NCF-ALeRT UK Casino 2019 Trial Summary Report

Focal's ALeRT BETTOR Protection System

Identify

Interact

Evaluate

Report

Focal Research Consultants
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ALeRT™ BETTOR Protection

NCF National Casino Forum

Preface and Acknowledgements

As the UK Trial for the ALeRT™ BETTOR Protection System draws to a close we want to express our appreciation to the many individuals and organizations contributing to this research over the past five years. The support and encouragement we received over the course of this challenging project has allowed us to develop a world-class solution that would not have been possible without the involvement of diverse stakeholders including regulators, public health providers, operators, casino management and host responsibility staff and, of course, the players themselves. While part of an international collaborative project involving nine operators from three different countries and over 18,000 casino player risk surveys, the contribution of the UK participants was especially valuable in terms of ensuring compliance with the highest regulatory standards for player protection and data privacy (GDPR).

In particular, we wish to acknowledge the role of Tracy Damestani, CEO and Director of the National Casino Forum (NCF), for her vision and leadership in advancing NCF membership participation, as well as management and the exceptional member teams at Aspers, Caesars, Genting, Grosvenor and the Hippodrome for their extended commitment and input over the course of the study. Special recognition is extended for the long-term contributions of Professor Yvonne Guerrier, Chair of the NCF Playing Safe ACE Panel; Laurie Norman, Casino Responsible Gaming Specialist & Addictions Counsellor; Jeff Stockhausen, Project Advisor, NRC-IRAP; and the team at Nova Scotia Business Inc. Export Growth Program, all of whom made valuable contributions to the success of this project.

During the trial, UK floor staff had over 1,500 personal interactions with ≈800 unique gamblers of interest (GOIs) at the 16 test sites. About 10% of these GOIs stopped playing through exclusion but for the majority who continued to gamble at the venues we observed positive impacts on all the key behaviour indicators still evident after six months of ongoing play. We share these positive outcomes with gratitude and pride and congratulate UK casino host responsibility staff for their role in actively reducing risk and harm among their casino customers.

As of October 31, 2019, participating UK casino operators can confirm their ability to 'Identify. Interact. Evaluate.' not only for compliance purposes but in helping high-risk customers.

We are extremely proud and grateful to be part of a project and collective team that we believe has left this space better than we found it five years ago.

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Overview – NCF-ALeRT™ Project

The National Casino Forum (NCF) was seeking an integrated solution for identifying and assisting casino customers who are most likely to be experiencing problems with their gambling now or in the future. From 2014 to 2019, NCF-CEO Tracy Damestani and five key member operators – Aspers, Caesars, Genting, Grosvenor and the Hippodrome – were part of an international research project with Focal Research. The goal was to introduce a coordinated program across UK's land-based casino properties and future platforms supporting regulatory compliance for player protection. The ALeRT™ BETTOR Protection System was purpose designed to provide UK operators with a complete evidence-based solution for meeting their current and future licensing objectives and priorities for action as outlined in the Gambling Commission's National Gambling Strategy, including the ability of licensees to 'identify' high-risk customers, 'interact' to assess and assist, and 'evaluate' success in reducing and preventing risk and harm, effective October 31, 2019. A live trial of ALeRT was conducted from November 2018 to October 2019 for slot machine gamblers with results presented to operators October 21–28, 2019, and to the UK Gambling Commission (GC) on October 24, 2019. During the trial, over 1,500 customer reviews and 1,550 interactions were conducted with ≈800 gamblers of interest (GOIs) identified by the ALeRT algorithms at the test sites (≈16 venues), producing measurable positive impacts for player outcomes. Based on the trial results, the ALeRT BETTOR Protection System will be moved from the test environment to the operator's environment for full deployment in January 2020. In conjunction with NCF and independent responsible gaming specialists, Focal Research also developed a companion training program, ALeRT™ BETTOR Customer Care, to assist casino staff in undertaking effective interaction with customers (GOIs), and has set baselines for a series of key behavioral indicators to evaluate and improve the impact of such interactions. Next steps include the addition of new model layers for detecting risk among electronic roulette customers (ER Models: January 2020) and tables games (TG/ETG Models: ≈April 2020) to continue to make gambling safer for UK casino customers, their families, and the wider community.

1 Project Background

1.1 Focal Research Consultants Limited from Halifax, Nova Scotia, Canada has built custom models using player data for gambling operators since 1998[1, 2] developing the first commercial risk detection algorithms deployed in casinos in 2005.[3]

1.2 For the past five years NCF and member UK operators Aspers, Grosvenor, Genting, Caesars, and the Hippodrome have been part of an innovative international collaborative research project with Focal Research using player technology to improve customer safety.

1.3 This research involved regulators, public health professionals, nine operators from three countries, and the National Research Council of Canada to develop a practical, responsible gambling (RG) tool for industry to use to actively reduce and prevent gambling risk and harm.[4]

1.4 The resulting ALeRT BETTOR Protection technology uses data routinely stored for an operator's customers (online, loyalty, machine data) to create complex models for identifying and managing high-risk play that otherwise may not be visible to operators or customers, providing infrastructure for monitoring risk, conducting customer interactions, evaluating player outcomes, and reporting.

1.5 By making sure operators are identifying and assisting the right people it is possible to measure and report upon the impact of interactions in achieving improved player outcomes, something that is not possible with less effective risk detection methods.

Risk identification is only one part of the solution; the **ALeRT BETTOR Protection System** includes functionality to assist operators to **identify** gamblers of interest (GOIs), **review** play history to prioritize action, **interact** with GOIs to assess and assist, **evaluate** impacts to see what works, and **report** on outcomes to the operator's internal and external stakeholders.

1 Schellinck, T., & Schrans, T. (1998). 1998 Nova Scotia Video Lottery Survey. Focal Research Consultants Ltd. – Halifax, Canada: Nova Scotia Department of Health. https://www.focalresearch.com/sites/default/files/publications/VL_players_survey_9798.pdf.

2 Schellinck, T., and Schrans, T. Understanding Gambling Behaviour Using Computer Simulation [online]. Gambling Research: Journal of the National Association for Gambling Studies (Australia), Vol. 14, No. 2, Nov 2002: 7–19. ISSN: 1832-4975. https://search.informit.com.au/documentSummary;dn=979957577939882;res=IELHSS.

3 In 2005 Saskatchewan Gaming Corporation and iView Systems retained Focal Research to develop the risk detection algorithms at the heart of the iCare Responsible Gaming System deployed in Casino Regina and Casino Moose Jaw in January 2006. The models were tested, updated, and used continuously for over nine years, generating 40,000+ customer interactions.

4 The National Research Council of Canada's Industrial Research Assistance Program (NRC–IRAP) provides co-funding for research to develop innovative technological solutions for a recognized business or industry problem associated with some degree of risk https://nrc.canada.ca/en/support-technology-innovation.

2 Problems with Traditional Risk Detection Approaches

2.1 Traditionally, operator staff has had to rely on less accurate, rule-based cues for taking action, such as how long a customer plays, how much they spend, or how often they play. However, gambling problems are related to affordability, gambling impacts, and 'how' someone plays, not 'how much' is spent.

2.2 Such triggers are largely based on prevalence studies and public health research coming out of work with alcohol and other substances, which seeks to set quantitative thresholds for safe gambling. The idea is that, like alcohol, gambling impacts are 'dose related'; the more one gambles, the greater the likelihood for harm.[5] By extension, the goal is to set standard safe limits for gambling with any behaviour that occurs outside these limits flagged for attention.

2.3 The key difference between alcohol and other substances versus gambling is that typically people share common physiology, which means common consumption standards can be set. With gambling, 'dose levels' are dependent upon resources that vary across people. Moreover, for some regular customers consumption even at low levels may be problematic whereas others have no issues with a higher spending budget.

2.4 Using simple time and expenditure rules to try to find and help problem gamblers means staff end up interacting with a lot of people, a minority of whom (≈10% or less) will actually be in the target group of high-risk players. This is an inefficient way to reach the right people, tying up staff resources and bothering patrons who are not the primary target.

2.5 Worse, systems based on simple rule-based criteria quickly become ineffective as players figure out the criteria and change behaviour to avoid detection without any accompanying decline in risk or harm, making such systems unreliable and obsolete in a short time.[6]

5 Shawn R. Currie, Low Risk Gambling Guidelines Scientific Working Group, A research plan to define Canada's first low-risk gambling guidelines, Health Promotion International, day074, https://doi.org/10.1093/heapro/day074.

6 See the Automated Risk Monitoring (ARM): Adelaide Casino System Report commissioned by SA Independent Gambling Authority Report, September 2017 (Authors: SA Centre for Economic Studies Associate Professor Michael O'Neil and Dr. Andreas Cebulla, Senior Research Fellow, ISBN: 978-1-921070-84-6.

2.6 Some new commercial systems use self-exclusion as a proxy for problem gambling. Models for detecting problem gamblers are built using the behaviour of self-excluded customers usually because this is an easy target group to access. However, if the model is built using self-exclusion as the target then the resulting model will identify those customers most likely to self-exclude (SE models).

2.7 UK research and staff experience confirm that self-excluders represent a narrow sub-segment of high-risk players, many of whom are not problem gamblers, making this group unsuitable for building risk models (i.e., not representative of high-risk players).[7]

2.8 If such SE algorithms are set too broadly, they will misdirect resources to where they are not needed. If the algorithms are set too narrowly, they will miss a significant number of customers who are at risk. Regardless, such models will leave most high-risk players unprotected and operators vulnerable to regulatory and public censure.

2.9 There are also ethical questions related to whether operators should be trying to predict and intervene with those likely to self-exclude, unless the goal is to accelerate such action. Otherwise, there is a perception operators could use SE models to prevent or delay a high-value, high-risk customer from excluding (i.e., preventing self-exclusion rather than preventing risk or harm).

In contrast, a good risk detection algorithm built to identify the desired target (high-risk and problem gamblers) will efficiently direct resources to where they are needed most without disturbing low-risk, social customers. Operators can then focus on supporting staff and helping high-risk customers rather than trying to find them.

7 See the PwC report Remote Gambling Research Interim Report on Phase II P. August 2, 2017 P.2 "Furthermore, this approach is not reliant on using self-exclusion as a proxy for problem gambling, which Phase 1 noted was problematic and our survey results have confirmed: 80% of self-defined problem gamblers have never used a self-exclusion tool; only 31% of those that have self-excluded in the past self-define as a problem gambler." https://about.gambleaware.org/media/1549/gamble-aware_remote-gambling-research_phase-2_pwc-report_august-2017-final.pdf.

3 ALeRT BETTOR Protection Solution

3.1 No model can find 'problem gamblers' but it can sift through millions of data points, alerting operators to 'gamblers of interest' (GOIs) who have play patterns associated with gambling problems.

3.2 Unlike other methods based on theory about how to recognize a problem gambler, ALeRT's algorithms are custom built and tested using a gold standard risk measure such as the Problem Gambling Severity Index (PGSI)[8] to identify real high-risk play patterns for real UK casino customers. This is important, as the cost of failing to identify 'real' problem gamblers is increasing as regulators introduce fines and sanctions for non-compliance.[9]

3.3 The science behind ALeRT means each model is tested so operators know how it will perform when used with their customers, and performance can be verified by a third party.

3.4 ALeRT triggers for identification are not obvious to customers and will continue to work even if a high-risk player tries to evade detection.

8 Ferris, J., & Wynne, H. (2001). The Canadian Problem Gambling Index: Final report. Ottawa: CCSA.

9 For example, the UK Gambling Commission issued more than £18m (€20.1m; $23.6m) in fines to gambling operators for failing to comply in identifying problem gambling from 2017–2018 (June 29, 2018) with mounting non-compliance fines in Australia in 2018, and the first prosecution for failing to take all reasonable steps to identify a problem gambler in New Zealand March 27, 2019. https://www.dia.govt.nz/press.nsf/d77da9b523f12931cc256ac5000d19b6/ccb99b3cc3059d06cc2583c900794f39!OpenDocument.

3.5 The models include multiple algorithms, hundreds of indicators, and cues to cover a broad array of high-risk behaviours specific to an operator's players, market, and practices, extending the life and value of ALeRT as a tool.

3.6 Not all high-risk customers have the same play patterns and the models need to be able to detect risk among all genders/non-genders, ages, socio-economic levels, and backgrounds.

3.7 When tested, almost all those regular customers flagged as 'gamblers of interest' (GOIs) by NCF's ALeRT models scored at-risk for having problems and most scored as high-risk and problem gamblers, using the PGSI, the same measure used to assess problem gambling rates in UK Gambling Prevalence Studies.[10] (See Section 4.0)

Compared to other rule-based methods (e.g., time or money limits) or models based on intensity or self-exclusion, staff would have to interact and screen over three times as many customers to find and help the same number of problem gamblers detected by ALeRT. Not only is ALeRT better at finding current problem gamblers but it also finds low-risk customers displaying responsible gaming patterns, as well as those engaging in high-risk play that can lead to problems in the future, making the models useful for prevention by intervening before harms occur, a key objective for UK operators.

10 2010 National Gambling Prevalence Study http://natcen.ac.uk/our-research/research/british-gambling-prevalence-survey/.

4 NCF–ALeRT Model Performance (Slots)

4.1 In presenting the accuracy of the models used in the NCF trial, we have combined the results for the five operators in order to maintain confidentiality.

4.2 Focal first obtained 24 months of slots wagering data for a random sample of regular loyalty customers from each operator (n ≈5,000) to assess play patterns and generate the variables to be used in the modelling process.

4.3 To build the models, a risk survey including the PGSI and FLAGS (Focal Adult Gambling Screen)[11, 12, 13] was administered to a total of 2,873 eligible UK casino customers (playing on six or more days using their player loyalty card) and linked to the previous 24 months of player data stored in the operator's system using an anonymous token.[14]

4.4 First, it must be understood that only a minority of regular casino customers score as problem or high-risk gamblers using the PGSI or any other measure, with the majority scoring at no- or low-risk. Therefore, to build an efficient model means that it must selectively find this small target group of high-risk customers.

4.5 The survey samples were divided into two sub-samples: a training sample (2014; n =1,437), which was used to build the models, and an independent validation sample administered 1.5 years later (2016; n =1,436) to assess model performance.

4.6 The custom risk detection models currently in place for the five UK NCF operators are comprised of four to eight different algorithms per operator, using between 109 and 302 unique behavioural cues.

11 Schellinck, T., Schrans, T., Bliemel, M., Schellinck, H., & Ontario Ministry of Health and Long-Term Care (2012). Raising the FLAGS: A Pilot Study Adapting FLAGS, A Next-Generation Gambling Risk Assessment Instrument, For Use in Identifying Risk among General Gambling. https://www.focalresearch.com/sites/default/files/publications/3170_Raising%20the%20FLAGS%20Final%20Report%20(Focal)%20Nov%2030%202011.pdf.

12 Schellinck, T., Schrans, T., Bliemel, M., & Schellinck, H.M. (2015a). Construct Development for the Focal Adult Gambling Screen for Electronic Gambling Machine players (FLAGS–EGM): A Measurement Instrument for Risk due to Gambling Harm and Problem Gambling Associated with Electronic Gambling Machines. Journal of Gambling Issues, 140–173.

13 Schellinck, T., & Schrans, T., Bliemel, M., & Schellinck, H.M. (2015b). Instrument Development for the Focal Adult Gambling Screen (FLAGS–EGM): A Measurement of Risk and Problem Gambling Associated with Electronic Gambling Machines. Journal of Gambling Issues, 174–200

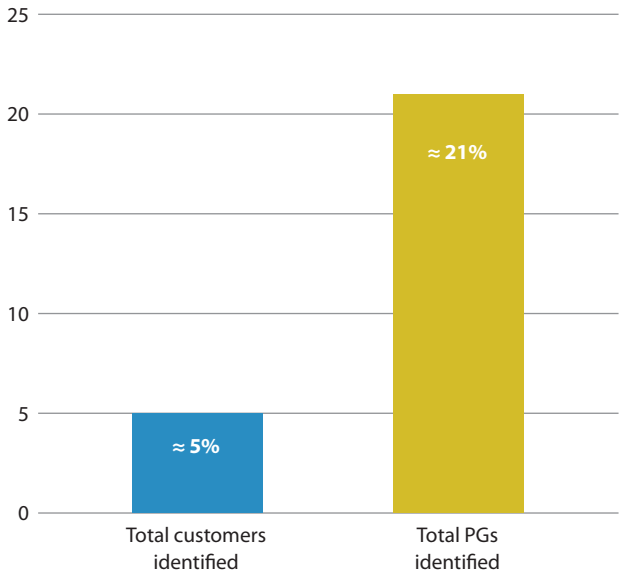
14 Focal Research Consultants. Using Player Loyalty Data to Detect Risk for Problem Gambling: Developing and Testing Risk Identification Models for Use in the UK Casino Market. February 2016. https://www.focalresearch.com/sites/default/files/publications/UsingCasinoLoyaltyDataReport.pdf.

4.7 Performance metrics reported in Tables 4.1 and 4.2 are based on model performance when tested using the independent validation sample (i.e., a sample that was not used to build the model) and the actual values for identification rates during the trial.[15]

4.8 Once implemented during the trial, the algorithms identified, on average, approximately 4.3% to 6.1% of the total regular UK casino player base each month as 'gamblers of interest' (GOIs) (i.e., high-risk or problem gamblers). When tested using the survey validation sample, the models found one in every five problem gamblers (21%) identifying about 5% of all regular customers (see Figure 4.1).

4.9 Over a year, new players would be identified each month and, therefore, the proportion of the regular customer base identified also increased over time, with estimated annual identification rates ranging from 8% to 11% of all eligible customers overall and able to detect over one-third of all problem gamblers.[16]

FIGURE 4.1
Number of customers (GOIs) detected each month versus number of problem gamblers (PGs) detected



15 Schellinck, T. & Schrans, T. (2011). Intelligent design: How to model gambler risk assessment by using loyalty tracking data. Journal of Gambling Issues, 51–68.

16 Note that in order to accurately identify high-risk playing patterns, the Focal models currently require records for a minimum of play on six or more days. During the development phase, Focal developed working models for detecting risk using anonymous/uncarded session data and this will be tested going forward. The Focal analytics team is also developing short-term models that will be ready for testing in early 2020.

4.10 When the models were tested two years later against the validation sample, almost 40% of those customers identified by the ALeRT models as GOIs scored at problem gambling levels on the PGSI (8+), with 68% of those GOIs identified in any given month scoring at high-risk (PGSI =5+) (see Figure 4.2).

4.11 Only 16% of GOIs scored at no- or low-risk levels (PGSI =0–1), yet these players were exhibiting the same playing patterns as high-risk customers and, therefore, are good candidates for prevention.

FIGURE 4.2
PGSI risk profile for ALeRT gamblers at risk (GOI)

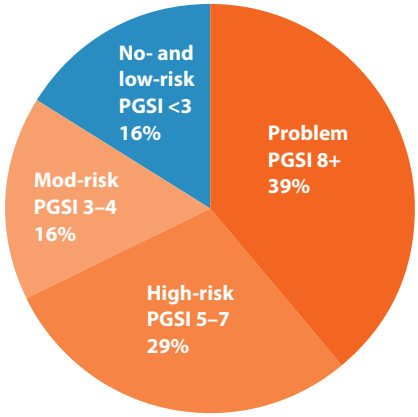


TABLE 4.1
Estimated model accuracy (% of GOIs in each risk category) (validation sample; n =1,436)

Percent of GOIs scoring at each level on the Problem Gambling Severity Index (PGSI) on the validation sample	Monthly model accuracy (n =1,436)	Annual model accuracy (n =1,436)
% of GOIs Scoring PGSI =8+ (problem gambling)	39%	32%
% of GOIs Scoring PGSI =5+ (high-risk gambling)	68%	55%
% of GOIs Scoring PGSI =3+ (moderate risk or higher)	84%	72%
% of GOIs Scoring PGSI =1+ (any risk)	87%	89%

TABLE 4.2
Estimated model reach (% in each PGSI category detected by model) (validation sample: n =1436)

Percent of those scoring at each level on the Problem Gambling Severity Index (PGSI) identified by the model	Each month (n =1436)	Annually (n =1436)
Percent of customers identified by model	≈4.3–6.1%	7.7–10.9%
% PGSI =8+ (problem gamblers) identified by model	17– 24%	25–35%
% PGSI =5+ (high-risk gamblers) identified by model	13–19%	19–27%
% PGSI =3+ (moderate-risk+ gamblers) identified by model	9–13%	13–19%
% PGSI =1+ (any-risk gamblers) identified by model	5–7%	9–13%

Not only were the models still performing accurately two years on but when tested the reach remained strong, with the models finding about one-quarter of all high-risk customers (≈19% to 27%) and about one in every three to four problem gamblers over the course of a year (25% to 35%), while flagging only 8% to 11% of a casino's customers for attention, emphasizing the efficiency of the models in finding the right target. Overall, almost 90% of those identified by the models scored at-risk, with the majority (68%) scoring at high-risk or problem levels.

5 Effective Interactions

5.1 Once an operator has a good risk detection model in place, staff can have confidence that they are interacting with the right people, leading to better outcomes for customers. For example, if operators target low-risk rather than high-risk players it is less likely their interactions will produce any measurable impacts, as these individuals don't need to change their play behaviour.

5.2 The ALeRT system not only identifies high-risk playing patterns associated with problem gambling, it permits operators to assign and monitor customer interactions for those GOIs identified by the ALeRT models, as well as those customers detected using other methods.[17]

5.3 Interactions can be entered and tracked within a single location or across multiple operator venues, with dashboards available for staff use on the floor or by management, for oversight and assurance reporting.

5.4 More importantly, interaction tracking means that an operator can evaluate the impact of customer actions.

5.5 Focal consulted with operators, floor staff, regulators, and public health and treatment providers, conducting interactive workshops and one-on-one interviews with industry and non-industry stakeholder groups throughout the trial to gather feedback and make improvements.

5.6 With funding through the Nova Scotia Innovation Fund, Focal retained Associate Professor Glen Hougan from the Nova Scotia College of Art and Design (NSCAD University) to do independent user testing of the ALeRT dashboard and features[18] and engaged Professor May Chung to assess the ALeRT materials and site design.[19]

17 ALeRT features include the option for an operator to manually add or import other players of interest identified by methods other than ALeRT so that interactions and outcomes for these customers can also be monitored.

18 Focal was awarded two rounds of funding through NSBI's Innovation and Productivity Program to retain professor Glen Hougan from NSCAD University to assist in user interface design testing in advance of the ALeRT trial with NCF (October 2017 to February 2018) and a second award to conduct independent research to assess the functionality of Focal's software supporting the ALeRT program (October 2018 to April 2019). A final report was submitted April 5, 2019, to NCF for review and all recommendations were incorporated into the ALeRT software. Glen Hougan is a product/service designer in the area of human factors, user experience, and product development, with special expertise in the area of health and well-being. In addition to teaching at NSCAD University, Glen is the principal of Wellspan Research and Design, focused on design thinking and health care issues. https://nscad.ca/study-at-nscad/divisions-and-areas/design/.

19 Professor May Chung holds a BA and a BFA from the University of Alberta and a Master of Graphic Design from North Carolina State University. She is a graphic designer with a background in information technology and exhibit design for corporations, government, and educational institutions. She final-scripted player support materials for operator branding.

5.7 Following the consultation process, Focal redesigned the five interaction levels of ALeRT to better reflect regulatory expectations and operator user experience (see Table 5.1 below).

5.8 Baseline measures were established for a set of nine key indicators for evaluating customer interactions in order to reliably assess the difference in GOI behaviour pre- and post-interaction (see Section 6.0).

5.9 Working with a problem gambling and responsible gambling specialist with a decade of experience in using risk detection models to trigger customer interaction on the floor, Focal initiated development of an online staff training program, ALeRT BETTOR Customer Care, to help staff in delivering effective customer support.[20]

TABLE 5.1
The Five Levels of ALeRT Customer Action and Interactions

ALeRT Customer Action Levels (observation and interaction)	Trial interactions (n =3,104)	Description
Level 1 Observations and Player Checks	1,581	• Investigate (i.e., check player history) • Observe (i.e., observe player) and prepare for interaction
Level 2 General Education, Brief Interactions	866	• Brief interactions (i.e., player check-ins) • Offer information (i.e., open the door)
Level 3 Player Education, Promotion and Support of Self-management	540	• Invite discussion (i.e., engage customer, make inquiries) • Offer self-management tools and resources (e.g., budgeting)
Level 4 Player Assistance, Promotion and Support of Self-help	27	• Provide self-help materials (i.e., assess) • Provide assistance and referrals (i.e., assist)
Level 5 Voluntary and Involuntary Exclusion and Referrals	90	• Barring and banning (i.e., self or venue initiated exclusion) • Third-party assistance (e.g., medical, mental health, debt counsellors, enforcement)

20 Laurie Norman has her BA, BEd, and 15 years of experience in the area of responsible gambling in a casino environment, which includes developing facilitating programing for the second Responsible Gambling Information Centre in Canada, managing a team of staff interacting with players from a responsible gambling perspective, developing policies and procedures, and contributing to the development of national responsible gambling standards for the gaming industry. Prior to that, she worked as an addictions counsellor for nine years, four of those years with problem gamblers, and also worked as a teacher with middle and high school students.

5.10 During the ALeRT trial period from November 2018 to October 2019, UK operators conducted over 3,100 customer actions consisting of 1,553 'check-in's' with 802 GOIs at the selected test sites. Staff completed interaction surveys detailing the nature of the interactions, interaction length, player response, observations, and next steps.

5.11 Focal also examined behavioural outcomes for those GOIs with one or more personal interactions when compared to pre/post baseline results set for GOIs without or prior to interactions (see Section 6.0).

5.12 Even a single personal social responsibility interaction by a staff member with a GOI identified by the ALeRT models had a measureable impact in achieving improved outcomes. These impacts were even stronger with multiple interactions, leading to positive changes in the desired direction for all the key behaviours and outcomes measured, and positive changes were still observed six months following initial staff interactions.

Over the course of the trial from November 2018 to September 2019, staff at each of the test sites conducted 1,581 player reviews and performed over 1,500 interactions with 802 unique customers identified as gamblers of interest (GOIs) by the ALeRT models. Staff also completed detailed surveys summarizing 1,445 interactions, providing player assistance and support to 597 customers, with 90 customers referred to the SENSE self-exclusion program.

6 Evaluation – GOI Interaction Behavioural Impact Analysis for Slot Machine Gamblers

6.1 To assess the impact of interactions, Focal conducted analysis of pre/post behaviours for 'gamblers of interest' (GOIs) using a baseline comparison to isolate interaction effects.

6.2 To comply with player privacy protection and ensure statistically valid results, the analysis was conducted on a group basis for eligible GOIs (see below).

The ALeRT Interaction Trial Design

6.3 Staff of the five NCF partner casino operators used the ALeRT system November 2018 to October 2019 to interact with their slots customers on-site at ≈16 test venues. To ensure a six month time period for the post comparison, only those interactions conducted from November 2018 to March 2019 were eligible for the evaluation.

6.4 ALeRT provided operators with a list of individuals each month designated as gamblers of interest (GOIs) based on their slots play behaviour (i.e., players who have been identified by Focal's algorithms as likely to be at-risk or problem gamblers).

6.5 Staff can access each GOI's play profile relating to 20 behaviours: 10 that are found to be closely associated with risk due to gambling (risk indicators) and 10 that profile the GOI's play behaviour in general (play profile). This allows host responsibility staff to become familiar with the players' habits prior to interacting with them, and to provide more relevant customer interactions.

6.6 Using the ALeRT system, users classify each observation and interaction into one of five categories, as listed in Table 5.1.

6.7 Evaluation of interaction impacts was restricted to GOIs meeting the following conditions:

- Only those GOIs with personal interactions at Level 2 or higher (excluding Level 1 – Player History Checks and Observations);
- Only those GOIs who continued to play after interaction, as it is not possible to reliably assess changes in play for those who stopped;[21]
- Only those GOIs whose interactions had occurred during the first six months of trial (November 19 to April 20) in order to generate pre/post comparison periods (key play behaviours for GOIs one to three months prior to interaction versus key behaviours for four to six months after interaction.)

6.8 Following consultation and data analysis, the following variables were selected as key behavioural indicators for evaluating pre/post interaction impacts:[22]

- Wagers/spins per hour (per session – speed of play);
- Turnover/amount bet per wager/spin (per session – intensity and expenditure);
- Hours per session of play (per session – length of play);
- Turnover/amount bet per stay hour (tolerance for risk);
- Turnover/amount bet per session (per session – amount risked);
- Monthly stay hours (total time at the venue each month);
- Average monthly sessions of active players (number of gaming sessions per month for those playing during the test period);
- Average monthly turnover (average amount wagered);
- Total monthly win/loss (the cumulative amount won or loss during the month).

6.9 The next step was to create baselines for each of the indicators. Baselines were set for all GOIs prior to any interactions to simulate what would occur if no interaction took place. Once the baselines were established, it was then possible to compare the results plus or minus the baseline to assess the impacts following an interaction (see Regression Effects, Section 6.22–6.28).

21 GOIs that stopped playing following an interaction were excluded from the analysis due to uncertainty as to whether the player had ceased gambling, simply switched to another venue, or stopped using their player card. See Addressing Potential Confounding Effects in the Field Trial, Section 6.32–6.35

22 This list of indicators is not exhaustive. Over 50 variables were initially considered as possible candidates but discarded using a taxonomy grouping the variables by the key measures identified for improving player outcomes. Regardless of absolute time and money spent by each player, most interactions to assist customers centre on reducing expenditure, frequency, length of play, and risky behaviour (intensity, speed, wagering rates). Before undertaking impact analysis, the list of key indicators was pared down to the nine items listed above as most representative of the key outcomes for evaluating the success of the interaction. While these indicators are not suitable on their own for use in detecting risk, it is helpful for describing and assessing outcomes.

6.10 The time period set for comparison was one to three months in advance of the interaction for each GOI (pre-measure) versus four to six months after the interaction (post-measure). Using this method, regardless of when the interaction occurred, it was therefore possible to create a common data set including all eligible GOIs relative to the point of interaction.[23]

6.11 The time period bracketing the interaction was excluded from comparison to ensure any differences observed were persistent and to control for frequency bias insofar as each eligible GOI had to be on-site at the point of interaction, and so aligning all plays at this point may produce inflated play activity surrounding the point of interaction (i.e., all eligible GOIs would be active).

Addressing Potential Confounding Effects in the Field Trial

6.12 Before analysing the impact of interactions on player outcomes, there were four issues Focal's analysts had to address in order to isolate the impacts of the interaction on player behaviour:

- Regulatory changes to the bet limits per spin on B2 machines during the trial (April 2019);
- Regression effect (i.e., extreme values tend to decline naturally with repeated measure);
- Possible differences in impact for single versus multiple interactions (i.e., identifying differences that may be masked at an aggregate level);
- Changes in card use and data capture following interaction (e.g., player movement to anonymous play or switching locations following interaction).

23 The purpose of setting a baseline is to assess what would occur after a players is identified as a 'gambler of interest' (GOI) if they did not receive an interaction. By comparing behaviours for three months prior to identification as a GOI by the model (Baseline Pre3 to Pre1) to behaviours at four to six months following identification (Baseline Post4 to Post6) we can determine if their behaviour naturally declines (i.e., regresses toward the mean for all players) or continues to persist or escalate (e.g., intensify). Once we have established these baseline values we can then compare the outcomes for GOIs in general to those for GOIs who received an interaction. In all cases the baseline values for GOIs flagged by the ALeRT models remained constant or were increasing suggesting the right people were being identified by the models. However, the next step is to determine whether or not customer interactions have any impact on these trends. As interaction impacts were stronger for those who received more than one interaction, for illustrative purposes the graphs were prepared comparing baseline results to the outcomes for those GOIs who received more than one interaction using the timing of the first interaction as the point for determining pre measures (Interaction Pre3 to Pre1) for comparison to behaviour after interaction (Interaction Post4 to Post6). To facilitate comparison of play patterns for the two groups the data for the pre-comparison measures (Pre3 to Pre1) were used to set a common starting point. These common data points were generated by creating an average mean value for each group over the three pre months for each of the behaviours presented in figures 6.1, 6.3, 6.4 and 6.5. The values for the baseline were then divided/multiplied based on the differences in the average mean pre-values for the interaction and baseline group to determine each monthly value. This meant that the patterns could be directly compared to assess impacts post interaction with the baseline values (overlaid to see how the patterns varied). In all cases, play patterns following interaction were different in the expected direction as compared to the play patterns for GOIs in general.

Reduction in bet limits on B2 machines

6.13 The Gambling Commission reduced the limit for bets per spin on B2 slot machines from £100 to £2 starting in April 2019 (six months after the trial started). Three of the operators participating in the trial have B2 machines and consequently some of the players with whom their staff interacted played on these machines.[24]

6.14 As expected, a dramatic drop was observed for these B2 players in their average bet values per wager/spin after March 2019, making it difficult to isolate the impact of the interaction versus the decline in stakes for these particular customers.

6.15 To control for this, any player spending on average more than £5 per wager (the bet limit for B1 machines) in any given month during the trial was excluded from the interaction evaluation. This removed 52 customers, 20 with one personal interaction at Level 2 or higher and 32 with two or more personal interactions. Among the remaining GOIs with interactions, B2 transactions accounted for less than 1% of all their slots activity.[25]

6.16 The final sample sizes used in the evaluation were 205 for those who had a single personal interaction at Level 2 or higher during the first six months of the trial, and 155 for those players with two or more personal interactions with staff.

6.17 Due to the limit reduction to £2 on B2 machines, it is reasonable to expect that players may increase session length (i.e., played longer for the same amount previously spent per session). Consequently, if analysis shows that session length decreased for slots players following interactions as compared to baseline, there is greater certainty we successfully controlled for the impact of the new regulation by removing those who had played at higher values before the change was introduced.

24 http://www.gamblingcommission.gov.uk/PDF/Review-of-gaming-machines-and-social-responsibility-measures-%E2%80%93-formal-advice.pdf.

25 Once we removed the B2 players wagering above £5 per spin, we examined the turnover per wager/spin for the months prior to and after April 2019 to determine if there was a significant and consistent drop, indicating the possible impact of the changes to B2 wagering limits. We did not find any evidence of a drop in turnover per spin in the sample that could be due to the new wagering limits.

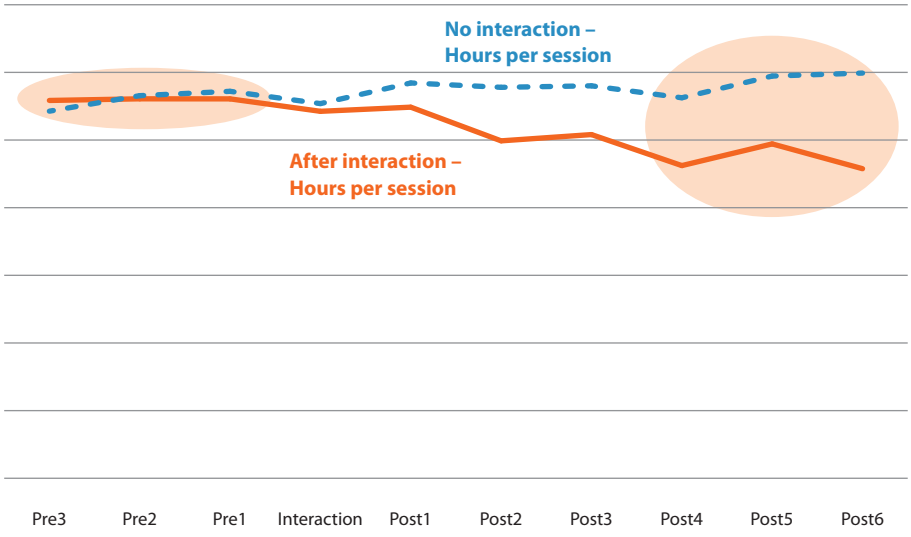
6.18 Figure 6.1 below illustrates the analytical approach used to determine the impact of the interactions for session length. The vertical axis shows the average length of sessions in hours. The length of sessions is graphed for three months prior to the month during which the first interaction occurred (months Pre3 to Pre1), the month during which the first interaction occurred (Interaction), and for six months after the interaction month (months Post1 to Post6).

6.19 The baseline (blue dashed line) shows the length of sessions was steadily increasing over 10 months for players identified as GOIs. In order to identify a change in behaviour, we compared mean values over the three months prior to the interaction (Pre3 to Pre1) with the average behaviour for four to six months after the interaction (Post4 to Post6).

6.20 When comparing the average length of sessions during the three months prior to being identified as a GOI to the four to six months after, the increase in length of sessions was 4.5% over the prior months for the baseline group (GOIs without and/or prior to interaction).

6.21 There was no impact observed for session length after a single interaction yet among those who experienced more than one there was a drop of 15.8% in the average length of a session. This suggests a combined drop of approximately 20.3% in session length due to multiple interactions with casino staff (see Table 6.1 Results for Multiple Interactions).

FIGURE 6.1
Session length pre versus post interaction compared to baseline for GOIs with multiple interactions



Regression effect

6.22 It is also possible that GOIs identified by the algorithms would have higher values for some play behaviours when compared to other regular players.

6.23 If this is the case, it is reasonable to expect that the level of these play behaviours for GOIs may regress toward the mean for all regular players, (i.e. the first measurement is high initially but closer to the average on its second measurement, irrespective of any intervention). In other words, any declines in play behaviours after interactions might be due to regression effect rather than due to the interactions.

6.24 To test for this effect, we created baseline projections for play behaviours for 2,590 GOIs calculated prior to having interactions, generating pre-measures for one to three months prior to identification as a GOI for comparison to post-measure four to six months following identification as a GOI. These players came from the same data sets used to generate the GOI lists triggering operator interactions.

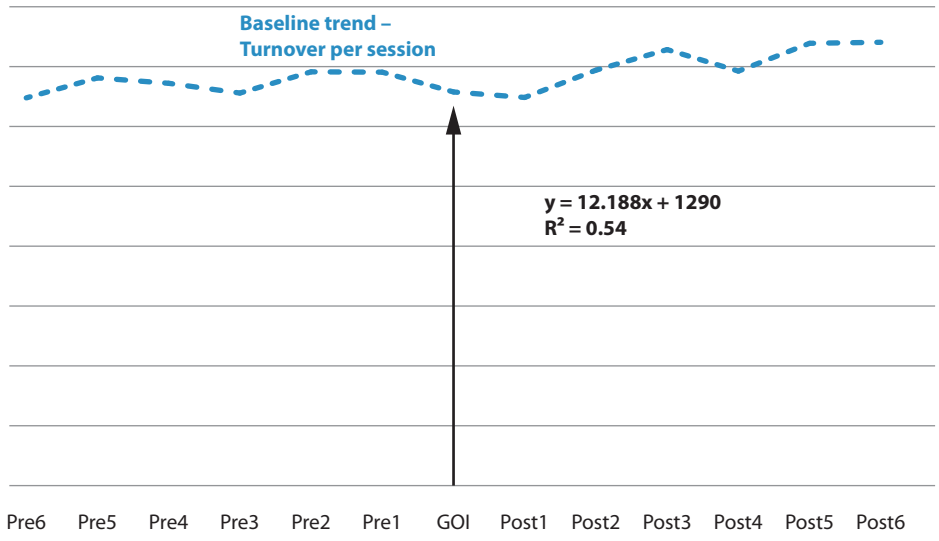
6.25 Baseline measures consisted of mean behaviour projections produced over 13 months for the nine variables selected as the most reliable indicators of successful changed behaviour (i.e., means for the six months prior to becoming a GOI, the month they were identified as a GOI, and then six months after becoming a GOI).

6.26 The resulting baselines did not show a regression to the mean. As presented in Table 6.1, the baseline for each of the nine indicators either remained constant or was gradually increasing over the months before and after a player was identified as a GOI by the ALeRT algorithm (see Figure 6.2 as an example).

6.27 The fact that most baselines were increasing is reasonable given that the models were designed to identify at-risk or problem gamblers for remedial or preventative attention. We assume that, in the absence of any interaction, these trends would be the same for those GOIs interacted with by staff and therefore, ideally, the impact of the interactions would be to reduce or prevent any escalation in the key behaviours.

6.28 Consequently, we concluded that using the baseline values and the actual values to determine the impact of the interactions was appropriate.

FIGURE 6.2
Baseline trend for GOIs turnover per session



Single versus multiple Interactions

6.29 As noted, the eligible sample of GOIs with interactions was further segmented into two groups: those with a single personal interaction versus those with multiple interactions.

6.30 For two reasons, we hypothesised that those who experienced multiple interactions were more likely to benefit from an interaction and to change their behaviour.

- Through reinforcement, two or more interactions are likely to have greater impact than one and may be more successful in changing the player's behaviour.
- Based on the players' responses and other cues during the first interaction, as well as their play profile on ALeRT, staff may decide these individuals are in greater need of support and assistance and a follow-up interaction is warranted.

6.31 Moreover, by breaking out the impacts for these two groups it is more likely that we will be able to detect pre/post differences that may not be evident or are masked when examined at an aggregate group level (i.e., impacts and player characteristics may be different for those receiving one versus those receiving two or more interactions).

Changes in card use and data capture following interaction

6.32 Finally, there was the possibility that, following an interaction, a customer may stop playing (i.e., informally self-exclude) in an effort to control or manage their play.

6.33 Alternatively, it is also possible that such players may start to gamble anonymously without using a card, or switch to another location or type of gambling.

6.34 Whatever the case, there is uncertainty as to whether play cessation is a function of harm reduction or of avoiding detection. Therefore, analysis to evaluate the impact of customer interactions was restricted to those active GOIs who continued to play in the months after interaction, as inclusion of zero values for those who were not active using the card would bring down the averages post-interaction and account for most of the differences observed.

6.35 The time of the interaction served as a common point for all active GOIs, and the testing period was set as any play in the three months prior to the interaction as compared to any play in months four to six following the interaction. The post time frame was set to ensure changes were persisting and did not occur as a transient improvement immediately following the interaction.

6.36 Additionally, key evaluation indicators assessed differences in session behaviours, as well as cumulative monthly impacts, as 'per session' characteristics are not influenced by reductions in card use. In the event that players may have reduced card use or displaced play activity elsewhere, the analysis will still assess changes in 'how' GOIs behaved pre- and post-interaction rather than just 'how much.'

TABLE 6.1
Changes in Key Indicators at Baseline, After Single Interaction and Multiple Interactions During Trial

Key Evaluation Indicators	Baseline after GOI % change (n =2,590)	Single Interaction (n =205)		Multiple Interactions (n =155)	
		After interaction % change	Estimated impact of interaction	After interactions % change	Estimated impact of interactions
Session[26] Behaviours					
Wagers/spins per hour	5.3%	5.4%	0.1%	–5.5%	–10.8%
Turnover per wager/spin	–2.3%	–19.8%	–17.5%	–4.6%	–2.3%
Hours per session	4.5%	4.5%	0.0%	–15.8%	–20.3%
Session Outcomes					
Turnover per stay hour	3.5%	–11.5%	–15.0%	–8.3%	–11.8%
Turnover per session	6.6%	–11.8%	–18.4%	–23.7%	–30.3%
Play Frequency					
Average monthly sessions	–1.4%	–8.5%	–7.1%	–9.3%	–7.9%
Monthly stay hours	4.5%	–13.3%	–17.7%	–26.1%	–30.6%
Expenditure Outcomes					
Average monthly turnover	4.8%	–26.0%	–30.8%	–40.1%	–45.0%
Total monthly win/losses	–1.3%	–7.7%	–6.5%	–32.5%	–31.2%

26 For the purpose of this analysis, a single session or play visit is defined as any set of play activity or transactions that have less than a three-hour break in activity/transactions.

Interaction Analysis

6.37 Once all conditions were met, there was a total of 360 unique eligible players who experienced Level 2 or higher interactions from November 1, 2018, to the end of March 2019, played during the specified pre/post time windows, and did not have average bet levels above £5 for any of the trial months or five months preceding the trial.

6.38 The sample was divided into those who experienced a single personal interaction during that time frame (n =205), and those with two or more personal interactions (n =155).

6.39 Table 6.1 presents pre/post changes in outcomes for the nine key behaviours by which we measured the impact of the interactions on player behaviour.

6.40 Generally, compared to changes at baseline, there were declines observed for seven of the nine indicators after even a single interaction, and declines for all nine indicators among those receiving two or more personal staff interactions.

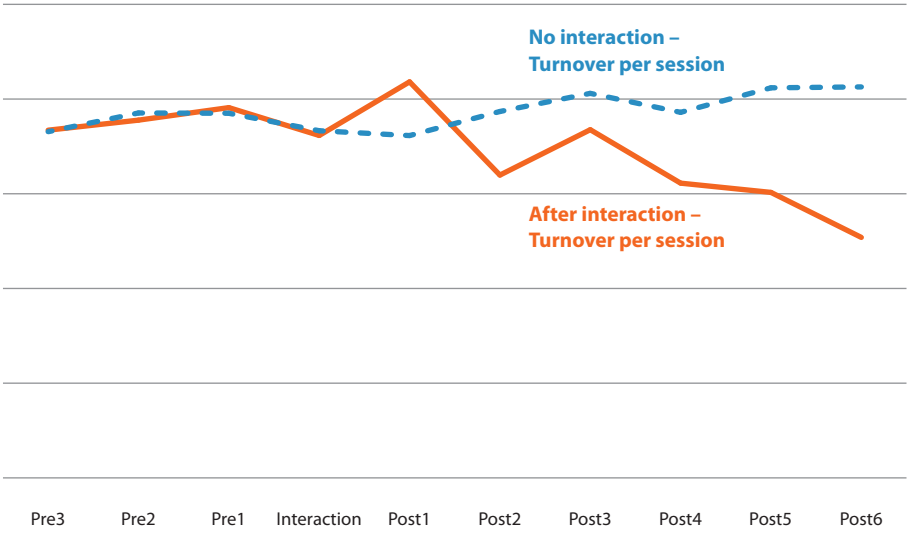
6.41 The top three indicators – speed of betting, amount risked per wager/spin, and length of the gambling session – are the basic behaviours that determine session characteristics and are under control of the players. If they want to reduce their risk of overspending during a session they must change one of these behaviours.

6.42 A single staff interaction had no effect on the rate of play or the length of sessions. However, players did substantially reduce their level of wagering, with the amount bet each spin declining by 17.5%. This change in play behaviour was reflected in a reduced rate of turnover per hour (–15.0%) and per session (–18.4%).

6.43 All three key behaviours declined after multiple interactions. These GOIs were most likely to reduce the length of their sessions (−20.3%), followed by wagers/spins per hour (10.8%) and, to a lesser extent, turnover per spin (−2.3% compared to baseline). The result of these changes in behaviour was a reduction of 11.8% in the amount wagered per hour and 30.3% in the amount wagered per session (see Figure 6.3 as an example).

6.44 The second set of indicators measures session outcomes in terms of the amount wagered (or risked) each session and each hour during the session (speed or rate of wagering). Following any interaction, there were reductions observed in session turnover and the rate of expenditure.

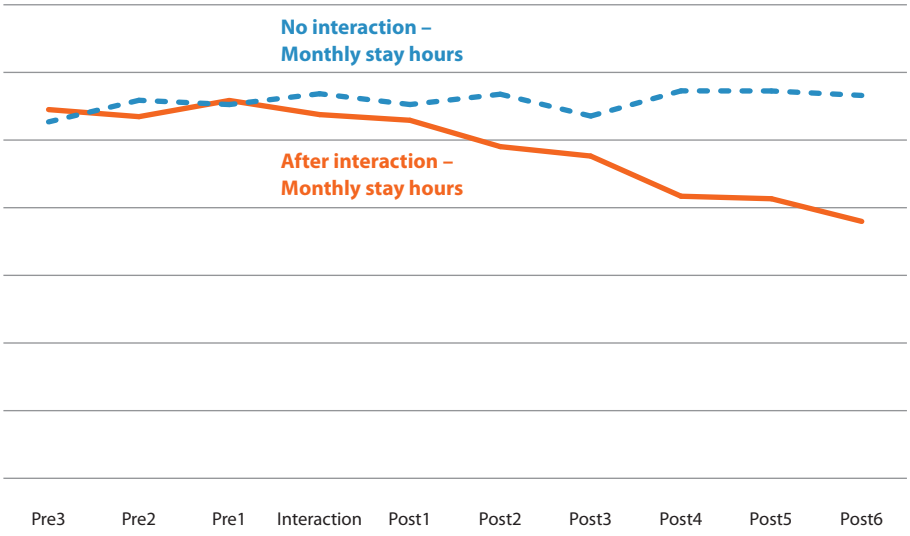
FIGURE 6.3
GOI pre–post turnover per session after interaction compared to baseline for GOIs with multiple interactions



6.45 After a single personal interaction, the average number of sessions per month dropped by 7.1% and total hours spent in the casino declined by 17.7% (see Figure 6.4 as an example). The end result was a reduction of 30.8% in turnover per month and a reduction in losses of 6.5%.

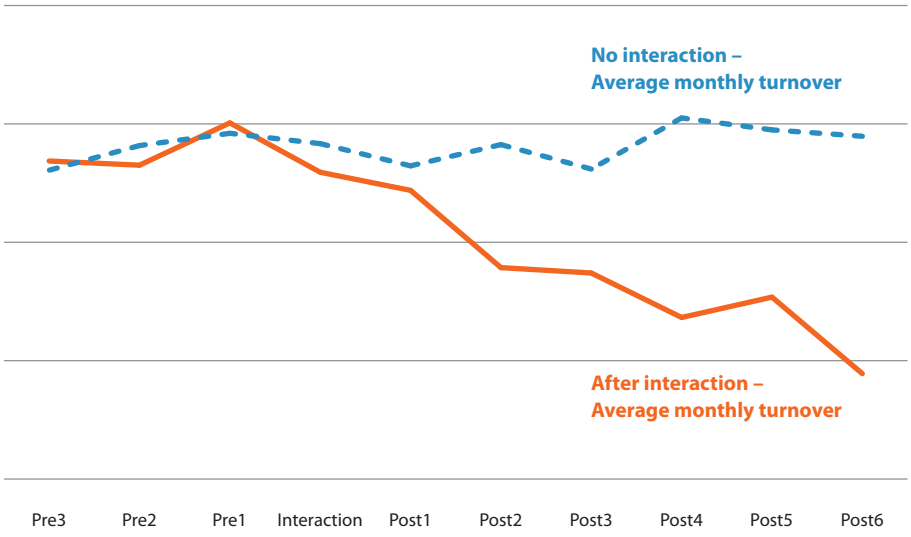
6.46 For those players who played at least once in months Post4 to Post6 after the interaction and experienced multiple staff interactions, the average number of sessions per month dropped by 7.9% and their average hours in the casino each month declined by 30.6%.

FIGURE 6.4
Monthly stay hours in casino pre vs post interaction compared to baseline for GOIs with multiple interactions



6.47 These changes, when combined, led to the total amount wagered per month for active players declining by 45.0% (see Figure 6.5 as an example) and the amount spent per month declining, on average, by 31.2%.

FIGURE 6.5
Average monthly turnover pre vs post interaction compared to baseline for GOIs with multiple interactions



Reduction in Active Players

6.48 In some cases, players may have stopped playing slot machines after interactions with staff. These individuals were excluded from the interaction impact analysis but still may have stopped in response to a customer interaction.

6.49 To estimate the percentage that may have stopped being active players at these casinos after the interaction, we defined an active player as one who played at least once in the months Pre3 to Pre1 (i.e., the three months prior to the interaction). We then calculated the percentage of players who were still active in months Post4 through Post6.[27]

- Approximately 4% of those customers with two or more personal interactions stopped playing or became inactive at that location.
- In contrast, about 17% of those with only one interaction appear to have stopped play. This suggests that the reason some of these players had only one interaction with staff is because they stopped being active visitors to the casino.

6.50 Play cessation for a small proportion of GOIs would be a reasonable outcome, especially for those experiencing a Level 4 referral for help or assistance, or Level 5 interaction supporting voluntary or involuntary exclusion (90 of which were reported during the trial).

6.51 As the trial was restricted to casino slot machine gamblers, there is some uncertainty as to whether those who stopped play switched to another product or venue.

Trial evaluation results indicate that staff interactions on the casino floor were effective in supporting improved customer outcomes. Not only were the majority of these slots customers continuing to play, six months later they were found to be wagering less (–18%), spent less time at the casino (–18%), and had fewer sessions (–7%), leading to a 31% decline in turnover and a 7% decline in spending, which is important, as high-risk GOIs are those most likely to be over-consuming. These impacts were stronger for those GOIs with two or more interactions, leading to reductions of 20% in session length, 30% drops in turnover per session, 8% declines in monthly sessions, and overall reductions in monthly turnover (–45%) and losses (–31%).

27 Most (94%) players who had two or more Level 2 interactions played at least once in the three months prior to interaction, with 90% active during the post evaluation period. Some of the players were not active in the specified months prior to interaction but became active in the post months, and vice versa. However, including these movements between active and inactive, the decline was about 4% of the players with whom staff interacted two or more times. The corresponding figures for those who interacted just once with staff was 93% active in months Pre3 to Pre1, 78% active in months Post4 to Post6, a drop of 17%.

7 Conclusions

7.1 Focal created risk detection algorithms that performed very well when applied to an independent sample of player data two years hence and tested against a gold standard such as the Problem Gambling Severity Index (PGSI). This suggests the algorithms will have a long shelf life and accurately identify at-risk players.

7.2 Workshops held with senior management, middle management, and staff of the NCF member operators over the course of the trial provided user inputs to the content and design of the ALeRT system that made it both user friendly and an effective tool for player identification, assessment, monitoring, and assistance.

7.3 Client feedback suggested the need for training modules on how to effectively use the ALeRT system features to interact with and help players, as well as training modules to educate staff on how to interact with players in a non-threatening but helpful manner to most effectively reduce and prevent gambling risk and harm.

7.4 Focal's five levels of interactions taxonomy worked to effectively describe the interactions and proved to be useful to staff and for analysis purposes.

7.5 Focal identified nine key play behaviours that would effectively summarize the impact of the interactions for the player. Focal was successful in creating baseline measures for these behavioural indicators.

7.6 Contrary to expectations, there was no regression to the mean once the player had been identified by the algorithms as a player of interest, and in fact the players continued to increase the intensity of play on most play behaviours measured after they were identified as a 'gambler of interest' (GOI), again underscoring the likelihood that the models are identifying the correct target.

7.7 Measured at an aggregate basis, one or more interactions of Level 2 or higher had an impact on key behaviours that led to reductions in turnover per month and reduced spending when compared to baseline measures.

7.8 Multiple interactions with GOIs had greater impact on play behaviour than single interactions. This emphasizes the need for casino management to commit staff time to assisting their customers to gamble responsibly, something that may take multiple interactions to achieve.

7.9 The effects of the interactions in terms of changed play behaviours still existed six months after the initial interaction.

7.10 Those customers who had multiple interactions with staff reduced the length of their sessions and, to a lesser extent, the speed of play and number of sessions per month, leading to reduced bet levels and reduced spend. In contrast, the single-interaction customers reduced the level of their bets each spin and, to a lesser extent, sessions per month, also leading to reduced turnover and a reduction in spend.

In conclusion, based on the results of the ALeRT Trial and Interaction Evaluation, expending resources to effectively identify and interact with high-risk gamblers has achieved the desired outcomes in reducing behaviours most commonly associated with customer risk and harm.

8 Next Steps

8.1 Next steps include addition of models for detecting risk among electronic roulette customers (January 2020) and table games (January to April 2020).

8.2 ALeRT Interaction Evaluation and Assurance Reporting will be activated during Quarter 1 of 2020 to allow operators to automatically generate outputs for compliance reporting.

8.3 The ALeRT Bettor Customer Care online web portal opened December 16, 2019, including 18 staff training videos and transcripts for educating employees on conducting effective customer interactions at each of Levels 1–5, including how to approach customers, myth-busting, player education for slots, progressives, electronic roulette and table games, providing self-help and management tools, making referrals for assistance, barring and banning, and dealing with friends and family.

Participating UK casinos are in a unique position to benefit from the evidence-based research that has guided the development and implementation of the UK ALeRT system to-date and to ensure it continues to meet future needs, including the GC's new National Strategy to Reduce Gambling Harms (April 2019) and more recent customer interaction implementation requirements (October 31, 2019).

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