RIKI Technical Research Note on the Licensing Key Indicator Predictor Methodology Threshold Updates, Regulatory Compliance, False Positives & Negatives, Data Dichotomization, and Licensing Measurement

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The purpose of this technical research note is to provide the latest updates to the Key Indicator Predictor Methodology and associated measurement issues, such as eliminating or reducing false positives and negatives, the use of data dichotomization with regulatory compliance frequency distributions.

It has always been recommended that a data dichotomization model be employed in distinguishing between the highly regulatory compliant from the low levels of regulatory compliance. The suggested model was 25/50/25 in which the top 25% constituted the highly compliant group, the middle 50% constituted the substantial – mid range compliant group, and the bottom 25% constituted the low compliant group. This was different from what had been done in the past in which fully compliant (100%) facilities were compared with those facilities who had any violations of regulatory compliance. It was found that by utilizing the 25/50/25 model a clearer distinction could be made between the high and low compliant groups. Generally, the top 25% are those facilities that are in full (100%) compliance, with the middle 50% are those facilities that have regulatory non-compliance ranging from 1 – 10 violations. The bottom 25% are those facilities that have regulatory non-compliance of greater than 10 violations. In this dichotomization model, the middle 50% are not used in the calculations, only the top and bottom 25%.

The dichotomization model described in the above paragraph has worked very well in producing licensing key indicator predictor rules by eliminating false negatives and decreasing false positives in the resultant 2 x 2 Key Indicator Predictor Matrix. The Fiene Coefficients for the licensing key indicator predictor rules have been more stable and robust by utilizing this model. It was made possible because of the increasing sample sizes selected for analyses and in some cases where population data were available. Also, the overall level of full compliance in states/provinces has increased over time and that has been a contributing factor as well in eliminating false negatives. False positives have been decreased because of the same factors but will never be eliminated because of the nature of the data distribution being highly positive skewed. Because of this distribution, there will always be false positives identified in the analyses. But that is the lesser of two evils: a rule being in compliance although it is present in the low regulatory compliant group.

However, are there ways to mitigate the impact of false positives. Based upon results from the *Early Childhood Program Quality Improvement & Indicator Model Data Base (ECPQI2MDB)* maintained at the Research Institute for Key Indicators/Penn State, there appears to be several adjustments that can be made so that the impact of false positives is not as pronounce as it has been in the past. The first adjustment that can be made is to increase the sample size so that additional non-compliance is identified. This is difficult at times because the nature of licensing or regulatory compliance data trends towards very high compliance for most facilities with little non-compliant facilities. It is the nature of a regulatory compliance or licensing program; these are basic health and safety rules which have had a history of substantial to full compliance with the majority of the rules. The data are extremely positively skewed. There is little variance in the data. So, increasing the sample size should help on all these accounts. In addition to increasing the sample size, an additional methodology was developed in order to increase the variance in licensing/regulatory compliance data by weighting rules/regulations based upon the risk children are placed in because of non-compliance. This proposal makes a great deal of sense but its application in reality hasn't played out as intended. What most jurisdictions do in implementing the risk assessment methodology is to identify the most heavily weighted rules but then to deal with these rules as high risk rules and not using the weights assigned to them for aggregating regulatory compliance scores. The use of the methodology in this way is very effective in identifying the specific rules based upon risk, but does little to nothing in increasing the variance in the regulatory compliance data distribution. The data distribution remains severely positively skewed.

Another way to mitigate the impact of false positives is to increase the data dichotomization of the data distribution but this is recommended only with the increase sample size. If it is done without an increased sample size, the resultant Fiene Coefficients for the licensing key indicator predictor rules will be less robust and stable. For example, the data dichotomization model of 25/50/25 could be increased to a 10/80/10 model which should help in decreasing the false positives in the analyses. But this is cautionary, for example, in going to a 5/90/5 model could again make the resultant Fiene Coefficients for the licensing key indicator predictor rules less robust and stable. The sample size needs to be very large or the full population needs to be measured in order to do these analyses and co-balance the increased data dichotomization because the cell sizes will be decreasing significantly. The following 2 x 2 matrix will depict these relationships for generating the Licensing Key Indicator Predictor Fiene Coefficients (FC).

Licensing Key Indicator Predictor Fiene Coefficient (FC) Table

Individual Rules/Groups ->	**High Compliant (Top 25%)**	**Low Compliant (Bottom 25%)**
Rule In Compliance	**FC (++)**	**FP (+)**
Rule Out of Compliance	**FN (-)**	**FC (--)**

((FC (++) + (FC (--)) > ((FN (-)) + (FP (+))

where FC = Fiene Coefficient which results in Licensing Key Indicator Predictor Rules (FC = .25 or >);

FN (-) = False Negative; FP (+) = False Positive

The cells represented by the Fiene Coefficients should always be larger than the False Positive and Negative results in the above table. With the above dichotomization 25/50/25 model and high levels of full 100% regulatory compliance, false negatives can be eliminated and by increasing the sample size, false positives will be decreased but never fully eliminated. Full 100% regulatory compliance increased levels will help to eliminate false negatives, but it will also increase the chances of false positives. There is a delicate balance with confounding the increased sample sizes (false positives will decrease) and increased levels of full 100% regulatory compliance (false positives will increase). This will take a bit of adjusting to get this balancing just right.

By utilizing the *ECPQI2MDB* it has demonstrated that the above-mentioned dichotomization models may be difficult to hit the percentages exactly. The actual models may be more heavily weighted in the percent for the high group as versus the low because of the regulatory compliance data distribution being highly positive skewed as mentioned earlier. This may have an impact on the Fiene Coefficients (FC) for licensing key indicator predictor rules but it will not impact the actual selection of the licensing key indicators – they will remain the same, just the FCs will change.

One last footnote on the relationship between regulatory compliance and program quality. This relationship has been addressed several times over the past four decades in the regulatory science and human services regulatory administration fields; but it needs to be re-emphasized as it relates to this discussion about licensing measurement. Regulatory compliance and program quality are linear and non-random in moving from low regulatory compliance to mid-substantial regulatory compliance as with low program quality to mid program quality. However, when one moves from substantial regulatory compliance to full 100% regulatory compliance the relationship with program quality is more non-linear and random.