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25 May 2019

[redacted]
Crown Melbourne
8 Whiteman Street
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Dear [redacted]

Re: Engagement to Provide Expert Opinion on the Crown Model [redacted]

I refer to your document dated 29 April 2019 requesting an expert opinion on the Crown mode [redacted] .

Crown Melbourne's terms of reference include a review on the following matte [redacted]:

1. Comments on the Crown Model and results of trials completed to date;

[redacted]

For consistency, the term 'patron' is used through the review to refer to 'patrons' and 'customers' where these terms appear in the various documents. RGLO in the context of this review refers to the Responsible Gambling Liaison Officer or appropriate member of the responsible gambling committee.

The Crown Model: *Attachment 2*
The Crown Model is designed to use objective player data derived from loyalty card records and demographics to generate a valid and reliable predictive model that can effectively identify patrons exhibiting potential problem gaming behaviours. The fundamental principles underlying the model are sound and consistent with the findings of a number of studies using online account data to form algorithms for purpose of mapping out patterns of behaviour that signal the possible presence of problem gambling or gambling disorders. Most of these studies use proxy measures, for example, self-exclusion or within-individual deviations in patterns of play, to identify the problem gambling status of account holders. In the majority of studies, no attempt has been made to match account data to clinical and/or psychometric measures of problem gambling status to validate the accuracy of their algorithms.

The decision to use patron data for the eighteen-month period prior to enrolling in the self-exclusion program has strong face-validity is the appropriate timeframe on which to construct the predictive model. Research indicates that the decision to enter self-exclusion programs is typically made in response to a financial or relationship pressures or stress, acceptance of impaired control over behaviour, and/or emotional distress. As Abbott, Francis, Dowling, and Coull (2011)[1] found, approximately 50% of self-excluded gamblers consider the decision to exclude for around a one-month period before taking action to enrol. Pickering, Blaszczynski, and Gainsbury (2018)[2] found 36 of a sample of 49 (73.5%) self-excluders reported a delay between obtaining information about the program and enrolling. The delay varied from 1 day (n = 3) to 3 years (n = 2), with an overall median of 14 weeks. Accordingly, the use of an eighteen-month timeframe can be considered to be appropriate in capturing the patterns of gaming behaviour that are instrumental in leading the majority of patrons to self-exclude. The period also covers the influen ce of seasonal variations in play (e.g., holidays).

It is important to note that the model is designed to identify the patterns of gaming behaviour that predict those patrons likely to be problem gamblers who are most likely to self-exclude, and not all problem gamblers in the venue. Only a minority of problem gamblers elect to enter self-exclusion programs. Therefore, there exists a wider population of patrons experiencing problem gamblers at the casino that elect not to be involved in self-exclusion programs, and may be missed by the algorithm.

The model was accurate in identifying 43% and 48% of self-exclusions, and conversely, slightly over 50% were not identified. The latter sub-group displayed potential indicators of problem gambling, but it is not clear if their problem gambling status was confirmed in any interaction with RGLO members. The percentage of patrons incorrectly predicted to self-exclude represent a relatively small to moderate minority. The findings of the trial are very positive but do argue for further refinement and enhancement in determining the most effective variables and predictive algorithms.

To achieve enhancements, the next step would be to a) to use the algorithms based on self-excluders to predict potential problem gamblers, and then to confirm accuracy by a more detailed interview to determine the patron's gambling status (thereby increasing confidence in the value of the predictive algorithm, and b) using observable behavioural indicators of problem gambling, confirm problem gambling status through interview and, if loyalty card users, incorporate their patterns of gambling into an enhanced algorithm. A live model with continued input from these two

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[1] Abbott, J., Francis, K., Dowling, N. A., & Coull, D. (2011). Motivators and barriers to joining a self-exclusion program. Presented at the NAGS 21st annual international conference, Crown Conference Centre, Melbourne, Australia.

[2] Pickering, D., Blaszczynski, A., & Gainsbury, S.M. (2017). Multi-venue self-exclusion for gambling disorders: A retrospective process investigation . *Journal of Gambling Issues,* http://igi.camh.net/doi/pdf.

approaches would result in an increasingly robust, reliable and accurate predictive algorithm.

Crown Melbourne Player Data Trial : *Attachment 3*
Comments on the player data review are as follows. The Crown model represents a significantly important value-added tool for use by Responsible Gambling Staff that can supplement the use of observable signs exhibited by patrons. A review of Australian studies on observable indicators of problem gambling in-situ indicated that although staff generally have the capacity to identify problem gamblers, multiple challenges remain. These include but are not limited to the absence of any single reliable indicator, the best indicators are rarely exhibited by problem gamblers, indicators vary across sessions, and the probability of observing two or more indicators concurrently remains low [3,4, 5].

The use of loyalty card data represents a major step forward in proactively detecting and responding to problem gambling behaviours. There are several advantages to this tool. Identifying and interacting with patrons identified by predictors can:

* Foster RG staff intervening at an earlier stage of the gambling trajectory,
* Encourage patrons to engage with the self-exclusion program and/or treatment services,
* Contribute to the development of a more refined and accurate predictive algorithm over time.

Reliance on loyalty card data has a number of limitations as indicated on page 2 of the *Crown Melbourne Player Data Trial* document. These are acknowledged in the document.

As noted, the eighteen-month period of tracked data is an appropriate time frame to provide a relatively reliable estimate of the typical profile of a patron's playing behaviour and expenditure considering the limitations as acknowledged.

The analytic team evaluated some 200 variables and selected 50 to build the model. It would be useful to state that reasons for selecting the 50; were these based on face-validity or consensus agreement among the analytic team? Some examples of the variables used would be informative and allow the reader to understand the types of variables selected. The same recommendation applies to the demographic data used.

In respect to the Methodology, it is not clear how the sample list of 100 members were selected. It appears that these were members who used their loyalty card in the last six months. Were these selected randomly only on the basis of using their cards or were these patrons who were ranked in the top 10% of predictive algorithms, randomly selected from the pool identified from the algorithm, or some other basis? This is important information setting out how representative this 100 is of the total subpopulation identified using the algorithm, and whether or not these were considered to be identified as potential problem gamblers.

The document states that identified members were approached d iscreetly and engaged in conversation. The interaction is an important responsible gambling component providing members information on services and programs. However, it remains uncertain if the interaction involved

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[3] Delfabbro, P., Thomas, A., & Armstrong, A. (2016). Observable indicators and behaviors for the identification of problem gamblers in venue environments. Journal of behavioral addictions, 5(3), 419-428.

[4] Delfabbro, P.H., Borgas, M., & King, D. (2011). Venue staff knowledge of their customers' gambling and problem gambling. Journal of Gambling Studies, 27, 1-15.

[5] Delfabbro, P.H., Osborn, A., McMillen, J., Neville, M., & Skelt, L. (2007). The identification of problem gamblers within gaming venues: Final report. Melbourne, Victorian Department of Justice.

some degree of confirmation of the predictive algorithm's accuracy, that is, did the patron disclose gambling-related problems, and/or whether he/she had considered self-exclusion, treatment or a reduction in gambling? This should be clarified by providing some indication if this information was gleaned from the member, and whether the determination was made by the RG member or self-report by the RGLO member to a question specifically asking about whether or not the gambling was problematic.

The document reports on the feedback from RGLO observations. The first bullet point on page 5 is a positive responsible gambling (RG) outcome for both the staff and patrons' perspective. It would be useful to emphasise further that the model fosters not only a proactive approach but increases staff confidence and sense of empowerment by providing a protocol guiding staff to intervene. The anticipated outcome will be staff satisfaction and enhanced quality of interactions.

The bullet point noting that patrons might respond negatively should be linked to the notion of staff training designed to increase interpersonal skills on the part of staff in managing and responding to defensive and hostile members. Staff should be appropriately trained in managing difficult patrons.

An overview of the summary of the findings derived from the six Tranches indicates that the model has value in achieving positive outcomes. It is instructive to note that across the six Tranches, an average of 21% of members had prior interactions with RGLO staff (range 14%-28%). These members could be assumed to be at high-risk or are problem gamblers given their repeated contact with RGLO staff, suggesting the need to introduce protocols to manage these members in a clearly defined systematic and intensive manner. It can be reasonably argued that the predictive algorithm is a valuable tool in identifying a significant minority of members experiencing ongoing problems or difficulties with their gambling who would benefit from assistance or specific interventions.

The data displayed in the table captioned Tranche 1-3 reveals a positive response post RGLO interactions on the variables of number of visits, hours per visit and average daily theoretical (ADT) expenditure. It would be useful to indicate if the changes for the various variables across the membership loyalty card levels are significant or not. For members, the interaction appears to be effective in reducing visits for Platinum and member status, and hours per visit and ADT for all membership status. The greater impact appears to be related to the lower level membership status. In contrast, the changes on the index variables are relatively stable and are most likely reflect minor variation in sampling error. There is a large anomalous increase for ADT post compared to pre-intervention for the Silver status. A check on the data integrity of this calculation (statistical or typographical error) might explain this discrepant figure.

In summary, the Player Data Trial shows very promising preliminary results that the predictive algorithm can identify a subset of members exhibiting problems as evidenced by repeated contact with RGLOs, and that RGLO interactions between identified members is effective in moderating gambling behaviours as assessed by changes in visits, hours and ADT as compared to the control group. As a live trial over time, the predictive algorithm can be refined as more data and information is incorporated in the statistical model.

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Conclusion

[redacted] The Crown model [redacted]
set the foundation for developing an effective [redacted]
lead to improved procedures and protocols. [redacted]

Yours sincerely,

[redacted]

Alexander Blaszczynski PhD.