The Psychology of Compliance: Logic Model and Algorithm for An Integrated Regulatory Framework Consisting of Predictive and Risk Rules, Aversion and Certainty Constructs, and Licensing Assessor Bias in Reducing False Positives and Negatives

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The purpose of this short paper is to continue the development of the Integrated Regulatory Framework (IRF)(Fiene, 2026) which should help us establish the parameters of the psychology of compliance within the human care licensing field. In this paper, a logic model and algorithm will be built consisting of predictive and risk rules taken from the Theory of Regulatory Compliance and Differential Monitoring (Fiene, 2025a), aversion and certainty constructs taken from Prospect Theory (Kahneman & Tversky, 1984), and addressing licensing assessor bias in reducing false positives and negatives (Fiene, 2025b).

In order to explain the logic model and to develop the algorithm, a 2x2 matrix will introduce all of the key elements to this new IRF. This matrix builds off previous studies (Fiene, 2024) and papers (Fiene, 2026) in which these key elements were introduced but in a slightly different format. For example, in previous matrices the risk assessment/weighting of rules was predominant with the predictive rules being a subset of the respective matrix. In the below matrix the opposite is true. See the following table for these key elements:

IRF: Integrated Regulatory Framework Logic Model

	Individual Rule Compliance-In **Individual Observation-In**	**Individual Rule Compliance-Out** **Individual Observation-Out**
Overall Compliance-High **Actual Observation-In**	**Weight of 4** **True Positive**	**Weight of 1** **False Positive**
Overall Compliance-Low **Actual Observation Result-Out**	**Weight of 8** **False Negative**	**Weight of 4** **True Negative**

Let's begin to decipher the above matrix into its key elements. The horizontal axis is measuring either individual rule compliance or the results of an individual observation made by a licensing assessor. Individual rule compliance is either in or out of compliance and would be listed as an individual observation. The vertical axis is measuring either overall compliance or the actual state of affairs with the observation being made. This is the actual reality in that the rule being measured is truly in or out of compliance and if the facility/program is in a high compliant group with few violations or in a low compliant group with a significant number of violations.

The four cells within the matrix are the results of the intersection between the horizontal and vertical axis. The four results are a true positive, the rule is in compliance and the overall compliance of the facility is equally high and that is truly the case in reality. A true negative is when the rule is out of compliance and the overall compliance of the facility is at a very low level of compliance and that is truly the case in reality. Now, it gets interesting in the decision-making process in dealing with false positive and negative. With false positive, an observation is made in which the individual rule is observed as being out of compliance when in reality it is not, it is in compliance and the facility is in the high compliant group. But what is really disturbing, is the false negative in which the individual rule is observed as being in compliance when in reality it is not, it is out of compliance and the facility is in the low compliant group.

Weights are used in each of the cells and these numbers are taken from a risk assessment scale where 1 = low risk; 4 = medium risk; and 8 = high risk. Results from several regulatory compliance studies (Fiene,2024) clearly indicate that high risk rules being out of compliance is generally not the case; but with low-risk rules this is where a higher rate of non-compliance will be found. At the same time, medium-risk rules are generally the good candidates for predictor rules via the key indicator methodology. This is an interesting intersection with Prospect Theory where aversion and certainty concepts may be playing a role. Aversion in the sense of avoiding at all costs being out of compliance especially on high-risk rules that could jeopardize a license renewal or in being granted a license. Certainty for low-risk rules where some nit-picking may be occurring in order to have a stricter regulatory compliance stance is the opposite concern in making licensing decisions.

These two concepts from Prospect Theory can also contribute to licensing assessor bias in which an assessor becomes either too lenient or too stringent in their interpretation of rule compliance and are either citing or not citing rule violations as they truly occur. False positives are a real problem for facilities or providers of service because they are being cited for rules, generally low risk rules, in a disproportionate manner. This can lead to increased liability insurance costs for the provider. False negatives are a real problem for the insurance industry because rule violations are not being cited when in reality these rules are truly out of compliance. This can lead to clients being in unsafe facilities resulting in injuries because of the increased non-compliance of individual rules going undetected.

From the above logic model, an algorithm can be constructed to deal with all these key elements in a unified Integrated Regulatory Framework model: risk, prediction, aversion, certainty, false positive or negatives, and assessor positive or negative bias. The following algorithm should address all these key elements:

IRF = (FC = .50+) + (F- = 0) + (F+ = wgt1 x 3)

Where:

IRF = Integrated Regulatory Framework; FC = Fiene Coefficient of .50 or above by using the following formula: FC = (true+)(true-) – (false+)(false-)/sqrt of true and false sums = statistical predictor rules; F- = no occurrences of false negatives; F+ = rules that are weighted 1 x 3 violations in order to mitigate the effect of false positives.

By using this above formula should help to increase the accuracy of licensing decision making in using regulatory compliance data. It maximizes the predictability of specific rules and at the same time eliminates false negatives and decreases false positives to a manageable number. At the same time it should keep aversion, certainty, and bias concerns in check. The IRF will need to be field tested as previous editions of the Early Childhood Program Quality Improvement and Indicator Model (ECPQIM)(Fiene, 2025a) has been done. The IRF represents a 6th generation edition of the ECPQIM.

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2. For more detailed information regarding the contents of this paper, the interested reader should check out the Research Institute's website: https://rikinstitute.com