# Revisiting Problem Gamblers' Harsh Gaze on Casino Services: Applying Complexity Theory to Identify Exceptional Customers

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## ABSTRACT

**This study revisits the theory, data, and analysis in Prentice and Woodside (2013). The study here applies fuzzy-set qualitative comparative analysis (fsQCA) to customer service evaluation data from seven mega casinos in the world gambling capital—Macau. The study includes contrarian case analysis and offers complex algorithms of highly favourable customer outcomes—an alternative stance to theory and data analysis in comparison to the dominant logic of statistical analyses that Prentice and Woodside (2013) report. The findings here include more complex, nuanced views on the antecedent conditions relating to high problem-gambling, immediate service evaluations and desired customer behavior measures in casinos. Contrary to the findings using symmetric testing via multiple regression analysis in Prentice and Woodside (2013), this study, using asymmetric testing via fuzzy-set qualitative comparative analysis (fsQCA), recognizes the occurrence of causal asymmetry, and draws conclusions on different algorithms leading to high scores in favorable and unfavorable outcome conditions. The findings indicate that not all problem gamblers gaze on casino services harshly; the minority of problem gamblers who view casinos positively versus harshly may be the most valuable customers for the casinos—the casinos' exceptional customers.**

**Keywords: fsQCA, algorithms, configurations, asymmetry, compulsive consumption, problem gambling.**

## INTRODUCTION

Using the "Problem Gambling Severity Index" (PGSI) and grouping gamblers into categories by severity, Prentice and Woodside propose (2013) that problem gamblers are unique in antecedent conditions and have a positive relationship with service evaluations of the service providers (i.e. the casinos). Using data collected from inside seven casinos in the world's largest gambling market (Macau), their study tests the two above hypotheses. The study finds statistically significant relationships between demographic and gambling behavioral antecedent and problem gambling. The study also finds statistically significant negative relationships with problem gambling and casino service evaluations, suggesting that problem gamblers view casino services harshly. This negative relationship finding is contrary to the hypothesis of the study, and Prentice and Woodside offer revisions of the theory by adapting Nataraajan and Goff's (1991) motive-control continuum: the harsh view is due to a blame of the service provider for likely negative outcomes (e.g., gambling losses) rather than oneself.

The contribution of the present study is in demonstrating an alternative perspective that leads to different routes to explain the antecedent conditions of problem gamblers and how problem gamblers versus non-problem-gamblers evaluate the casinos in addition to the hypotheses and findings in Prentice and Woodside (2013). The present contribution is also in demonstrating the application of fuzzy-set qualitative comparative analysis fsQCA—a method that rests on both a quantitative and qualitative approach to data analysis and theory in that the method is able to generalize across cases while still being able to explain complexity at the case level.

The present study demonstrates asymmetrical way of thinking about relationships for complex antecedent conditions and outcomes—which allows for a more nuanced understanding of the underlying configurations how customers' combine service facets when evaluating casinos. In doing so, the study includes contrarian case analysis (CCA). CCA includes recognizing that nearly all data sets includes cases whereby an indicator (independent variable) associates with an outcome (condition or dependent variable) in a manner counter to the reported principal symmetric relationship. Thus, while Prentice and Woodside (2013) report a negative association between problem gambling scores and casino evaluation variables, at the individual case level a few cases occur showing high problem gambling scores associating with highly positive evaluation scores. The study labels such cases as "contrarian type 1" cases, that is, cases showing contrarian high scores for an antecedent condition and positive scores with the outcome condition (dependent variable) while the main effect indicates a negative relationship. Contrarian type 2 cases are those cases with low scores in the indicator (antecedent condition or independent variable) associating with low scores of the outcome condition (dependent variable) when a study reports a negative variable main-effect relationship. The study here calls for and shows how to model complex antecedent conditions for both types 1 and 2 contrarian cases.

The findings from the present study allows for new perspectives of both theory and methodology. Specifically the findings support the value in understanding more complex configurations regarding casino evaluations than findings from symmetric-based statistical analysis (e.g., multiple regression analysis), and so it does not support the conclusion that high problem gambling associates only with lower overall casino evaluations, but rather low evaluations of casinos are part of more complex antecedent configurations. In terms of method, the study here supports the proposals by Ragin (2008) and Woodside (2008, 2013) that fsQCA is useful in providing information beyond hypothesis testing using multiple regression analysis (MRA).

Following this introduction, the next section provides a brief review on complexity and configural theory, laying the groundwork of applying fsQCA to the Prentice & Woodside (2013) data. Section three reviews the study by Prentice & Woodside (2013). The next section presents a reanalysis of the study applying fsQCA to the available data. The final section offers conclusions and suggestions for future research.

## THEORY OF COMPLEXITY AND CONFIGURAL THEORY

"Relationships between variables can be non-linear with abrupt switches occurring, so the same "cause" can, in specific circumstances produce different effects" (Urry, 2005, p. 4). The prior research on problem gambling and casino evaluations makes use of symmetric tests of statistical hypothesis using tools to calculate net effects on outcome conditions. Such statistical tools like multiple regression analysis (MRA) implicitly assumes a symmetrical relationship between variables, thus high values of a simple or complex variable X (i.e. X can take form of a simple continuous variable, or can be made up of constructs or equations containing several constructs) is associated with high values in a depended variable Y, and vice versa are low values of X associated with low values of Y. Thus, stating that for Y to be high X must also be high; and for Y to be low, X must also be low.

However, in comparison to the rectangular distribution of XY scores indicating no significant relationship (Figure 1a) or a symmetrical XY relationship (Figure 1b), asymmetrical relationships are often present in most real-life contexts and XY relationships are rarely symmetrical (Ragin, 2008). This perspective suggests that either high values of X are sufficient but not necessary for high values of Y as Figure 1c shows, where high values of Y both occur with low and high values of X. Another asymmetrical relationship is where high values of X necessary but not sufficient for high values of Y as Figure 1d shows, where high values of Y occur only with high values of X.

Figure 1 here.

With his claim, "Scientists' tools are not neutral," Gigerenzer (1991) argues, that research methods and instruments shape the way we think and test theories. Too often then, when examining net effects of variables an indirect assumption of symmetry in data is taken, even though, real-life contexts have proven to take on asymmetrical relationships. This thinking enhances the point of complexity. It is too simplistic to think of high outcomes of Y as associating only with high outcomes of X. On his work on complexity theory, Byrne (2005) points out those evidently causal processes in complex systems cannot be accessed by simple analysis. The trajectories of complex systems will be always directed by complex and contingent causes (indicators). As such, depending on the configuration, both high and low scores of X can lead to high outcomes of Y. "In the diversity-oriented view, causes combine in different and sometimes contradictory ways to produce the same outcome, revealing different paths" (Ragin, 2000).

The analysis and findings in Table 1 are from the Prentice and Woodside (2013) data set on problem gambling's association with customers' evaluations of casino services. The findings in Table 1 and the additional findings in the Prentice and Woodside (2013) study demonstrate a significant negative association between problem gambling and customers' casino evaluations. Table 1 shows respondents to survey of customers conducted inside seven casinos; the respondents are segment from very low to very high scores on the PGSI. Table 1 reports the findings for just one four global evaluations, "overall service quality" (OSQ) but the findings are consistent for all four global measures and for six intermediate service dimensions — the findings show an overall negative association between PGSI scores and OSQ evaluations. However, examining Table 1 deeply at the case level indicates contrarian type 1 and 2 cases. Contrarian type 1 cases here include the 20 percent of the cases having high scores on problem gambling having high scores on OSQ. Contrarian type 2 cases include the 39 percent of the cases having low scores on problem gambling having low scores on OSQ.

Table 1 here.

While the overall variable level analysis by Prentice and Woodside (2013) supports their harsh-gaze-on-casino-services-by-problem-gamblers finding, CCA adds serves to deepen and partially refute their implications for theory and casino management practice. Modeling indicators for contrarian type 1 and 2 cases that go beyond the use of symmetric statistical tests supports the conclusion that some problem gamblers view casino service performance very favorably and some non-problem gamblers view casino service performance very unfavorable. More generally, recognizing the near universal presence of contrarian type 1 and 2 cases supports the call for "embracing complexity theory by performing contrarian case analysis and modeling multiple realities" (Woodside, 2014, p. 9).

Both complexity theory and configural theory build from the core principle of equifinality (von Bertalanffy, 1968) which states that several possible complex configurations of antecedent conditions (i.e. algorithms) lead to the same outcome. Configural theory also builds from the principle of causal asymmetry. Following the criticism of the symmetrical approaches of MRA and analysis of variance, This concept states that the causes leading to the presence of an outcome might be very different from the causes leading to an absence of the outcome (Ragin, 2008). Thus, when analyzing problem gambling using MRA one might find that having a casino reward card associates positively with problem gambling, which also means that not-having-reward card associate with low problem gambling. The principle of causal asymmetry however suggests that not being in possession of reward card is not necessarily an ingredient in all configurations leading to low problem gambling, even if having a reward card is an ingredient in all configurations leading to high scores of problem gambling.

The present study adds value to the literature by employing the data analysis tool FsQCA (Ragin, 2009) that carries out analysis using algorithms to examine outcome conditions in an asymmetrical framework. This approach allows for complex analyses of configurations leading to high outcomes in problem gambling, immediate service evaluations, and positive action measures for casinos.

Figure 2 here.

Using the framework appearing visually in Figure 2 and asymmetric testing procedures, a re-analysis of the Prentice and Woodside (2013) data provides informative complex antecedent conditions that accurately indicate problem gamblers as well as non-problem gamblers. The arrows in Figure 2 are subject to testing leading to following propositions. (1) A few specific demographic combinations and casino-gambling behavior configurations indicate problem gamblers. (2) A few specific demographic combinations and casino gambling behavior configurations indicate non-problem gamblers. (3) Problem gambling and demographics as well as casino gambling behavior configurations influence immediate casino service evaluations. (4) Problem gambling and immediate service evaluations configurations influence overall service quality. (5) Problem gambling and immediate service evaluations as well as overall service quality influence desired customer behavior among casino guests.

## PRENTICE AND WOODSIDE'S STUDY OF "PROBLEM GAMBLERS' HARSH GAZE ON CASINO SERVICES"

Based on an extensive relevant literature review, Prentice and Woodside (2013) propose that problem gambling is explainable through unique antecedent conditions. Furthermore the study discusses the numerous consequences of problem gambling from the service providers' viewpoint (i.e. the casino managers).

In testing theory of antecedent conditions leading to problem gambling, the study proposes numerous hypotheses of net effects of antecedent conditions on problem gambling. Furthermore the study proposes that higher problem gambling is associated with more positive evaluations of immediate service quality of the casinos. Finally, it proposes that positive evaluations of immediate outcomes has a positive effect on overall service quality of the casinos, and in turn, high evaluations of overall service quality leads to desired casino customer behavior. A total of 22 hypotheses was proposed and tested. In general, the main subject being tested in the study is a first look at the perspectives and profiles of problem gamblers from inside casinos (Prentice & Woodside, 2013 p. 1111). H1: Problem gamblers have unique antecedent conditions. H2**:** Problem gamblers evaluate their casino service more favourably than non-problem gamblers.

### Study Method to Test the Hypotheses

Prentice and Woodside (2013) uses the "Problem Gambling Severity Index" (PGSI, aka Canadian Problem Gambling Index) to define what constitutes a problem gambler. The PGSI system is a well-developed tool, used to assess the degree of problem gambling in general population samples. According to Ferris and Wynne (2001), problem gambling is defined when participants score three or more based on the gambling behaviors and concerns.

The PGSI is a self-reporting system, where participants are asked to report on nine questions regarding the last twelve months to assess their level of problem gambling: (1) wagered larger amounts to get the same feeling of excitement; (2) tried to win back losses; (3) borrowed money or sold something to get money for gambling; (4) felt a gambling problem existed; (5) gambling caused health problems including stress and anxiety; (6) been criticized for betting or told a gambling problem exists; (7) gambling caused financial problems; (8) felt guilty about gambling; and (9) bet more than could be lost. Four choices are available for answering each of the nine items: "0 Never, 1 Sometime, 2 Most of the time, 3 Almost always."

To compute a measure of problem gambling Prentice and Woodside (2013) summed up each individual item to measure problem gambling in five categories: "non-problem gambler (score of zero), low risk gambler (score of 1 – 2), moderate risk gambler (score of 3 – 4), high risk gambler (score of 5 – 6), and severe risk gambler (score of 7 or more). Moderate, high risk and severe risk gambles were combines into one group (referred to as problem gamblers).

The data were collected using a survey form. The antecedent conditions includes demographics measures such as: age, gender, education, income and occupation and measures of casino gambling behavior: possession of a casino reward card, length-of-play each visit, average bet size and number of annual visits. Depending on the measurement, the participants would assign to an appropriate group or give open-ended responses to the questioner. The casino evaluation included 6 immediate outcomes which were constructs using items of service experiences uniquely to casinos. The construct were built off evaluation questions ranging from a one-to-seven scale. The six evaluations used to measure customer casino service experience; (1) casino has up-to-date appealing facilities; (2) quality of service responsiveness; (3) casino has best interest at heart plus employees care; (4) quality of games; (5) food and beverage quality; (6) ambience. The purpose of these immediate outcomes is the hypothesis that they have direct influence on the four global outcomes: (1) overall service quality, and the three desired casino customer behavior measurements: (2) casino is my first choice; (3) positive word-of-mouth for this casino; (4) propensity to switch from this casino. Regarding the global outcomes Prentice and Woodside (2013) furthermore propose that overall service quality is a lynchpin influence on the rest of the global outcomes (i.e. desired customer behavior) supporting prior research (see Chang, et al., 2013; Woodside et al., 1989) modeling customer evaluations of specific acts, overall satisfaction and the intention to visit the same service provider in the future.

Prentice and Woodside (2013) collected data from seven mega casinos in the Special Administrative Region of China; Macau. In recent years, Macau has become the World's biggest gambling centre, and the data is collected at the seven largest casinos measured on revenue. The participants in the study were adults confirmed to be engaged in gambling in any of the seven casinos. In total, the dataset consists of 411 individual cases.

Following Figure 2 in Prentice and Woodside (2013), antecedent conditions were individually regressed on problem gambling, and problem gambling in turn was regressed on both immediate and global outcomes, immediate outcomes was regressed on overall service quality and the other global outcomes, and finally overall service quality was regressed on the three remaining global outcomes. (Prentice & Woodside, 2013 p. 1111)

Rather than focusing on individual main effects, an alternative approach to the analysis would be to look at combinations (i.e. configurations) of antecedent conditions leading to high outcomes in the variable being analysed; such an analysis serves to maintain the data at the individual case level and allows for a more nuanced, complex view of the data. The analytic procedure to perform such analysis (i.e. QCA) is able to analyse the data across all the antecedent conditions and propose different combinations leading to high problem gambling, high overall service quality or high scores in desired customer behavioral outcomes, thus being able to offer profiles of antecedent conditions leading to high outcome in the above mentioned results. The "fsQCA of Prentice & Woodside (2013) Data" section in this paper offers such an analysis.

**Prentice and Woodside Findings and Conclusions**

Prentice and Woodside (2013) main findings include regressions of each antecedent condition on problem gambling. All estimated relationships are statistically significant except for education which is not associated with problem gambling. The findings suggest that the following antecedent conditions are positively associated with problem gambling: age, gender (male = 1, female = 0), income, casino reward card (card = 1, no card = 0), length-of-play each visit, average bet size, number of annual visits. Occupational status is negatively associated with problem gambling, however is tedious in the sense that it is only partially confirmed. The findings generally support the hypothesis proposed for unique antecedent conditions associated with problem gamblers except for the income variable.

The findings of problem gambling and immediate outcomes of casino service evaluations plus overall service quality shows consistently negatively associations between problem gambling and casino service evaluations. The findings for the desired customer behavior indicates that problem gambling is negatively associated with "Casino is my first choice", "Positive word of mouth" and "Propensity to switch" which means that the second hypothesis proposed by the authors needs revision.

In conclusion the study revises the proposed relationship based on the findings in Prentice and Woodside (2013, p. 1118) and offers the following explanation; "Problem gamblers are likely to recognize, that their casino gambling is unhealthy – and that the service provider is at least partially (if not entirely) to blame for their behaviors. Blaming the service provider may be preferable than blaming oneself for surrendering to a highly intense desire." The revisionist expands on Urry's (1990) "tourist gaze" in explaining this surprising relationship.

The examination of these findings indicates that the analysis predicting net effects using simple and multiple linear regression models is simplistic. As Prentice and Woodside (2013 p. 1118) points out when discussing the findings, McClelland's (1998) recommendation to look beyond simple linear relationships when examining variables is confirmed by these findings. The adoption of an fsQCA case-based (i.e. individual) level analysis uses combinatorial configurations to explain outcome conditions and hence solves for some of the underlying complexity suggested in the analysis. The following section applies fsQCA to the Prentice and Woodside (2013) data and shows the applications and findings using the case-based approach.

**FsQCA OF THE PRENTICE & WOODSIDE (2013) DATA**

As noted earlier, one important aspect when analysing data using a configural, set-theoretic relations approach is that relationships are asymmetrical rather than symmetrical as in correlational relations between variables. For the present study this means, that an asymmetrical relationship with the possession of a reward card on problem gambling scores low in the PGSI index indicating they are problem gamblers, does not challenge the fact that people with the reward card are problem gamblers. Supporting a symmetrical version of the same statement would be, "People with a reward card are problem gamblers and people without a reward card are non-problem gamblers."

The consistency index in fsQCA gauges the degree, that cases share a simple or complex configuration (i.e. combination) in displaying the outcome condition. Thus, consistency can be viewed as analogous to correlation in classic correlation statistics. The coverage index assesses the degree to which a simple or complex configuration "accounts for" instances of an outcome condition. The coverage index is analogous to the $r^2$ value in regression analysis, i.e. how much of the variation in the outcome is being explained by the complex statements, and indicates empirical relevance or importance.

Consistency ($\mathbf{X_i} \leq \mathbf{Y_i}$) = $\sum$ [min ($\mathbf{X_i}$, $\mathbf{Y_i}$)] / $\sum$ ($\mathbf{X_i}$). Where $\mathbf{X_i}$ indicates case i's membership score in the set denoted **X**; and $\mathbf{Y_i}$ is case i's membership score in the outcome condition denoted **Y**. ($\mathbf{X_i} \leq \mathbf{Y_i}$) is the subset relation, to which the "min" indicates the selection of the lower of the two values in the subset relation. Coverage ($\mathbf{X_i} \leq \mathbf{Y_i}$) = $\sum$ [min ($\mathbf{X_i}$, $\mathbf{Y_i}$)] / $\sum$ ($\mathbf{Y_i}$), where the $X_i$ in the denominator has been replaced by $Y_i$ in comparison with the formula for consistency. "Thus, the measure of fuzzy-set coverage is simply the overlap ($\sum$ [min ($\mathbf{X_i}$, $\mathbf{Y_i}$)]) expressed as a proportion of the sum of the membership scores in the outcome ($\sum$ ($\mathbf{Y_i}$))" Ragin (2008, p. 57).

The main difference between QCA and other conventional quantitative methods is captured in Ragin (2008, p. 9) "The key difference between the two is captured in the idea of a causal 'recipe' [configuration]—a specific combination of causally relevant ingredients linked to an outcome. In set-theoretic work, the idea of a causal recipe is straightforward, for the notion of combined causes is directly captured by the principle of set intersection." To fully elaborate on, and describe the method would be substantial, and thus an overview of key concepts and a brief introduction has been given in this section. Ragin (2008) provides extensive theory and user guidance on the use of QCA – furthermore a user guide for the software FsQCA is available at www.fsQCA.com.

**Estimating Complex Causal Statements**

For fuzzy-sets, the researcher needs to calibrate the original data into scores between 0 and 1 indication their degree of membership. The next step is to assess each case degree of membership in a given causal recipe, which is given as the intersection of the fuzzy-set causal conditions that comprise the recipe using Boolean algebra (Zadeh, 1965). Considering estimating high scores for problem gambling by demographic features of a case using the antecedent conditions in Prentice and Woodside (2013) that includes age, gender, education, occupational status and income, a complex antecedent configuration as the following model indicates:

age●gender●~education●~occupational_status●income ≤ problem gambling (1).

Model 1 proposes that older, males, low in education, low in occupation status, and in high income have high problem-gambling membership scores. The tilde (~) represents the negation (full non-membership) in the variable which is equal to 1-the calibrated score, and the filled dot (●) represents the "logical and" in fuzzy sets; this intersection is the minimum of scores among the pre-specified configuration.

Using actual cases from the Prentice and Woodside (2013) case A, an old customer (age = 0.95), male (gen = .99) with low education (edu = 0) and low occupational status (occ = 0.05) but high income (inc = 0.82); his degree of membership to the causal recipe would be 0.82 which indicates a membership level of more-in-than-out to the complex causal recipe. Analogous to this example, consider case B—a young female with high education and high occupational status but low income; her degree of membership to the causal recipe would be 0.01 which indicates full non-membership.

**Calibration of Antecedent conditions to Fuzzy-set Scores**

The fuzzy-scores for simple antecedent conditions range from 0.00 to 1.00. These values indicate the degree of membership of the case in each condition. A transformation from the original scores into fuzzy-sets has to be made by the analyser. The set scores are not comparable to probabilities, but instead looked upon as truth values to a statement. The reason, that fuzzy-set values, unlike conventional variables has to be calibrated is, as Ragin (2008, p. 174) argues; "Because they must be calibrated, they are superior in many respects to conventional measures, as they are used in both quantitative and qualitative social science. In essence, I argue that fuzzy sets offer a middle path between quantitative and qualitative measurements. However, this middle path is not a compromise between the two; rather, it transcends many of the limitations of both".

The calibration from conventional scores to fuzzy-set values makes use of external information to assess the degree of membership of each variable. Within the endpoints 0.00 for full non-membership and 1 for full membership, three breakpoints must be assessed. The first being 0.05 for the threshold for full non-membership, second being 0.50 – the crossover point of membership ambiguity, and 0.95 for full membership.

Table 2 here.

Table 2 shows the antecedent conditions carried out in the analysis. Each antecedent has descriptive statistics from the sample and the final calibrated score. Notably all the antecedents regarding constructs using items of 7-point scale evaluations by customers has been given a fixed calibration of full non-membership equal to two, which is a rather poor evaluation of the construct; the cross over point is an evaluation of 4 which is the neutral point in a 7 point Likert scale; full membership is given as a 6 which is a rather positive evaluation of that particular construct. Depending on how many items the constructs were made up of, this method has been scaled to fit that number.

## FINDINGS

The findings follows the conceptual model in Figure 2, comparing them with the result from the analysis carries out by Prentice and Woodside (2013).

### Findings for High and Low Scores Problem Gambling

Table 3a reports the findings for high scores of problem gambling using fsQCA and shows two complex recipes predicting high scores of problem gambling. The two models for high problem gambling consist of males (both young and old), one with low education and high income, and one with high education and low income. Both algorithms have high occupational status and are in position of a casino reward card, while their length of play of each visit to the casino is low. One has high average bet size and low annual visits, while the other one has low average bet size and high annual visits.

Tables 3a and 3b here.

Table 3b shows complex recipes that work in predicting low scores of problem gambling. The four models all consists of females, two of which are young and two of which are old. They have high education and low income with high occupational status. In three of the four models is the casino reward card present as a negative, which means that the respondents do not possess such a card. For the young females length of play in each visit is low, as is number of annual visits, low average bet size pops up in one of them. For one of the old non problem gamblers, length of play and average bet size is low, whereas for the other they are high. In both models number of annual visits is high.

The findings partly supports the MRA results in Prentice and Woodside (2013) in that the antecedents; gender and reward card, are in alignments with the regression results and are the antecedents with highest beta values. However, the findings brings up two strong points regarding the application of fsQCA; causal asymmetry and equifinality. The findings shows, that both when predicting high and low problem gambling, different routes can lead to the same outcome showing support for causal asymmetry. Furthermore, the findings confirm equifinality, in that the models that work for low problem gambling are not mere negations of the models that work for high problem gambling. Thus, the analysis in this study offers a more complex view of configurations leading to problem gambling, rather than individual net effects.

**Findings for Immediate Service Evaluations**

The findings for immediate service evaluations are extensive, since there's a total of six outcome conditions. The analysis then has been tweaked to overcome the multiple outcomes by creating one complex statement using the immediate service evaluations as an output condition. Thus, the findings in this section need to be interpreted differently.

Table 4 here.

Table 4 shows the complex antecedent conditions that work in achieving high scores. These conditions have been created using the logical "and" analogy meaning that it is made up of each case minimum evaluation, since it returns the minimum value in the complex statement. As such, Table 4 shows antecedent conditions that work in achieving high evaluations of the combined immediate service evaluations.

The findings for immediate service evaluations only partly support the main claim by Prentice and Woodside (2013) that problem gamblers gaze harshly on casino services. In three of the four complex configurations figures, using the non-problem gambling as an antecedent, non-problem gamblers give casino positive evaluations on their immediate services. However, in one of the configurations leading to high immediate service evaluations, severe problem gamblers figures in; thus suggesting, that there are indeed problem gamblers that do not gaze harshly on casino services, depending on the rest of the complex configurations.

**Findings for Desired Casino Customer Behavior Evaluations**

Table 5 shows a mean comparison table of positive word of mouth by two-layered groups. The first layer is problem gambling grouped into five groups, while the second layer is the problem gamblers overall service quality evaluation by five groups. The findings from this table suggest, that when rating overall service quality high (i.e. a four or a five), the most severe problem gamblers have the highest means in positive word of mouth of 10.000 and 12.000. When rating overall service quality mediocre (i.e. a three), it is the second most severe problem gamblers that has the highest mean in positive word of mouth.

Table 5 here.

The findings suggest that when casinos manage to match the service expectations of the problem gamblers and thus satisfy them, they form a tight bond between customer and service provider. Thus, the star customers for casino are actually the satisfied problem gamblers, who are loyal and return to that casino every time they want to fulfil that service need, who are willing to share positive experiences with other potential customers.

For complex configurations including problem gambling, Table 6a reports the overall service quality and immediate service evaluations predicting the casino as my first choice. The findings indicate that in 3 out of 4 models, overall service quality is evaluated low, as long as specific immediate service factors are high.

Table 6 here.

Table 6b shows the complex configurations leading to high positive word-of-mouth. The findings are similar to the ones of casino as my first choice, and so models 1, 3 and 4 from Table 5a are what constitute the three models leading to high positive word of mouth. This suggests, that people who are choosing their casino as their first choice are very similar to people that spread positive word of mouth about that casino. The findings suggest, that in order to secure behavior in the casinos best interest, a complex configuration of service evaluations must be achieved depending whether the customers have a gambling problem, and the importance of immediate service elements changes – it is difficult to please all customers. Note that Appendix B reports the findings for low propensity to switch, they offer no value to the analysis of this paper, since the complex solutions are difficult to interpret.

**Findings for Overall Service Quality Using Complex Configurations of Demographics Plus PGSI**

Building complex configurative statements that include demographics and PGSI to indicate high scores for overall service quality (OSQ), the findings partially support and challenge the claims presented in Prentice and Woodside (2013). The claim that is challenged is, as the title suggests, not all problem gamblers view the casinos' OSQ harshly. In fact, Table 7a includes two models where high PGSI scores in combination with specific additional demographic combinations associate with high OSQ scores and two models where negative (low) PGSI scores in combination with alternative additional demographic combinations associate with high OSQ scores. The conclusion by Prentice and Woodside (2013) that problem gamblers view casinos' OSQ harshly is too much of a blanket statement—the contrarian case analysis via fsQCA supports a more contingent perspective that some problem gamblers view casinos' OSQ positively and some view casinos' OSQ negatively—the positive versus negative turn by problem gamblers depends upon specific demographic profiles.

Tables 7a and 7b here.

Table 7b incudes the negation of OSQ as the outcome condition that is, ~OSQ. The first model does not include PGSI or ~PGSI; thus, the inclusion of a high score in PGSI or its negation in a complex otherwise demographic condition is not necessary in all cases for predicting ~OSQ.

The additional seven models in Table 7b include either PGSI or ~PGSI in the complex statements that include demographic conditions. the models in 7b are not the mirror opposite of any of the models in Table 7a; these findings support the principle of causal asymmetry, that is, the negations of simple antecedents in complex statements indicating high scores in an outcome condition are not going to be accurate in predicting low scores in the same outcome condition. Thus, the study of negative evaluations and customer loss is unique and worthy of separate attention from the study of positive evaluations and customer gain.

See Appendix A for additional configurations for high overall service quality evaluations. Notably in the table is that high problem gambling appears in several models that work in predicting high overall service quality evaluations. The findings then, support the claim that depending on the configurations, problem gambling plays a part in several solutions leading to high overall service quality.

**CONCLUSIONS, LIMITATIONS, AND CONTRIBUTION TO THEORY**

The present study shows the effectiveness of contrarian-case analysis using configural causal recipes versus the use only of conventional net-effects analysis via MRA or ANOVA. The solutions of the present study offer nuanced complexity and depth, in understanding the unique configural antecedent conditions of problem gamblers, service evaluations of the casinos, and how to achieve desired behavior from different types of customers.

The study offers additional information by comparing QCA to MRA as tools of analysis. The contribution here lies in examining the usefulness of modeling causal recipes and choosing appropriate tools for the analysis at hand which the scientists use to offer different results and conclusions as Gigerenzer (1991) proposes. This study focuses on the differences in the findings and in insights from the findings via the use of matrix-algebra based tools (MRA) versus Boolean-algebra based tools (fsQCA).

The claim that problem-gamblers' gaze on casinos harshly is too simplistic to represent reality. Some problem gamblers evaluate specific service dimensions and the overall service quality of casino high rather than low. Furthermore the present study shows that severe problem gamblers who evaluate casino services positively are the real star customers for the casinos, as they are loyal and share their positive views on the casino with others more than equally satisfied non-problem gamblers. One restriction of this study and in Prentice and Woodside (2013) is that the data were collected from one casino environment—Macau. Behavior in this one market might be different for casino customers in other large location (e.g., Las Vegas, Monaco) and even other Asian markets. Future research should collect data from a variety of locations in order to draw global conclusions for casino gamblers. Furthermore, the sample size for each casino was small; larger samples sizes for specific periods would be helpful for confirming or refuting findings of this study and that of the Prentice and Woodside (2013).

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# Appendix A

**Antecedent Conditions for High Scores of Overall Service Quality**

| Model | PGSI | Up to date fac | Service res | Emp care | Q of games | Q of f&b | Ambience | Coverage: Raw | Coverage: Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | ● | | ○ | ● | | ● | 0.4613 | 0.0730 | 0.9629 |
| 2 | | ● | ○ | ○ | ● | ○ | | 0.2596 | 0.0005 | 0.9610 |
| 3 | ● | ● | ● | | ● | | ● | 0.3372 | 0.0101 | 0.9812 |
| 4 | ● | | ○ | ○ | ● | ○ | ● | 0.1569 | 0.0005 | 0.9771 |
| 5 | | ○ | ● | ● | ● | ● | ○ | 0.1992 | 0.0000 | 0.9739 |
| 6 | ○ | ● | ● | ● | | ● | ● | 0.5501 | 0.2588 | 0.9783 |
| 7 | ○ | ○ | ○ | ○ | ○ | ○ | ○ | 0.1370 | 0.0021 | 0.9618 |
| 8 | ○ | ○ | ○ | ● | ● | ○ | ● | 0.1578 | 0.0008 | 0.9789 |
| 9 | ○ | ● | ● | ● | ● | ○ | ○ | 0.1696 | 0.0004 | 0.9818 |
| 10 | ● | ○ | ● | ● | ● | ● | | 0.1499 | 0.0000 | 0.9855 |
| 11 | ● | | ● | ● | ● | ● | ● | 0.2860 | 0.0017 | 0.9902 |

solution coverage: 0.856913

solution consistency: 0.948209

Note. Filled dots (●) means the presence of the antecedent condition in the model predicting the outcome, empty dots (○) means the negations of the antecedent and blanks means that particular antecedent is not figured in the model. **Appendix B**

**Antecedent Conditions for Low Scores in Propensity to Switch**

| Model | PGSI | Service Qual | Up to date fac | Service res | Emp care | Q of games | Q of f&b | Ambience | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | ○ | ○ | ○ | ○ | ○ | ○ | ○ | 0.3688 | 0.0301 | 0.8977 |
| 2 | ● | ● | ○ | ● | ● | ● | ● | | 0.3185 | 0.0415 | 0.8679 |
| 3 | ○ | ○ | ○ | ○ | ● | ● | ○ | ● | 0.3333 | 0.0160 | 0.8910 |
| 4 | ● | ○ | ○ | ○ | ○ | ● | ○ | ● | 0.2754 | 0.0032 | 0.8730 |
| 5 | ● | ○ | ● | ○ | ○ | ● | ○ | ○ | 0.2676 | 0.0021 | 0.8689 |
| 6 | ○ | ○ | ○ | ● | ● | ● | ● | ○ | 0.3456 | 0.0162 | 0.8912 |
| 7 | ○ | ○ | ● | ● | ● | ● | ○ | ○ | 0.3530 | 0.0244 | 0.8901 |

solution coverage: 0.547163

solution consistency: 0.820644

Note. Filled dots (●) means the presence of the antecedent condition in the model predicting the outcome, empty dots (○) means the negations of the antecedent and blanks means that particular antecedent is not figured in the model.

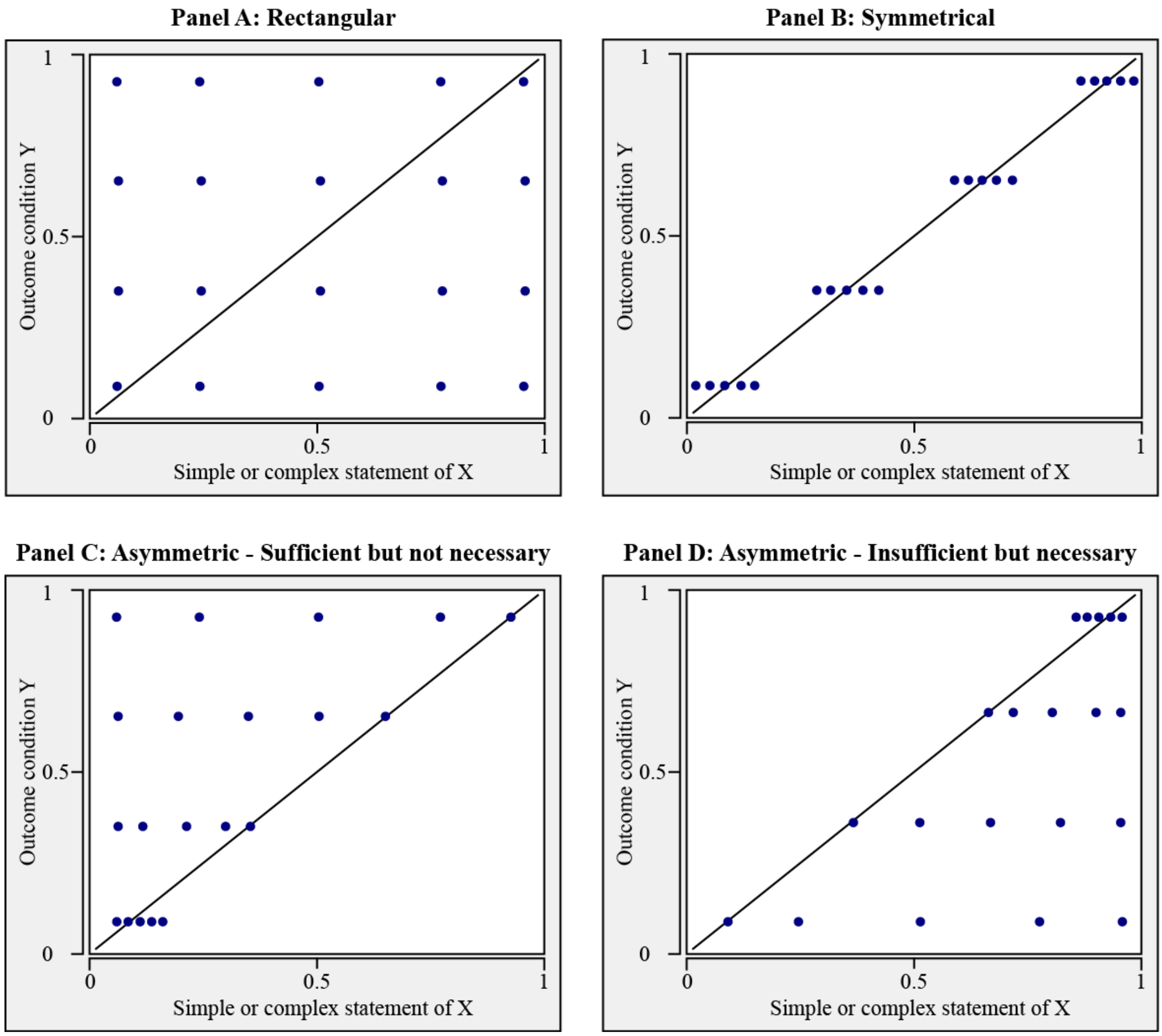


**Figure 1**

**Rectangular, symmetric, and asymmetric relationships of 20 variables**

# Table 1
## Problem Gambling Symmetric and Asymmetric Associations with Overall Service Quality

Contrarian type 2 cases: 39% of customers with zero to very low problem-gambling scores gave low scores on overall service quality

30% of customers with zero to very low problem-gambling scores gave high scores on overall service quality

| | | | Overall Service Quality Grps | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | 1.00 | 2.00 | 3.00 | 4.00 | 5.00 | Total |
| problem gambling segments | None | Count | 58 | 29 | 69 | 37 | 39 | 232 |
| | | % within problem gambling segments | 25.0% | 12.5% | 29.7% | 15.9% | 16.8% | 100.0% |
| | | % of Total | 14.1% | 7.1% | 16.8% | 9.0% | 9.5% | 56.4% |
| | 1-2 | Count | 14 | 6 | 16 | 3 | 3 | 42 |
| | | % within problem gambling segments | 33.3% | 14.3% | 38.1% | 7.1% | 7.1% | 100.0% |
| | | % of Total | 3.4% | 1.5% | 3.9% | 0.7% | 0.7% | 10.2% |
| | 3-4 | Count | 12 | 8 | 20 | 11 | 4 | 55 |
| | | % within problem gambling segments | 21.8% | 14.5% | 36.4% | 20.0% | 7.3% | 100.0% |
| | | % of Total | 2.9% | 1.9% | 4.9% | 2.7% | 1.0% | 13.4% |
| | 5-6 | Count | 8 | 10 | 13 | 9 | 4 | 44 |
| | | % within problem gambling segments | 18.2% | 22.7% | 29.5% | 20.5% | 9.1% | 100.0% |
| | | % of Total | 1.9% | 2.4% | 3.2% | 2.2% | 1.0% | 10.7% |
| | 7+ | Count | 15 | 6 | 14 | 1 | 2 | 38 |
| | | % within problem gambling segments | 39.5% | 15.8% | 36.8% | 2.6% | 5.3% | 100.0% |
| | | % of Total | 3.6% | 1.5% | 3.4% | 0.2% | 0.5% | 9.2% |
| Total | | Count | 107 | 59 | 132 | 61 | 52 | 411 |
| | | % within problem gambling segments | 26.0% | 14.4% | 32.1% | 14.8% | 12.7% | 100.0% |
| | | % of Total | 26.0% | 14.4% | 32.1% | 14.8% | 12.7% | 100.0% |

48% of customers with high to very high problem-gambling scores gave low scores on overall service quality

Contrarian type 1 cases: 20% of customers with high to very high problem-gambling scores gave high scores on overall service quality

Note. For the distribution of cases, the symmetric main effect is negative; phi = .288, $p < .081$. ANOVA findings indicate significant differences in overall service quality by problem-gambling segments that supports a significant symmetric negative main effect, means (standard errors) for the five PG segments from low to high: 9.82 (.10); 9.31 (.21); 9.67 (.19); 9.66 (.24); 9.05 (.26); $F = 2.68$, DF= 4/406, $p < .032$. The findings include contrarian type 1 cases: cases with high scores on the outcome condition that counters the negative symmetric main effect; the findings include contrarian type 2 cases: cases with low scores on the outcome condition that counters the negative symmetric main effect.

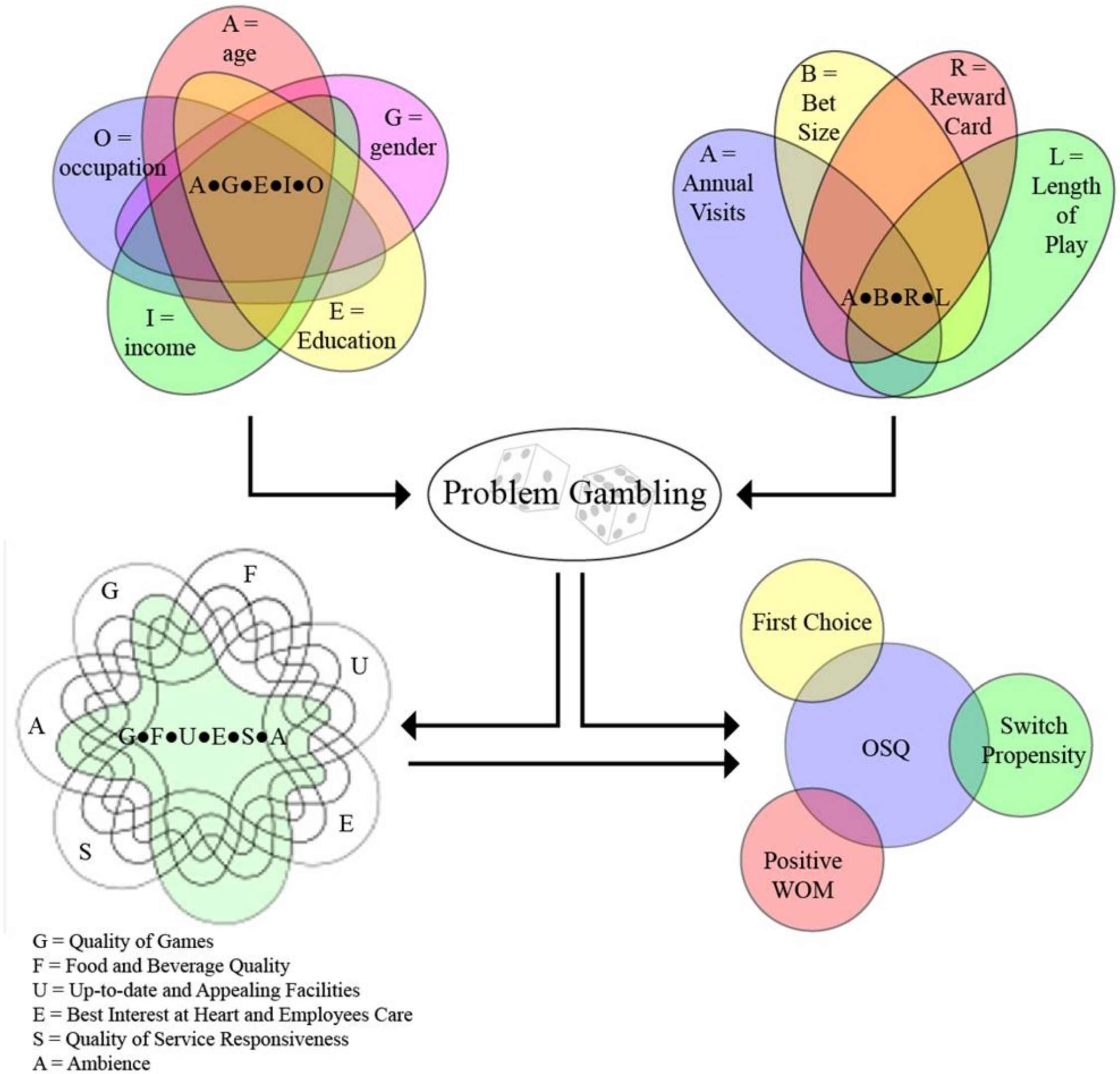


**Figure 2**

**Conceptual Configural Modeling of Problem Gambling, Immediate Service Evaluations and Overall Service Evaluations plus Casino Positive Behavior Measures**

| | Table 2: Calibrations of All Conditions | |
|---|---|---|
| **Variable/Antecedent** | **Descriptive Statistics** | **Calibrations (.95, .50) (.05)** |
| Problem Gambling Severity Index (PGSI) | μ = 11.09, σ = 3.14, min = 9, max = 24 | (16, 11, 9) |
| **Demographics** | | |
| Age (age) | μ = 2.98, σ = 1, min = 1, max = 6 | (5, 3, 1) |
| Gender (gen) | male = 250 [1], female = 161 [0] | (1, 0.5, 0) |
| Education (edu) | μ = 2.75, σ = .84, min = 1, max = 4 | (4, 3, 2) |
| Income (inc) | μ = 2.21, σ = 1.44, min = 1, max = 8 | (5, 3, 1) |
| Occupational status (occ) | μ = 3.17, σ = 1.629, min = 1, max = 6 | (6, 4, 2) |
| **Casino Gambling Behavior** | | |
| Casino reward card holder/user (rwc) | yes = 234 [1], no = 171 [0] | (1, 0.5, 0) |
| Length of play each visit, hours (lop) | μ = 3.03, σ = 1.54, min = 1, max = 10 | (5, 3, 1) |
| Average bet size (abs) | μ = 1.98, σ = 1.79, min = 1, max = 5 | (3, 2, 1) |
| Number of annual visits (nav) | μ = 2.66, σ = 1.79, min = 1, max = 7 | (5, 3, 1) |
| **Casino Immediate Service Evaluation Ratings** | | |
| Casino Up-to-date appealing facilities (uaf) | μ = 20, σ = 3.29, min = 10, max = 28 | (24, 16, 8) |
| Quality of service responsiveness (qsr) | μ = 14.37, σ = 2.61, min = 6, max = 21 | (18, 12, 6) |
| Casino has best interest at heart plus employees care (hep) | μ = 26.31, σ = 6.06, min = 9, max = 41 | (36, 24, 12) |
| Quality of the games (qog) | μ = 15.65, σ = 2.68, min = 8, max = 21 | (18, 12, 6) |
| Food and beverage quality (fbq) | μ = 14.25, σ = 2.45, min = 8, max = 21 | (18, 12, 6) |
| Ambience (amb) | μ = 10.18, σ = 1.74, min = 5, max = 14 | (12, 8, 4) |
| **Casino Quality Ratings** | | |
| Overall service quality (osq) | μ = 9.66, σ = 1.55, min = 5, max = 14 | (12, 8, 4) |
| Casino is my first choice (fch) | μ = 4.26, σ = 1.32, min = 1, max = 7 | (6, 4, 2) |
| Positive Word-of-mouth for this casino (wom) | μ = 8.24, σ = 2.43, min = 2, max = 14 | (12, 8, 4) |
| Propensity to switch from this casino (psw) | μ = 9.55, σ = 1.85, min = 2, max = 14 | (12, 8, 4) |

**Table 3a**

**Antecedent Conditions for High Problem Gambling**

| Model | Age | Gender | Education | Income | Occ status | Rw card | Len of Play | Ave bet | No. ann vis | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ○ | ● | ● | ○ | ● | ● | ○ | ○ | ● | 0.1696 | 0.1015 | 0.8384 |
| 2 | ● | ● | ○ | ● | ● | ● | ○ | ● | ○ | 0.1426 | 0.0745 | 0.8462 |

solution coverage: 0.244132

solution consistency: 0.818719

**Table 3b**

**Antecedent Conditions for Low Problem Gambling**

| Model | Age | Gender | Education | Income | Occ status | Rw card | Len of Play | Ave bet | No. ann vis | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ○ | ○ | ● | ○ | ● | ○ | ○ | | ○ | 0.1342 | 0.0098 | 0.9845 |
| 2 | ○ | ○ | ● | ○ | ● | | ○ | ○ | ○ | 0.1635 | 0.0401 | 0.9670 |
| 3 | ● | ○ | ● | ○ | ● | ○ | ○ | ○ | ● | 0.0440 | 0.0024 | 0.9900 |
| 4 | ● | ○ | ● | ○ | ● | ○ | ● | ● | ● | 0.0403 | 0.0049 | 0.9891 |

solution coverage: 0.183530

solution consistency: 0.969382

Note. Filled dots (●) means the presence of the antecedent condition in the model predicting the outcome, empty dots (○) means the negations of the antecedent and blanks means that particular antecedent is not figured in the model. Table 2a: The presence of gender, occupational status, reward card and the absence of length of play is present in all the models. Thus, suggesting that they are necessities for high problem gambling. Table 2b: The absence of gender, income, and reward card and the presence of education and occupational status is present in all the models. Thus, suggesting that they are necessities for low problem gambling.

**Table 3**

**Antecedent Conditions for High Scores 4 Immediate Service Evaluations**

| Model | PGSI | Age | Gender | Education | Income | Occ status | Rw card | Len of Play | Ave bet | No. ann vis | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ○ | ○ | ○ | ● | ○ | ● | ○ | ○ | | ○ | 0.155661 | 0.104926 | 0.909749 |
| 2 | ○ | ● | ○ | ● | ○ | ● | ○ | ○ | ○ | ● | 0.053482 | 0.003032 | 0.953548 |
| 3 | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ● | ● | 0.048366 | 0.004453 | 0.941014 |
| 4 | ● | ○ | ● | ○ | ○ | ○ | ● | ● | ● | ● | 0.089910 | 0.072619 | 0.917352 |

solution coverage: 0.237043
solution consistency: 0.899191

Note. Filled dots (●) means the presence of the antecedent condition in the model predicting the outcome, empty dots (○) means the negations of the antecedent and blanks means that particular antecedent is not figured in the model. The absence of income figures in all the complex configurations suggesting that the absence of income is a necessity in achieving high scores among all immediate service evaluations.

**Report**

positive_wom

| problem_gambling | Overall Service Quality Grps | Mean | N | Std. Error of Mean |
|---|---|---|---|---|
| No (9) | 1.00 | 6.8966 | 58 | .33875 |
| | 2.00 | 8.4138 | 29 | .31198 |
| | 3.00 | 8.5942 | 69 | .25978 |
| | 4.00 | 9.4324 | 37 | .34121 |
| | 5.00 | 10.0000 | 39 | .38878 |
| | Total | 8.5172 | 232 | .16300 |
| Low (10-12) | 1.00 | 6.9545 | 22 | .55236 |
| | 2.00 | 8.0000 | 11 | .57208 |
| | 3.00 | 7.9655 | 29 | .41369 |
| | 4.00 | 8.3000 | 10 | .91954 |
| | 5.00 | 9.0000 | 6 | .44721 |
| | Total | 7.8077 | 78 | .26636 |
| Medium (13-15) | 1.00 | 6.5000 | 6 | .61914 |
| | 2.00 | 9.2857 | 7 | .35952 |
| | 3.00 | 7.4118 | 17 | .52900 |
| | 4.00 | 9.8571 | 7 | .55328 |
| | 5.00 | 9.0000 | 3 | 1.73205 |
| | Total | 8.1500 | 40 | .34072 |
| High (15) | 1.00 | 8.0000 | 6 | .51640 |
| | 2.00 | 7.8333 | 6 | .90982 |
| | 3.00 | 10.0000 | 3 | .00000 |
| | 4.00 | 9.8333 | 6 | .54263 |
| | 5.00 | 8.0000 | 2 | 2.00000 |
| | Total | 8.6957 | 23 | .37424 |
| Highest (16+) | 1.00 | 6.6000 | 15 | .71581 |
| | 2.00 | 7.8333 | 6 | .54263 |
| | 3.00 | 6.9286 | 14 | .57860 |
| | 4.00 | 10.0000 | 1 | .00 |
| | 5.00 | 12.0000 | 2 | .00000 |
| | Total | 7.2895 | 38 | .41300 |
| Total | 1.00 | 6.9065 | 107 | .24069 |
| | 2.00 | 8.3220 | 59 | .21951 |
| | 3.00 | 8.1591 | 132 | .19353 |
| | 4.00 | 9.3443 | 61 | .27048 |
| | 5.00 | 9.8269 | 52 | .32461 |
| | Total | 8.2433 | 411 | .11968 |

**Table 5: Mean analysis of the construct positive word of mouth grouped by two layers**

Note. First layer is problem gambling and second layer being their overall service quality evaluation.

**Table 6a**

**Antecedent Conditions for High Scores in Casino First Choice**

| Model | PGSI | Service Qual | Up to date fac | Service res | Emp care | Q of games | Q of f&b | Ambience | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ● | ● | ○ | ● | ● | ● | ● | | 0.1702 | 0.0570 | 0.9060 |
| 2 | ○ | ○ | ○ | ○ | ● | ● | ○ | ● | 0.1740 | 0.0105 | 0.9087 |
| 3 | ○ | ○ | ○ | ● | ● | ● | ● | ○ | 0.1819 | 0.0100 | 0.9165 |
| 4 | ○ | ○ | ● | ● | ● | ● | ○ | ○ | 0.1854 | 0.0166 | 0.9130 |

solution coverage: 0.271415

solution consistency: 0.901584

**Table 6b**

**Antecedent Conditions for High Scores in Postive Word of Mouth**

| Model | PGSI | Service Qual | Up to date fac | Service res | Emp care | Q of games | Q of f&b | Ambience | Coverage Raw | Coverage Unique | Consistency |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ● | ● | ○ | ● | ● | ● | ● | | 0.1786 | 0.0655 | 0.9040 |
| 2 | ○ | ○ | ○ | ● | ● | ● | ● | ○ | 0.1926 | 0.0114 | 0.9226 |
| 3 | ○ | ○ | ● | ● | ● | ● | ○ | ○ | 0.1967 | 0.0188 | 0.9213 |

solution coverage: 0.276871

solution consistency: 0.908867

Note. Filled dots (●) means the presence of the antecedent condition in the model predicting the outcome, empty dots (○) means the negations of the antecedent and blanks means that particular antecedent is not figured in the model.

**Table 7a**

**Complex Configurations with High Scores of Complex Antecedent Demographic Statements plus PGSI Associating with High Scores for the Outcome Condition of Overall Service Quality**

| | raw coverage | unique coverage | consistency |
|---|---|---|---|
| emp_cc*~income_c*~edu_c*gender*age_c*~pgsi_c | 0.156276 | 0.104896 | 0.755970 |
| emp_cc*~titlestatus_cc*~income_c*~edu_c*gender*~age_c*pgsi_c | 0.138510 | 0.065800 | 0.809357 |
| emp_cc*titlestatus_cc*income_c*edu_c*~gender*~age_c*~pgsi_c | 0.053518 | 0.036848 | 0.916432 |
| emp_cc*titlestatus_cc*income_c*edu_c*gender*~age_c*pgsi_c | 0.075671 | 0.015353 | 0.842491 |
| solution coverage: 0.295607 | | | |
| solution consistency: 0.756525 | | | |

Note. Table 7a displays four models whereby high scores on each model indicate high scores for overall service quality (OSQ) membership. Note that two of the models include the negation of PGSI and two models include positive scores for PGSI. All models are complex statements of six to seven simple antecedent conditions.

**Table 7b**

**Complex Configurations with High Scores of Complex Antecedent Demographic Statements plus PGSI Associating with High Scores for the Outcome Condition of the Negation of Overall Service Quality**

| | raw coverage | unique coverage | consistency |
|---|---|---|---|
| emp_cc*~titlestatus_cc*~income_c*~edu_c*gender | 0.274216 | 0.046962 | 0.870692 |
| emp_cc*~income_c*edu_c*gender*~age_c*~pgsi_c | 0.125379 | 0.025216 | 0.842137 |
| emp_cc*titlestatus_cc*~income_c*~gender*age_c*~pgsi_c | 0.087203 | 0.015464 | 0.799437 |
| emp_cc*titlestatus_cc*edu_c*gender*~age_c*pgsi_c | 0.150947 | 0.032597 | 0.859215 |
| emp_cc*income_c*~edu_c*gender*age_c*pgsi_c | 0.147300 | 0.048105 | 0.822218 |
| emp_cc*titlestatus_cc*income_c*edu_c*~gender*~age_c*~pgsi_c | 0.040021 | 0.011861 | 0.855399 |
| emp_cc*titlestatus_cc*~income_c*~edu_c*age_c*~pgsi_c | 0.170715 | -0.000000 | 0.842037 |
| emp_cc*~income_c*~edu_c*gender*age_c*~pgsi_c | 0.130387 | 0.001669 | 0.787270 |
| solution coverage: 0.500506 | | | |

Note. Table 7b displays eight models for the negation of overall service quality (~OSQ) membership. Note that five of the models include the negation of PGSI and two models include positive PGSI scores. All models are complex statements of five to seven simple antecedent conditions.