Independent Gambling Authority

Predictive monitoring consultation

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Using Loyalty Data to Identify High-Risk Gambling Patterns

Understanding the use of Behavioural Analytics and Predictive Modelling for Customer Care

Discussion Paper

Final Report

PREPARED BY FOCAL RESEARCH CONSULTANTS

7071 Bayers Road, Suite 326

Halifax, Nova Scotia,

Canada B3L 2C2

PH: 1-902-454-8856

Fax: 1-902-455-0109

Toll Free: 1-888-454-8856

E-mail: focal@focalresearch.com

www.focalresearch.com

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Using Customer Loyalty Data for Identification of High-Risk Gambling Patterns

Overview: The Independent Gambling Authority (IGA) is engaging with stakeholders about the use of data in loyalty systems as a tool to support identification of high-risk gambling patrons. On November 24, 2015, the Independent Gambling Authority will undertake public consultation mandating the use of predictive analytics in gambling loyalty programs effective as of July 1, 2016 pending the outcome of the consultation process. The goal of consultation is to "to enable the Authority to not only receive information and submissions regarding predictive monitoring, but to foster a proper dialogue on this important opportunity to protect people at-risk". To help inform the dialogue the Principals at Focal Research, an independent Canadian research company, were invited by the IGA to contribute to the hearing as part of expert input before hearing from operators and industry representatives. For over a decade, Focal has been developing and evaluating algorithms and models using player data for risk identification applications in various markets around the world. Since developing the first commercial gambling risk identification algorithms implemented in two casinos in 2005, we have adapted this approach for identification of risk among electronic gambling machine, slots, and video lottery gamblers, casino table game players and subsequently online gaming, sports betting and racing (e.g. horse, dogs) also developing complementary algorithms to identify other patterns of play for compliance and marketing purposes. Focal has worked independently and collaboratively in this area of inquiry with operators, regulators, public health organizations, and government bodies around the world creating a balanced and integrated understanding of market dynamics impacting system design, implementation, compliance and stakeholder accountability. We believe the integrity and transparency of our work in this area, in combination with meticulous standards for information confidentiality, data security, and privacy protection provides added-value by instilling confidence in research outcomes among all stakeholders.

The following discussion paper is intended to provide general information about risk identification models and how they work to assist SA stakeholders in understanding the technology from a practical perspective evaluating the potential value and utility of the technology as a tool to assist players and operators in identifying, managing, and ultimately preventing high-risk and problem gambling.

Authours: Dr. Tony Schellinck (CEO Focal Research Consultants; Past F.C. Manning Chair in Economics and Business, Rowe School of Business, Dalhousie University, Halifax Nova Scotia Canada) & Tracy Schrans (President Focal Research Consultants, Halifax, Nova Scotia Canada)

Loyalty data and player tracking systems permit consistent monitoring of gaming activity over time in order to inform ongoing decision-making by players and operators. The introduction of additional capacity to assess such activity by risk for gambling problems enhances the value of the system in setting performance metrics and evaluating the relative success of various initiatives in achieving desired outcomes to reduce risk and broader gambling harm.

1. Focal's Risk Modeling Credentials

1.1. The team at Focal Research has been examining the behaviour of gamblers for the past 29 years completing the first comprehensive study demonstrating at-risk machine gamblers could be identified solely using behavioural measures in 1998, with longitudinal follow-up tracking changes over time in 2000. Much of our early work in this area involved the design and administration of ground breaking surveys with regular and at-risk gambling patrons that consequently enabled us to identify their specific patterns of behaviour and to evaluate the impact of responsible gaming initiatives by risk (Schellinck & Schrans, 2003, 2004, 2007)

1.2. At the same time, the Focal 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.

1.3. In 2001 we 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 (slots, video lottery, pokies, EGMs) in casinos and other wide area gaming networks in Canada, Europe, Australia, and New Zealand .

1.4. In 2005, we used casino loyalty data to build the first bespoke models for detecting behaviour 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 RG program. The models were deployed in two casinos for 8 years triggering 39,000+ customer interactions. During this time, management reported that there were no customer complaints, the player base increased, risk declined, & staff embraced the tool as an essential part of their customer service.

1.5. Since then Focal has designed and implemented various predictive models for use in multiple gambling environments around the world.

1.6. Despite the value of these models as a tool for gaming operators in better targeting their RG resources, custom models are labour intensive and expensive to build and maintain, placing this technology beyond the reach of some operators.

1.7. Starting in January 2012, Focal initiated a pilot study with government funding and operators in three different countries to develop a prototype to automate the customization process in an attempt to making the technology more accessible, affordable and user friendly for operators.

1.8. In May 2014, in collaboration with the UK National Casino Forum Focal worked successfully with multiple casino operators over an eight month period using different gaming systems to develop standardized data sets and test the prototype automation system creating customized behavioral indicators and preliminary models for identifying risk across different UK casino venues (Report to be released December 2015).

1.9. Phase 2 of the project will commence in January 2016 including operator trials as well as the development of models to identify risk using 'uncarded' data sources.

2. Regulatory Context

2.1. The Independent Gambling Authority is engaging with stakeholders about the use of data in loyalty systems as a tool to support identification of gambling patrons for whom an interaction or intervention might be of value in reducing or preventing gambling harm.

2.2. South Australia's Gambling Codes of Practice, Clause 55(2), requires predictive monitoring to be included in all gambling operator's loyalty programs, as of July 1, 2016, pending the outcome of the consultation process, with automated risk monitoring for all gaming machine licensees in place by Dec 2018.

2.3. South Australia is not alone, with gambling operators in various markets around the world, in particular, Canada, Europe, the United Kingdom (UK), Australia and New Zealand, actively seeking to develop world class expertise and leadership in player protection and sustainable gambling practices.

2.4. This interest is largely compliance driven. The gaming market globally is at a point of transition, poised for growth yet increasingly constrained by a precautionary regulatory environment focused on containing and managing risk associated with gambling.

2.5. Initially, legislation specified identification of vulnerable persons and probable problem gamblers (e.g., 2001 Swiss Social Contract; New Zealand 2003 Gambling Act; UK 2005 Gambling Act).

2.6. As technology advances there is a corresponding shift towards creating algorithms for assessing customer risk, moving responsible gaming (RG) responses from reactive solutions (e.g., referral of problem gamblers for treatment, self-exclusion or self-banning) to proactive prevention, risk and harm reduction expanding the use of behavioral data analytics to assist in detecting and preventing problem gambling and gambling-related harm among customers.

2.7. With opportunities for innovation and expansion contingent upon regulatory compliance and increased competitive pressure from the remote and online gaming market, established gambling operators are striving to meet licensing requirements while remaining relevant to their customer base and profitable going into the future.

2.8. Currently, the onus is on operators to demonstrate they are meeting, or preferably, exceeding objectives for customer safety, gaming probity and integrity.

2.9. At the same time, there is a clear regulatory expectation in SA, and other markets, that gaming operators will use technological advancements to monitor play, identify risky behaviour patterns, and then have suitable programs in place to respond appropriately including support to customers needing help to manage or control their gambling.

2.10. Despite these directives, there is little information or consensus about how to achieve these goals, few portable commercial systems exist, and little to no definitive research is publicly available as to the performance of these proprietary systems.

2.11. Industry has been quick to use loyalty data for fraud detection and marketing purposes (e.g., rewarding and shaping consumer behaviour), both of which comprise core business services for gaming operators, but much slower to adapt this same data for RG, harm minimization and prevention, primarily due to uncertainty about the value and impact of high-risk gambling detection for operations, profitability and resource allocation.

2.12. However, in cases when operators have not responded preemptively through innovation and/or research and development, regulatory directives have become more prescriptive in nature specifying specific actions and solutions for operators that may or may not be uniformly effective (Swiss Social Contract 2001, New Zealand, Gambling (Harm Prevention and Minimisation) Regulations, 2004; Australia, Gambling Codes of Practice, 2015; UK, Licence Conditions and Codes of Practice, 2015).

2.13. It appears operators would benefit from undertaking independent and collaborative research in this area to understand and evaluate the value of risk identification for commercial and business applications.

3. Use of Loyalty Data to Identify Risk

3.1. Williams, West and Simpson (2012) undertook a comprehensive review of the many approaches used to combat the issue of problem gambling concluding that other than restricting the general availability of gambling most other interventions could be classified as "moderately low" in terms of success. Thus, finding a better method for monitoring and managing prevention and harm reduction has become compelling for operators.

3.2. Delfabbro, King and Griffiths (2012) have extensively reviewed the limited research in this area, and concluded that a methodology in which behavioural information is combined with transactional data could be a successful strategy for improving the identification of those with gambling related issues.

3.3. More recently, the Responsible Gambling Trust in association with NatCen and Featurespace recently undertook to identify harmful patterns of play by linking loyalty card information with transactional data from five UK bookmakers (Excel et al., 2014). This is the first group to undertake a behavioural analytic approach similar to that used by Focal (Schellinck & Schrans 2007, 2011). Despite the preliminary nature of the findings and the development of rudimentary models, as one of the few studies publishing the data in the public domain, it has served to increase the pressure for gaming operators to start using loyalty data for risk mitigation.

3.4. The research achieved some success in detecting problem gamblers; however, in general, the authours indicated that it was difficult to find appropriate markers that would identify problem gamblers and yet exclude those who were not in danger of harm. They called for further research into determining how to make predictive modeling more accurate in this context (gamblingcommission.gov.uk).

3.5. This conclusion was echoed by one reviewer who praised the work as providing "an excellent foundation to build on" (Blaszczynski, pg 1, 2014) but suggested that more combinations of variables must be examined to improve accuracy of outcome and noted that existing measure of problem gambling such as the PGSI may not be suitable in this context.

3.6. Based on our own work in this area, Focal's current modelling is significantly more complex and sophisticated, progressing well beyond simple measurement of gambling intensity by generating over 700+ single and multi-cue variables for developing multi-layered models. In addition we have designed and validated a new gambling risk measure (FLAGS) to assist in identifying early risk and serve as suitable target variables for prevention models.

3.7. Moreover, a number of systems have been developed and implemented in Canada, Europe, and the UK over the past decade including the earliest systems, iCare (2005; Canada) and Playscan (2006; Sweden), as well as recent additions such as Technlink's My Play RG System (2007, NS), Neccton's Mentor (2012, Vienna), ARIC Featurespace (2014, UK) and GR Systems (2015, Italy) as well as other proprietary systems developed in Australia and by gaming system vendors such as Bally & G-Tech.

3.8. We have been fortunate to work with many of these companies assisting them in developing the algorithms at the core of their systems.

3.9. However as noted by Andreas Holmström, CEO of Playscan AB, "Today, there are several variations of responsible gambling tools like Playscan on the market. Behavioral tracking tools are a recognized responsible gambling methodology, used for consumer protection. Our solution has been ahead of this curve, leading the way, which is really inspiring. However, we see that many operators pursue their own solutions, making demand for an off the shelf solution low." (July 2015 http://playscan.com/category/press-releases/)

3.10. One of the key reasons for this low demand is evidence that such solutions are not directly transferable and need to be customized to meet the unique needs of specific markets and operators.

3.11. Gaming markets, customers, products, data systems, the data captured by the system, regulations and policies differ dramatically over operators and our experience is that this is also true for risk identification and the algorithms at the heart of such systems.

3.12. It is not possible to identify all problem gamblers using predictive models; not all exhibit distinctive playing patterns that can be detected by the models. Yet, at any given time such models can identify as many as one in every 4 to 5 customers at high-risk for experiencing problems with a high-degree of accuracy providing operators with a new tool for assessing RG efforts and for targeting limited resources more effectively and efficiently.

3.13. Over time the number of high-risk and problem gamblers identified increase as they trigger on various harm indicators during their play experience.

3.14. The challenge for operators is determining how to comply in implementing a system that will be appropriate for its specific business and how to manage the potential impact for staff, customers, revenue and operations.

4. Assessing Model Performance (Metrics)

4.1. Assessing model performance can be confusing and intimidating. It is often difficult for operators and stakeholders to understand exactly what is being measured when vendors claim resulting models are highly accurate.

4.2. Therefore, it is helpful to have a basic understanding of the key metrics used to evaluate model performance and the various factors influencing these metrics as this information has implications for system design and implementation.

Defining a Target Variable

4.3. When building predictive models there must be a target variable that you are trying to predict in order to report on how well a model performs in identifying that target.

4.4. If you do not have a target variable for high-risk or problem gambling then you cannot measure nor report on how well the model performed in identifying players in this group.

4.5. While a model can be self-learning or adaptive, the accuracy and performance of the model in identifying high-risk or problem gambling cannot be determined without testing it against an independent measure of gambling risk. This provides proof about how well the model works when applied to the general population of gamblers.

4.6. Some models are built or updated using profiles for specific players such as players who self-exclude, or exhibit changes in their gambling intensity. In all cases, the generalizability of these targets to high-risk among regular gamblers at large is unknown. They may or may not be high-risk gamblers but this information is not available.

4.7. To obtain a definitive identification of high-risk and problem gamblers Focal administers a standard problem gambling instrument such as the Problem Gambling Severity Index (PGSI) (Ferris & Wynne, 2001) and/or the Focal Adult Gambling Screen (FLAGS) to a random sample of eligible customers and then links the risk score to their loyalty data in order to develop an algorithm (i.e., predictive model) specific to this target.

4.8. The key advantages of this method:

- It provides the analyst with greater versatility in the modelling process allowing us to include more complex targets (e.g., High-risk-prevention versus Low-risk-marketing)
- The model will be representative of the entire target population rather than a narrow subset of gamblers
- It provides the operator with information about how the model will work when applied to the full population of customers

- It can be used to prioritize targets and interactions ensuring appropriate resources and infrastructure are in place in advance
- It can be rolled out in stages, targeting the most urgent targets first (e.g., severe problem gamblers for interaction) and then expand model applications to introduce or assess preventative targets (e.,g., those scoring for impaired control for setting a budget)

4.9. For other approaches using target variables such as those who self-exclude or increase their gambling intensity as a proxy for problem gambling, without the use of an external risk measure it is not possible to assess how well these other methods perform in identifying risk in the broader player population. We can only determine how well it performs in identifying the specific targets.

Using a Validation Sample

4.10. In order to build and test a model, the sample size must be large enough to be sub-divided into a training sample, used to build the model, as well as a validation sample used to assess how well the risk identification models perform in identifying risk.

4.11. Reported accuracy and model results must be based on the validation sample as this is an indication of how the model will perform when applied to the wider population of customers.

4.12. Reporting results based on a training sample is not appropriate as it can overestimate the accuracy of the algorithms.

4.13. This process is essential 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 use in a venue or specific gaming environment.

Performance Metrics

4.14. High accuracy rates do not necessarily mean that the model is accurate in targeting high-risk gamblers. It may simply mean that the model was good at classifying the majority of players into the right category. For example, a simple yet useless model could assign all players as non-problem gamblers and achieve 90% accuracy even though problem players made up 10% of the sample and all of these players were misclassified.

4.15. Usually researchers report on how well a model classifies players into each of four categories; True Positive, False Positive, True Negative, False Negative.

4.16. From an operator perspective the primary goal is to maximize the number of targets identified (True Positives - e.g., Problem Gamblers) and, even more importantly, minimize the number of non-targets identified (False Positives - e.g., Non-Problem Gamblers).

4.17. Therefore there are two key measures of interest to operators in terms of model performance (See figure below):

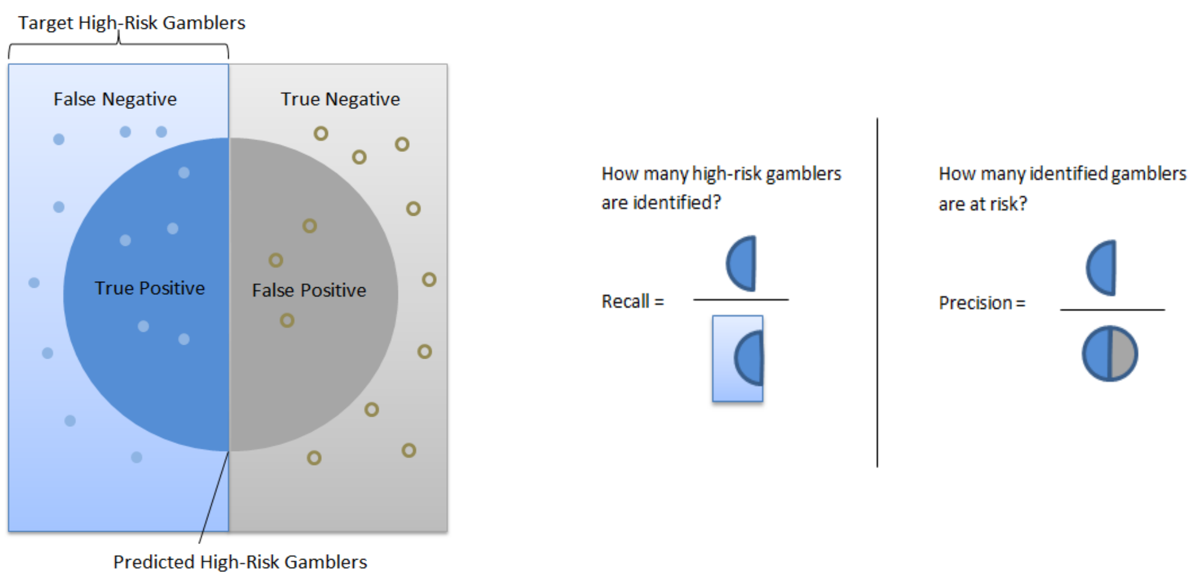
- Model Recall (Sensitivity) **How many targets (e.g., high-risk/problem gamblers) are correctly identified?** Refers to the percentage of individuals in the target group (e.g., high-risk gamblers) that are identified by the model (True Positive versus False Negatives)

Model Recall = (True Positive)/(True Positive +False Negative)

- Model Precision (Accuracy) **Of those identified how many were in our target group?** Refers to the percentage of individuals correctly identified as part of the target group versus those identified by the model who are not part of the target group (e.g., low-risk gamblers) (True Positives versus False Positives)

Model Precision = (True Positive)/(True Positive +False Positive)

Model Performance Matrix – Precision & Recall[1]



Managing False Positive Identification

4.18. It is important to note, that there is a trade-off between making sure you are reaching as many high-risk gamblers (maximizing True Positives) as possible without needlessly disturbing low-risk customers (minimizing False Positives).

4.19. As noted earlier, from an operator perspective this is a critical consideration. The only way to be certain a model will minimize the identification of False Positives, is to make sure you use an independent risk measure as your target variable so you can check your model recall (reach) and precision (accuracy).

[1] 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 International.

4.20. Identification rates should always be evaluated over time to assess model consistency and performance in situ. This generally consists of a trial over an extended period to ensure the model is performing as expected including forward (e.g., next 12 months) or backward testing (e.g., past 12 months).

4.21. Aside from model trials, there are other things you can do when building the model to improve model precision and reduce the degree of False Positive identification rates.

4.22. For example, we use a five stage process to build a series of algorithms that specifically target key segments to refine identification rates:

1.	Build High-risk Models to detect gaming behaviors outcomes and playing patterns with a high probability high-risk for High-Tier/VIP Players.
2.	Build High-risk Models to detect gaming behaviors outcomes and playing patterns with a high probability high-risk for Mid -Tier customers Models.
3.	Build High-risk Models to detect gaming behaviors outcomes and playing patterns with a high probability high-risk for Low-Tier/ Players.
4.	Build Low-Risk Models to detect gaming behaviors outcomes and playing patterns with a high probability of No risk for All Players.
5.	Assign all other Players to Unknown Risk Category

4.23. Not only does this improve the precision of our models but it lets us selectively target segments to customize client needs.

4.24. It also ensures that we are identifying high-risk within all the player tiers and not just among the high spend/high frequency customers (Red Model).

4.25. It also identifies those customers exhibiting no or low-risk gambling patterns (Green Model). This is important as most high-risk gamblers will be missed by any algorithm and, therefore, a separate model is required to distinguish low-risk players from those who are simply missed by the high-risk (Red) models.

4.26. However, as more high-risk gamblers are identified at a single point in time, the chance of including low-risk gamblers also increases meaning that model accuracy usually declines. In other words, the model will identify a larger proportion of the target group (e.g., high-risk gamblers) but at the same time include a greater proportion of non-targets too (e.g., low-risk gamblers).

- This may be appropriate for circumstances when tolerance for False Positives is high (e.g., ensuring as many high-risk gamblers as possible do not receive promotional material or other potential gambling inducements) but greater accuracy will be required when identifying high-risk customers for a personal interaction.

5. Stage 1 Identification- Theory Based Approach to Risk Modelling

5.1. For the most part, player data and associated behavioral analytics are highly proprietary and protected business intelligence rarely if ever available in the public domain.

5.2. In the absence of actual player data, researchers have attempted to translate general learnings from treatment populations, player surveys, prevalence studies, or accessible online government operated gambling data sets as a proxy for gambling behaviour patterns.

5.3. Using a theory based approach researchers have concluded that gambling intensity is a critical defining characteristic of problem gambling. Therefore, they have set intensity variables such as session length, frequency of play, amount spent, amount bet, and theoretical loss, as key markers of harm.

5.4. This has resulted in the following methods for basic risk identification that form the basis of most systems currently on offer:

- Identification of customers who exceed certain pre-set thresholds, typically consisting of frequency (number of visits or wagers) and/or spend variables (net expenditure, theoretical loss), with those exceeding certain pre-set thresholds flagged for interaction or other remedial action.
- Identification of customers who deviate from established norms whereby a normal play pattern is established either for the specific customer or the overall customer base and any significant deviation from this norm will trigger a customer interaction or remedial action.

5.5. Advantages of systems based on intensity harm markers and normative models include:

- Intensity variables are easy to generate.
- It is relatively cost-effective to implement with minimal infrastructure investment.
- Regulators, operators and staff have a specific simple and clear set of criteria for triggering an interaction/action
- It is easy to oversee and to report upon
- Performance metrics consist of how many customers met the threshold, how many interactions took place and then related outcomes (e.g., player's behaviour dropped down below the threshold)

5.6. The operator does not need to conduct a player survey to gather a target variable (e.g., measure of risk for problem gambling) in order to build the models. But nor can they use risk measures to assess model performance in identifying high-risk gamblers, and, therefore, cannot generate and report metrics to stakeholders surrounding false positive and true positive rates.

5.7. A key consideration in using intensity variables is that while these markers are very good at discriminating between problem gamblers and non-problem gamblers in the general population they do not perform well in identifying problem gamblers within the regular gambler population.

- Almost all problem gamblers are regular gamblers. As a result, frequency of play and other related variables are significantly higher for these individuals compared to the general population although this is not the case when comparing problem gamblers to other regular players, many of whom gamble just as often as problem gamblers.
- Although all problem gamblers play regularly, a minority of regular players are problem gamblers (the proportion of regular players scoring as problem gambler ranges from lows of 3% to highs of 25%).
- As a result, among regular gamblers using intensity criteria is more likely to identify non-problem than problem gamblers.

5.8. Disadvantages of systems based on intensity harm markers and normative models include:

- Intensity variables and normative models will specifically target an operator's highest tier players.
- While rates of problems gambling may be relatively higher among these players, the vast majority will not be problem gamblers.
- Thus, most of those identified by such a model will be non-problem gamblers in the highest customer tier.
- Intensity variables will miss detection of high-risk players in the lower spending segments especially those on fixed income for whom changes in intensity are unlikely to occur due to a capping effect.

5.9. From an operator perspective using intensity variables to identify customers for interaction means you will be targeting your 'best' customers with no certainty as to whether or not you are reaching high-risk or problem gamblers.

5.10. Thus, reliance on theory based results conducted on random samples of the population rather than regular gamblers, leads to the setting of markers that may have no practical value as predictors.

5.11. The challenge then becomes how do operators distinguish problem gamblers from their other regular players all of whom play frequently?

6. Stage 2 Identification – Theory & Discovery Based Approach to Modelling

6.1. In 1998, Focal Research started exploring the use of loyalty data & player tracking systems with predictive modelling techniques to detect high-risk behaviour offering gaming operators a new tool for supporting host responsibility & risk management.

6.2. The use of predictive modelling, machine learning and data mining techniques introduces 'discovery-based' analysis providing more versatility and creativity in using the information stored in data warehouses to create multiple variables to identify a target group, in this case high-risk gamblers.

6.3. By using a variety of data mining techniques from Bayesian to cue-based association analysis the analyst is not limited by theory grounded in player surveys or treatment data. Instead we can use the loyalty data to generate and explore unique combinations of indicators that are tested to determine whether or not they are good predictors of risk regardless of pre-existing theory.

6.4. Using a wide range of risk indicators, it is possible to balance accuracy (model precision) and reach (model sensitivity) to detect a broader range of client and customer needs from identification of high-risk for customer interactions to supporting responsible marketing practices.

6.5. Every customer is different and can encounter many different situations while gambling so these models need to be able to cover many different types of risk indicators or cues so customers don't fall through the cracks. But the models also need to be very accurate so that resources are targeting the right customers at the right time.

6.6. It is necessary to administer a Player Risk instrument to a random sample of eligible customers in order to build and validate the models but this is an important step in removing the uncertainty in terms of the number of customer identified and the impact for gaming operators, staff members, customers and gaming operations.

6.7. If the rate of 'false positive' identification is too high, that is, the people identified by the model are not actually at-risk, than neither staff nor customers will trust the outcomes and the system will ultimately have no value to users.

6.8. For example, Focal has developed over 700 variables that can be used to build models that are effective in identifying risk among the highest and lowest player tiers since many of those experiencing problems fall in the lowest spending categories.

6.9. Advantages of a predictive models using a risk for problem gambling

- Greater certainty about model impacts (Performance Metrics)
- Identifies and tracks risk among all regular customers not just a specific segment
- Customized to reflect risk within the operator's player base
- Can detect change in behaviour as well as current behaviour
- Can assess the impact of RG strategies and other business practices for customer risk
- Can identify and reinforce low-risk gambling patterns (Prevention)
- Can use the information for responsible marketing, as well as, harm reduction
- Risk is calculated anonymously and securely within a protected environment
- Thresholds can be adjusted to prioritize targets

6.10. Disadvantages of a incorporating a discovery approach

- A risk measure must be administered to build and validate the models
- The model must be monitored and updated periodically
- It cannot identify all high-risk gamblers (but over time may pick up most)
- Operator support and systems are required for acting on the information

7. Implementing the Model

7.1. Risk Identification algorithms can be implemented as part of gaming operators' pre-existing RG program(s)/system(s) or as part of a standalone monitoring system.

7.2. At the heart of any proposed risk identification system are a set of advanced highly accurate predictive models (i.e., complex algorithms) that are 'always on' monitoring player tracking data to identify certain targeted behaviors so that appropriate actions can be triggered.

7.3. Such an identification system is versatile and can be adjusted to conform to evolving market needs and implemented to meet each operator's specific needs.

7.4. For example, in the case of identification of risk for problem gambling, identification can be limited to customer access only, host responsibility staff access only, or combinations of both; how such a system is configured is determined by the operator and its gaming market.

7.5. There are two levels of possible risk identification consisting of voluntary or discretionary identification (e.g., 'seatbelt' type features) versus mandatory or universal identification (e.g., 'airbag' features).

- Discretionary Risk ID ('seatbelt' approach) lets players and/or staff chooses to use the feature to check on personal risk or play patterns for an individual player.
- Universal Risk ID ('airbag' approach) means that the model is always on and proactively alerts customers and/or staff when someone's play behaviour is triggering for high-risk gambling.

7.6. Universal Risk identification can also be automatic or discretionary for marketing and promotional use as well; it is automatically deployed to exclude high-risk customers from any promotional campaigns and it is selectively used to exclude or include targets in specific campaigns such as responsible gaming information and support. As high-risk and problem gamblers are already highly engaged customers advertising and promotional support is better directed to non-problem customers.

7.7. Regardless of how an operator decides to introduce the identification system, automated risk monitoring helps operators cost-effectively direct resources and attention where it is most likely to have the greatest benefit either for customers to access the information privately or, in those cases when operators are required to identify risk proactively, for compliance with host responsibility and regulatory requirements (e.g., proactively assist for prevention or harm reduction outcomes.)

7.8. Identification thresholds can be adjusted for different purposes depending on the goals of the user.

8. Other Points of Interest

Information Security

8.1. The system is already protected within the secure gaming environment. Depending on how the system is configured outputs from the models can be restricted to player access only, authorized host responsibility staff at the gaming venue or both but typically cannot be shared with others without the customer's informed consent.

8.2. The behavior patterns monitored by the models are invisible to others. The system automatically uses the data stored by the casino without the need for any person to supervise or monitor. It is a mathematical algorithm that the system understands but would be meaningless to anyone outside of this system. All analysis, model development and evaluation are conducted anonymously. The only identification information used by the system is the customer id number without any other identifiers attached.

Risk Identification

8.3. Scoring for possible risk doesn't necessarily mean that someone is a problem gambler, although it does mean that the person might be gambling in a way that could put them at greater risk for having problems now or in the future. In some cases, problems may already exist. So this is a good time to alert the customer or to have staff check in with the customer to make sure that everything is okay.

8.4. Each cycle (e.g., month) the system automatically checks all the loyalty data for these customers and assigns each to a risk category based on how they have gambled over the past year. Customers are then assigned to one of three categories: those showing high-risk gambling patterns (High-risk customers), those showing low-risk gambling patterns (Low-risk customers), or those whose risk level is unknown at this time (Uncertain risk customers).

8.5. Risk can go up and down depending upon other things that are going on in a customer's life. Host responsibility staff at gaming venues may already be checking in with customers on a regular basis. However, contact with players identified as possible high-risk by the system each month can prioritize action to make sure information and support services are being reaching the right people at the right time.

8.6. Customer action can take many forms depending upon each customer's individual needs and the operator's programs including provision of customer education or information, use of player management tools, risk screening or self-assessment of risk, referrals for treatment or assistance, and/or self-banning options.

8.7. The system can be designed to make sure that almost all of the customers identified each month are at some level of risk with the vast majority falling at high-risk to problem levels. For example, about 80% or more of all those players identified by the Focal's models are at some level of risk (Model Precision = 80%). This means that if the system identified 100 players in a particular month at least 80 or more of these people would be at-risk for having problems now or in the future.

8.8. Each cycle the system identifies about one in every four or five high-risk and problem gamblers at the gaming venue (i.e. Model Recall ≈ 20%). Not all high-risk gamblers will have distinctive playing patterns that can be detected by the system in a particular running cycle but as time goes on the system will continue to identify new high-risk players and, over time, the percent of high-risk and problem gamblers flagged by the system increases.

8.9. The models can only identify risk using the available information stored in the loyalty data sets. It can detect certain playing patterns or combinations of behaviour that are related to having problems but it can't tell us if that customer is an actual problem gambler or 'why' they might be having problems.

8.10. To find out if someone might be having a gambling problem requires interaction to learn more about the impact gambling is having for them or the people they care about. Alternatively customers can also complete a problem gambling screen or other self-assessment tool to learn more about their risk. So even though the system can't diagnose problem gamblers it can alert gaming staff and customers to risky practices that if they are not causing problems today are likely to lead to problems in the future.

Impact for Staff

8.11. Management attitudes, operator infrastructure and support have a significant impact on how staff supports the system.

8.12. For staff and operators already involved in RG activities a risk monitoring system is perceived to make their job easier and more rewarding.

8.13. Using staff observation and a gambling risk identification model means that the two methods can complement each other. The models are always on checking and alerting gaming staff to those players who are most likely to be at high-risk.

8.14. Once identified the responsible gambling personnel on the floor can use visual cues and interactions to check actual customer risk and assist them as needed.

8.15. RG staff endorses the system as it helps them in knowing when and where to intervene, adjusting their interaction to suit the situation. RG staff reported patrons never complained and appreciate the operator's concern and assistance.

8.16. Success is due in part to the RG program in place at the site and the training of RG staff with suitable interaction techniques, material and aids available to staff to assist patrons, as well as commitment from upper management to make it work.

8.17. Investments in risk identification can be expected to have longevity as gaming becomes increasingly digitalized. Future developments are likely to include online player account management services, player feedback mechanisms.

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