hodgins 2001, Schellinck & Schrans 2004a).

The lack of action on the part of problem or at risk individuals is of concern to gambling providers. They have a duty of care to ensure that the services provided are safe for their customers and that those who may be having problems are identified and given the opportunity to receive assistance. Moreover, providers may face litigation and financial penalties in lawsuits against them; if it is proved that they are responsible for the negative effects of their business practices. Hence, it is important for those gambling operators to put in place an appropriate gambling environment that enables them to identify problematic gambling behaviours, make those At-Risk or Problem Gamblers aware of their circumstances, and potentially assist them in modifying their gambling behaviour.

Considerable effort has already been taken to identify Problem Gamblers in non-clinical situations. Survey administered screens such as the Canadian Problem Gambling Index (CPGI) (Ferris & Wynne 2001), the Victoria Gambling Screen (VGS) (McMillen et al 2004) and the eight-screen (Sullivan 1999) have already been developed. These screens are based upon criteria similar to those found in clinical diagnostic screens, including the South Oaks Gambling Screen (Lesieur & Blume 1987) and the DSM IV (American Psychiatric Association, 1994). Moreover, research has suggested that Problem Gamblers be identified based on visible signs or behaviours within gaming venues. In the review conducted by Australian Gaming Council (AGC), various researchers suggested possible indicators that can differentiate Problem Gamblers from other gamblers on the “floor” (Allcock et al, 2002). While using each individual indicator may not result in a high confidence level in identifying Problem Gamblers, the accuracy of identification might be improved by combining these visible cues to assess the negative gambling impacts.

Schellinck and Schrans (2004b) analysed the connection between a variety of observable cues and problem gambling in order to determine their potential for identifying Problem Gamblers *in-situ*. Two different types of cues were assessed. Visual cues included kicking the machine, continuing to gamble until the venue closed and taking out additional cash from ATMs. Semi-visible cues or cues that could be identified by an observer included feelings of nausea or anger while gambling. The authors determined that using combinations of visible cues exhibited by gamblers while at a venue could lead to 86% of Problem Gamblers on the floor being identified with a 94% confidence level. These findings demonstrated that behaviours at the site may be indicative of problem gambling and that Problem Gamblers could be identified using multiple cues. The value of many of the indicators in the Schellinck and Schrans study were validated in other

has decided to change their behaviour, usually within the next month, and has already made small behaviour changes; 4. action when the person has modified their behaviour, experiences or environment in order to overcome their problem and 5. maintenance when the person works to avoid relapse and consolidates their gains achieved during the action stage.

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field research (Delfabbro, et al. 2007) as useful predictors of Problem Gambler status, where the authors concluded that the identification of Problem Gamblers within the venue environment was theoretically possible, as a number of on-site visible signs and behaviours were found highly prevalent in Problem Gamblers.

While the ability to assess player behaviour in such a way should improve the effectiveness of existing host programs in identifying Problem or At-Risk gamblers, all types of “on the floor” programs have limitations. Specifically, to be effective, observers would have to collect information and combine cues over time. As these observers are usually casino staff employed to provide customer service to gamblers, their ability to simultaneously attend to all of these cues is limited. As well, the only choice the staff may have in terms of an intervention is a “tap on the shoulder” as they may not know the player’s name. Attendants are likely to be hesitant to act in this manner as a gambler may resist and demand evidence for the intervention. The observer may also be biased in his observations. For example, a big tipper may never be singled out as a person of interest. The collection and analysis of data provided by a loyalty based program could overcome these problems.

The Use of Gambler Tracking Data Based on Loyalty Programmes

Loyalty programs have been introduced by casinos in jurisdictions around the world. Such loyalty programs require that gamblers insert their card into the machine or present it to a table attendant so that their play behaviour is recorded, making them eligible to receive bonus rewards. In general, retailers use loyalty data to model and segment their customer base for purposes of developing customer relationship plans. This technology has considerable potential to provide the database for developing a model to identify Problem Gamblers. In contrast to an “on the floor” program, a loyalty program based system could identify At-Risk and Problem Gamblers by analysing behavioural cues that have been measured in an unbiased manner over time. The development of a loyalty based model would also provide a measure of comparison for the “on the floor” observation program. This would enable providers to use two methods of identification of At-Risk individuals, with one measure being used to verify the other. Once the respondent is identified, a variety of interactions would be available to the host staff.

Loyalty data based models have the potential to be superior in many ways compared to traditional measures of problem gambling. The PGSI and other screens tend to focus on behaviours and the negative impacts of gambling on the person in order to identify those who are suffering from or are at risk from problem gambling. These scale items were developed by psychologists focused on the gambler they would be meeting at the clinic or in the lab and may be appropriate for those circumstances. However, the relationship between gambling behaviours and problem gambling are not obvious and accurately testable in that context. The people who developed these screens did not have access to the information such as tracking data that is available today and could not therefore

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develop a screen measuring gambling behaviours that adequately identifies Problem Gamblers.

The approach described here is based on standard data mining techniques for classifying customers. The model is developed to optimize accuracy for a specific customer base which means it has the potential to be more accurate than traditional screens based on samples in particular geographic locations and applied to different populations.

To have a better understanding of this, take one behaviour measure in the PGSI “When you gambled, did you go back another day to try and win back the money you lost?” The loyalty data can identify days that they lost large amounts of money and also determine if they returned within the next day, or the next couple of days to gamble again. What loyalty data does not tell us is what the motive was for returning the next day. Was it to win back their losses or was it simply to continue gambling? If they continually return the next day after a loss, is this because they only gamble on Fridays and Saturdays each week so any loss on Friday will be followed by gambling on Saturday? We have developed several different measures that would capture chasing behaviour if it is occurring. These include defining a loss as a fixed amount of \$200 or more and defining it as a multiple factor of their average losses over the previous loss sessions. It also includes coming back the next day, or within the next couple of days. These variables can then be tested to determine their ability to predict problem gambling as defined by the PGSI and those found to be significant included in our model development phase. The key is however that chasing behaviour by itself is a relatively poor predictor of problem gambling, but in combination with other behavioural cues, for example playing for an average of more than six hours per session and betting at maximum bet levels on the machines most of the time may allow us to accurately categorize this person as an At-Risk or Problem Gambler.

Screens such as the PGSI (Ferris and Wynne 2001) tend to rely on only one or two measures related to behaviour, though they have the advantage of being able to ask about the motive behind the behaviour at the same time (e.g., Have you needed to gamble with larger amounts of money to get the same feeling of excitement?). The loyalty based model can measure actual increases in expenditure (i.e., not based on a person’s estimate and not subject to method bias) along with a hundred other measures that collectively may be more accurate in identifying problem gambling behaviour than a nine item screen with two questions about gambling behaviour. However it is difficult to really determine this and we are left with attempting to predict a score on the PGSI which itself may be a flawed measure of problem gambling.

The loyalty data has certain strengths over data that has been collected using retrospective questioning and observation techniques.

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1. The sample though not representing all gamblers at the venue, will be far more representative of regular gamblers than samples found in surveys and experiments where response rates can be very low and frame bias substantial.
2. The sample size can be in the tens of thousands which will allow for very detailed analysis of behaviours.
3. Also, given the large sample size the confidence intervals around the data estimates will be minimal, giving the regulators and researchers far more confidence in the information derived from analysis of the data.
4. Models and relationships can be developed using test samples and then validated using large hold-out samples.
5. The sample can be updated on a regular basis so that it is always up-to-date. Analysis can be repeated inexpensively and quickly to ensure past findings still hold.
6. The sample monitors behaviours of individuals so that the dynamics of gambling behaviour over time can be measured. If individuals are able to be identified as Problem Gamblers then their behaviours over the next several years could be tracked for detailed analysis of their behaviours (However, see limitation described below.).
7. Information that is collected over time can be analyzed using time series analysis and lagged variables rather than relying on snapshot samples which sometimes leads to erroneous conclusions concerning the relationship among variables.
8. Also, because data for the same sample are collected over time, the impact of specific events such as new regulations, the change in the technology of the machines, etc., on segments of interest can be monitored and assessed.

There are some weaknesses in using loyalty data however:

1. The gambling behaviours measured exclude gambling at other venues and all other forms of gambling in which they may partake where tracking data is not available. However, for the majority of gamblers, gambling on EGMs or tables games where the play behaviours are tracked may represent the bulk of their gambling.
2. The data by itself does not contain information that will allow a researcher to definitively identify a person as being in a category of problem gambling. This means that the only way the data can be used for analysis of problem gambling is if they are surveyed and administered a problem gambling screener.

Specifications of Gambling Risk Assessment System

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Based on experience with Gambler Risk Assessment Systems over the last eight years we have derived a list of specifications that need to be considered when designing such a system.

1. **Model Accuracy: Specificity, Sensitivity and False Positives.**

The GRAS algorithm produced for purposes of identifying the risk classification of gamblers must meet criteria for accuracy. There are several possible criteria for examining the power and value of any model derived. To determine the value of a predictive model, the researcher usually assesses a classification matrix. In the example of a classification matrix below (Figure 1), we have a sample of 1,000 gamblers of whom 100 have been classified as Problem Gamblers using a screen. This leaves 900 that for purposes of this example we are designating as non-Problem Gamblers. We run our model which predicts (classifies) that 80 of the gamblers are Problem Gamblers and 920 are Non-Problem Gamblers. The matrix now provides us with the measures to estimate the accuracy of the model.

There several commonly used measures used to characterize the effectiveness of the model using the results of the classification matrix (Peng and So, 2002). These are:

1. **Sensitivity** is defined as the proportion of observations correctly classified as an event. In this case the event is whether they are a Problem Gambler and we correctly classified 60 of the 100 Problem Gamblers producing a sensitivity of 60%. Another way to look at this is to say we are effective in correctly identifying 60% of the Problem Gamblers.
2. **Specificity** is defined as the proportion of observations correctly classified as a non-event. In this case 880 out of 900 Non-Problem Gamblers were correctly classified giving us a specificity of 97.8%.

For our purposes, there are four other very important measures that need to be used to assess the value of a model.

3. **Confidence Level**, the proportion of those classified by the model as an event that are correctly classified. In our example, 80 gamblers were classified by the model as Problem Gamblers of which 60 were correctly classified and actually are Problem Gamblers according to the screen. This gives us a confidence level of 75 %.(i.e., 60/80). If we approach someone in a venue the model has identified as a Problem Gamblers we would want to be quite confident that they are in fact Problem Gamblers.
4. **False Positive Rate**, is the proportion of those identified as an event that are in fact not an event. In this case 20 of the 80 gamblers identified as Problem Gamblers are not, which gives us a false positive rate of 25%.

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5. **False Negative Rate**, is the proportion of those identified as a non-event when they in fact are an event. Of the 920 gamblers identified as Non-Problem Gamblers 40 are in fact Problem Gamblers according to the screen so we would say we have a False Negative rate of 4.3% (i.e., 40/920).
6. **Overall Accuracy** is the proportion of all gamblers correctly classified. In this case 60 of the Problem Gamblers are correctly classified and 880 of the Non-Problem Gamblers are correctly classified. The overall accuracy is therefore 94% (i.e., (60+880)/1000).

Figure 1
Example of a Classification Matrix for a Model Identifying Problem Gamblers

Classification Matrix

		Predicted	
		Problem Gamblers	Non-Problem Gamblers
		80	920
Actual	Problem Gamblers N = 100	60	40
	Non-Problem Gamblers N = 900	20	880

It is important to know these measures when appraising a model to be used to identify gamblers of different risk levels for several reasons.

Most models look good on one or more of these measures so they should all be considered. For example, in the above example, if all gamblers were classified as Non-Problem Gamblers then the model's overall accuracy would be 90%, and its specificity would be 100%, and its false negative rate would be 10%, which sounds good. However the sensitivity would be 0% and we could not calculate a confidence level or false positive rate. The model would be useless for identifying Problem Gamblers.

Secondly, when the model is designed, the modeller has a choice of which of these criteria to maximize, though increasing the score on one dimension usually reduces the score on another. The best example is the trade off between sensitivity and confidence level. When we increase the model's sensitivity we maximize the proportion of Problem Gamblers we will identify (reach), but this usually means that our confidence level will drop. The more Problem Gamblers we classify as Problem Gamblers, the more difficult it becomes to do this correctly and we increasingly have more false positives. Some Problem Gamblers may behave in such a manner that they can be clearly identified as

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Problem Gamblers, while others share many characteristics with Non-Problem Gamblers. When we classify the Problem Gamblers in this latter group, we also will classify the Non-Problem Gamblers who are similar to them as Problem Gamblers.

Whether one maximizes sensitivity or confidence depends on what the model output is used for. If the goal is to cost effectively reach as many PGs as possible, maximizing sensitivity makes sense. If reaching a false positive is an issue (as might be the case if one were interacting with a gambler on the floor), a high confidence rate is desired. If a gambling provider specifies a minimum confidence level of 90%, the modeller may be forced to reduce sensitivity to 20% (i.e., 20% of Problem Gamblers are correctly classified by the model) before this level of confidence is achieved. The cost therefore of a having a high degree of confidence in the classifications is that a large proportion, perhaps even the majority of Problem Gamblers, will not be identified.

2. Correct Approach to Classification

An algorithm produces output used to classify a gambler. Usually the higher the score, the greater the probability the gambler is a Problem Gambler. Sometimes it is assumed that the higher the score (i.e. probability of belonging to the target segment), the greater the risk faced by the gambler. Thus the probability continuum is used to assign gamblers to categories representing varying degrees of risk (e.g., Problem Gamblers, medium risk, low risk, no risk groups). However, people assigned a medium probability of being in the target group do not necessarily have a medium degree of risk. They could be Problem Gamblers whose gambling behaviour is too similar to low risk gamblers to have them confidently categorized as high risk by the model. To assume that a medium score in the model means the gamblers is at a medium risk level is therefore wrong and potentially problematic.

Figure 2 below illustrates the point. The model may assign a probability that each gambler is a Problem Gambler and this is used (incorrectly) to label them as high risk (often denoted by a red traffic light symbol), medium risk (Yellow Light) and Low or No Risk Gamblers (Green Light). These three model groups may make up 6%, 34% and 60% of the gambler population. Of those in the High Risk category, 90% are Problem Gamblers. We can therefore say we have a 90% confidence level that gamblers in the High Risk category are Problem Gamblers. Similarly, only 10% of those in the Low Risk category are Problem Gamblers and we can be 90% confident they are not Problem Gamblers if someone has been placed in this category.

Caution must be exercised in interpreting these categories as a risk continuum. The majority of Problem Gamblers fall into the Medium Risk category and comprise 50% of the gamblers in that category. Thus they are not at medium risk, they are simply placed in this category because they cannot be confidently assigned to the High Risk category.

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Similarly caution must be exercised when considering the Green Light category. This is the largest group of gamblers, and even though Problem Gamblers comprise only 10% of the group, this is 20% of all Problem Gamblers, as many as were categorized in the High Risk category. It would be incorrect to say that it is safe to target these people with a campaign to increase their gambling expenditure at the venue until the number and proportion of Problem Gamblers is sufficiently low in this category.

Figure 2
Sample Risk Classification

Model Score Probability of being in Target Segment	Model Category	% of gamblers that fall into each Model Category	% in each model category that are Problem Gamblers	% of Problem Gamblers in each Model Category
50% - 100%	High Risk (Red Light)	6%	90%	20%
10% - 49%	Medium Risk (Yellow Light)	34%	50%	60%
0% - 9%	Low Risk (Green Light)	60%	10%	20%

3. The algorithm derived and reported accuracy measures need to be validated using a holdout sample.

When developing algorithms, the modeller creates two (and sometimes three) samples. The first is called the training sample and this sample of gamblers is used to create the models. However, modeling techniques such as regression analysis, decision trees and neural networks all maximize their ability to predict/classify. This means that they use the specific characteristics of the training sample to arrive at an optimal model. That sample profile may differ however from the population at large on several variables that the model ends up using to predict group membership.

For example, it may be that Problem Gamblers in this sample were more likely to play on Tuesdays than Non-Problem Gamblers and the model based on this training sample uses play on Tuesday as one of its variables to classify the gamblers. However, it may be that in the general gambler population, Problem Gamblers are **no more** likely to play on Tuesdays than Non-Problem Gamblers. The randomly selected training sample just happened to have more Problem Gamblers playing on Tuesdays. To help guard against this possibility, modellers create a hold-out sample called a validation sample, which, assuming the Tuesday play by Problem Gamblers was a random anomaly, would **not** have Problem Gamblers playing more often on Tuesdays. When the model is applied to the hold out sample, it cannot predict as well because this variable no longer works, just

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as it would no longer work if it were applied to the general gambler population. The ability of the model to correctly classify gamblers is therefore reduced when applied to the validation sample. This is generally the case, though in rare instances the model may perform better on the validation sample than the training sample. The results of the model when applied to the validation sample are felt to be a better estimate of the true accuracy of the model and should always be the criteria by which a model is judged. Thus we use the classification matrix for the validation sample when estimating measures such as sensitivity and confidence levels, not the classification matrix from the training sample.

4. The validation sample must match the training sample and should not be based on a self selected sample

Following on from the point 2, the validation sample used should **not be** based on a self selected sample unless it is first weighted to reflect the distribution of the original training sample. This assumes that the training sample has the same profile as the general gambling population.

Some models now available have been validated by having gamblers fill out a self administered screen. The results of the model and screen are compared and accuracy rates of in excess of 90% are reported. This is problematic as the self selection process could create an artificially inflated estimate of the model's accuracy. The example below illustrates how this could happen using hypothetical numbers, though these numbers are close to those found in several studies of gambler populations the authors have examined over the last four years.

First, we assume that if a standard screen were administer to a sample of a venue's yearly customers that 40% would be classified as At-Risk or Problem Gamblers (we will refer to these groups collectively as At-Risk Gamblers). Second, when presented with the opportunity to fill out an online self administered problem gambling screen, we assume that those who are At-Risk are much more likely to fill it out. If we estimate that At-Risk gamblers are four times more likely to fill out the screen, 73% of those who fill out the screen will be At-Risk gamblers and the rest (27%) will be Not At-Risk gamblers.

A model might achieve the classification rate in Figure 3 below.

Figure 3

Classification Matrix Based on Self Administered Screens to Validate Model

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Self Administered Screen Classification Matrix

		Predicted	
		At-Risk Gamblers	Non At-Risk Gamblers
		78	22
Actual	At-Risk Gamblers N = 73	70	3
	Not At-Risk Gamblers N = 27	8	19

This classification matrix reports a sensitivity of 96% (70/73), a confidence for identifying At-Risk gamblers of 90% (70/78) and an overall accuracy of 89% (70% + 19%). These are very good numbers by most standards. However, they are inflated because they are not applied to a representative sample of gamblers. If a random sample of gamblers was used as a validation sample then we might expect the classification matrix shown in Figure 4.

Figure 4
Classification Matrix Based on a Random Sample of Gamblers

Validation Sample based on a Random Sample of Gamblers: Classification Matrix

		Predicted	
		At-Risk Gamblers	Non At-Risk Gamblers
		56	44
Actual	At-Risk Gamblers N = 40	38	2
	Not At-Risk Gamblers N = 60	18	42

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We assume the sensitivity of the model would remain the same and that 96% ($\approx 2/40$) of At-Risk gamblers would be identified. We also assume the Not At-Risk gamblers are identified with the same accuracy, but their numbers become larger because in a random sample of gamblers they make up a larger portion of those analysed. In this case, the overall accuracy drops to 80% (38% + 42%) and the confidence level drops to 68% (38/56). This means that overall twice as many people are misclassified (10% versus 20%) and rather than one in ten being false positives, the number in this example is one in three.

Arguments can be made that our example underestimates the amount of bias due to self selection (e.g., the sensitivity would also likely drop with a random sample) or overestimates the bias (e.g., the likelihood of At-Risk gamblers filling out the screen is not that different from Not At-Risk gamblers), but we feel this example clearly illustrates the potential for bias in such an approach. There are methods of estimating the bias due self selection but these methods would need to be applied and new numbers produced before the accuracy of the model is reported. The bottom line is that the accuracy numbers reported using this form of validation cannot be compared to more legitimate forms of validation until the potential for bias has been assessed and dealt with.

5. The responsiveness of the algorithm to changes in gambler behaviour

The model utilizes behaviours that occur over a specific period of time, say a year, and then creates variables from this recorded behaviour and makes a prediction as to the category of risk to which that gambler belongs. A year's worth of data may be required to collect enough information to make accurate predictions. However, it is also important that the model be responsive to changes in behaviour that results in the gambler being in another risk category (either increased or decreased risk). If a gambler stops gambling because they exclude themselves from gambling or they change their play patterns to those consistent with responsible gambling, the model output should reflect this within a short period of time, when the improved behaviour continues. However, the algorithm should not be so responsive that it changes a person's categorization if they temporarily change their behaviour. Algorithms that rely more on play patterns rather than the frequency or extent of gambling will more likely have sufficient momentum to not respond to these temporary changes in behaviour.

6. Reach in terms of different levels of gambler expenditure

Modellers will have an easier time assigning those who exhibit more extreme behaviour to the high risk categories. So those who spend more and gamble more frequently will likely be categorised as those At-Risk or Problem Gamblers. However, the majority of those who are At-Risk may not fall into the extremes. It becomes more difficult to identify a Problem Gambler who does not exhibit extreme behaviours. However, a good

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model should be able to identify a significant proportion of At-Risk and Problem Gamblers who are not high spenders as well as identifying those who are.

A similar concern is that not all of those in the high end, for example “high rollers”, be categorized as At-Risk or Problem Gamblers. It is relatively easy to maximize sensitivity (reach of At-Risk and Problem Gamblers) by including most of these high rollers in the high risk category, but at a cost of including too many false positives. A good model should be able to minimise the number of false positives in the high expenditure segments.

7. The screen used to measure risk levels needs to be appropriate

A typical model uses the output of a risk screen such as SOGS or the PGSI that assigns gamblers to risk categories as a dependent or target variable. The dependent variable is used as a benchmark in designing the model to classify gamblers by risk level. An underlying assumption in this modeling process is that there is no error in the dependent variable. That is, the gamblers are correctly classified by the screen. However, we know that application of these screens to the same samples often results in only 60% overlap in classification (e.g., Ferris and Wynne 2001) so that the results depend very much on the choice of screen. The gambling provider must therefore have confidence that the screen utilized is appropriate for the venue setting and the type of gambling (i.e., EGMs and table games) since the behavioural data used to classify gamblers is based on these forms of gambling.

8. The shelf life of the algorithm

The legal and social environment in which gambling occurs, the alternative attractions available for entertainment and the nature of people’s preferences and perceptions change over time. Changes in all of these factors can lead to deterioration in the model’s effectiveness. Models once developed are said to have a shelf life. The gambling provider should specify that the accuracy of the model be reappraised at least every three years and the model be updated if necessary. A representative sample of gamblers should be used when testing and recalibrating the model.

Data miners sometimes claim their models update themselves over time. However, to update their effectiveness the models must have up-to-date values for the dependent variable, that is, the current status of the gambler in terms of risk. The source of this updated information could be screens completed by those who are self administering the screen, or those who have sought assistance and the screen score is supplied to the modeller. However in both these cases the sample being used to update is very likely biased toward those gamblers who are more at risk. This is the same issue we identified in the discussion concerning validation of the model. Use of this sample to recalibrate the model over time will lead to a biased model that cannot be applied to the gambler

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population as a whole, but is only valid for those who self identify. As well, its reported accuracy will likely be inflated due to the sample used to create it when comparing the model's accuracy to others that use a general gambling population to calibrate.

9. Variables used should have valid values over the life expectancy of the model

A common problem in data mining and modeling is the use of information collected at a point in time that may no longer be valid as time passes. Obvious examples are demographic variables such as income, work status or family composition that become out of date and deteriorate in value as predictors over time. However, this would also include any other information collected at a single point of time such as attitudinal variables, recent behaviour and experiences, perceptions/beliefs and other measures often collected in surveys. Some of these variables can change quite quickly and frequently (e.g., work status) and their inclusion can cause the model accuracy to deteriorate rapidly. Other variables based on psychological measures can change even more quickly and should be used with extreme caution. Our recommendation would be that a model that does not rely on variables of this type is preferred over ones that do.

10. Variables should not be based on gambling behaviours from more than a year previous to the time the model is run and a classification made

A minimum amount of information needs to be gathered on a gambler before a model can be developed and applied that categorizes them. For a gambling risk model the gamblers need to have had their gambling behaviour recorded a set number of times (this could be a minimum of anywhere from three to fifteen times) so that the predictor variables used will be populated sufficiently for modeling. Typical of most consumption processes, the majority of gambling activity is accounted for by a relatively small proportion of those who gamble over a year. The actual number varies by venue and jurisdiction, but it can be expected that as many as 50% will only have between one and five sessions of gambling recorded over a year. If it is determined that a minimum of ten sessions is required in order to provide enough information for accurate modelling of gamblers then this proportion could be further reduced to 25% of the yearly gambler population.

The amount of information (i.e., sessions) needed to produce an accurate model can be determined empirically using a set of criteria. However, once the minimum number of required sessions is set, the proportion of people included in the modeling process can be increased by expanding the time frame for inclusion. That is, rather than relying on one year's worth of data the modeller could use two year's worth of data which could have the impact of doubling the number of gamblers who are classified by the model.

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We would recommend one year's worth of gambling behaviour be used as this corresponds to the length of time used by most risk measures. If a shorter period is used then we recommend the risk instrument administered to the gambler should also use the same time frame.

11. The training and validation samples must accurately represent the profile of the gambling population to which the model will be applied

The sample used to develop the model should be representative of the sample to which it is applied. If the model will be used to assess regular gamblers, defined as those gamblers who gamble at least twelve times a year then the model needs to be trained on a sample with the same profile. There are a couple of ways this might not be the case. The model could be developed based on patrons of one type of venue, one specific venue or customers from a particular jurisdiction and then be applied to other types of venues, other venues not similar to the one used for training, or even customers of venues in other jurisdictions. As mentioned previously, the validation sample may not represent all regular gamblers either if self selection is used.

Risk measures such as SOGS and the PGSI are applied to jurisdictions around the world, so the question is why these data-based algorithms can't be similarly applied to other jurisdictions as well. The answer is that screens such as SOGS have indicators of inappropriate behaviours and negative consequences due to gambling that are fairly universal. Stealing to pay for gambling debts is inappropriate behaviour in all jurisdictions and therefore the statement works as a measure to determine risk levels for players in most parts of the world. However, gambling behaviour measures used as predictor in statistical models are less transferable. There is a defined relationship (usually isotopic) between the dependent variable (am I a Problem Gambler) and the independent variables (maximum rate of play in a session) such that above a certain value for the dependent variable (e.g., I spend more than \$11.50 per minute) the gambler is likely to be classified as a Problem Gambler. A model developed in Canada where the maximum bet per spin on a VLT is usually around \$2.50 will have a lower value for this variable that is associated with problem gambling than is the case in Victoria Australia where the maximum bet per spin on a Pokie machine can be \$10.00 per spin. In this case a maximum spend of \$18.75 per minute may be necessary before a gambler is designated as a Problem Gambler by the model. The same variable may be effective in both jurisdictions; it is the level that designates one as a Problem Gambler that is likely to be different. The appropriate level can only be determined through empirical research using a sample that is representative of the gamblers (and play behaviour) in the jurisdiction where it will be applied.

12. The system for collecting the play behaviour must ensure that the behavioural data being collected is that of the loyalty member

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The system set up to apply the model needs to have certain characteristics for it to work effectively/correctly.

- a. Gamblers who lose a card or obtain a new card need to be connected to their existing play behaviour information if it occurred within the time frame of the model (i.e., in the previous year)
- b. Gamblers can only use one card at time
- c. Gamblers cannot share their cards with others in order to gain more loyalty points or to allow others access to EGMs/table games who might otherwise be unable to do so.

Summary

Existing means of identifying At-Risk and Problem gamblers such as problem gambling screens and the use of cues exhibited on “the floor” of the venue are limited in value and can be augmented effectively using a Gambling Risk Assessment System based on player tracking data. The paper provided a list of specifications that are not exhaustive but should give gambling providers and jurisdictions setting policy guidelines for such systems a better understanding of the characteristics of an effective Gambling Risk Assessment System. Above all the system should provide the users with accuracy, broad coverage of gambler segments, real value in terms of identifying At-Risk or Problem Gamblers in a timely and effective manner and confidence that the system is valid in its categorization of gamblers over the life of the model. There is considerable opportunity for the implementation of these systems in jurisdictions and markets world-wide and there will be continued development of the techniques for developing these models that will meet the specifications presented here.

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