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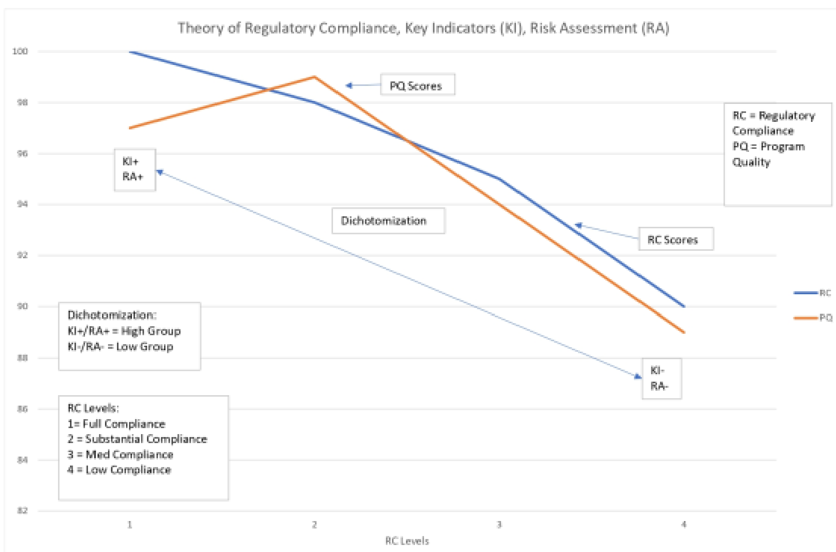
Theory of Regulatory Compliance, Key Indicators, Risk Assessment and Dichotomization Graphic

Posted on December 24, 2023 by Dr Fiene

Here is a graphic that captures the relationship of the Theory of Regulatory Compliance, Key Indicators, Risk Assessment, and the dichotomization of licensing data (all these topics have been discussed at great length in the RIKINotes Blog over the past year):



A picture is worth a 1000 words, but in the above case, I am sure a couple of words of explanation would be helpful for those who are left hemisphere dominated rather than right hemisphere dominated as I am. Here are the essential elements of the above graphic.

RA = Risk Assessment rules insures that all the high risk rules are in compliance. This is non-negotiable, all of them are in place for any type of inspection review: full, comprehensive and/or abbreviated. KI = Key Indicators are a bit more flexible because it is based upon probabilities and the predictor rules are generally not as heavily weighted as is the case with risk assessment rules.

The bottom line is that regulatory compliance is important in ensuring that clients are safe and healthy. However, the relationship with quality is a bit more complex based upon the Theory of Regulatory Compliance. There is not the same relationship to program quality as there is to health & safety. Substantial compliance appears to be more effective in determining overall program quality rather than full regulatory compliance with all rules. That is depicted in the curvilinear relationship between Regulatory Compliance (RC) and Program Quality (PQ) as one moves along the RC Levels (1 – 4 = Full – Low Compliance).

And finally, data dichotomization helps to eliminate false negatives and decrease the impact of false positives when taken to the extremes (moving from a 25/50/25 model to 5/90/5 model in distinguishing between high and low regulatory compliance (KI+/RA+ & KI-/RA-)). The rules will not change usually but their phi coefficients will increase significantly. Data dichotomization is not generally recommended but with the extreme skewness in licensing data it is warranted and fits with the measurement of licensing data at the nominal level as well as the theoretical structure of the data distribution based upon full and substantial levels of regulatory compliance being the predominant number of programs. There generally are far fewer programs at a medium or low level of regulatory compliance.

The above graphic helps to summarize several concepts related to differential monitoring and the theory of regulatory compliance. It is suggested that previous RIKINotes posts and the RIKI Selected Publications webpage be consulted for a more detailed rendition of what is presented in this post. The technical research notes on the RIKI Selected Publications provide a more in-depth analysis of the above concepts.

About Dr Fiene

Dr. Rick Fiene has spent his professional career in improving the quality of child care in various states, nationally, and internationally. He has done extensive research and publishing on the key components in improving child care quality through an early childhood program quality indicator model of training, technical assistance, quality rating & improvement systems, professional development, mentoring, licensing, risk assessment, differential program monitoring, and accreditation. Dr. Fiene is a retired professor of human development & psychology (Penn State University) where he was department head and director of the Capital Area Early Childhood Research and Training Institute.

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Full versus Substantial Regulatory Compliance

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December 2023

This research abstract builds off several other research abstracts/notes in this series on regulatory compliance. It will attempt to take a more overview approach than the more technical and methodological approaches utilized in previous posts.

There is an important distinction when it comes to regulatory compliance related to levels of compliance: Full or 100% regulatory compliance with no violations and substantial regulatory compliance where there may be 1-2 violations of low-risk rules/regulations. The goal of any licensing or regulatory system is to have programs meet all rules/regulations/standards. This has been an important focus of all licensing/regulatory agencies throughout the US, Canada and the world.

But this goal needs to be altered a bit based upon several research studies conducted by this author over several decades in which full regulatory compliance does not equate with a high-quality program. While this empirical result may change our thinking about the relationship related to full regulatory compliance and substantial regulatory compliance which appears to be more related to program quality, it does not alter the need for full regulatory compliance in making predictions of overall regulatory compliance in the selection of key predictor rules. In order to eliminate false negatives in licensing decision making, full regulatory compliance is critical as a continuous goal.

Substantial regulatory compliance turned out to be an important discovery related to the theory of regulatory compliance where programs at this level demonstrated a higher level of program quality than those programs that were in full 100% regulatory compliance. It had been assumed up until the introduction of the theory of regulatory compliance that full regulatory compliance equated to high program quality. Since then, substantial regulatory compliance and the issuance of licenses based upon substantial rather than full regulatory compliance is a sound public policy approach.

However, when utilizing the key indicator methodology for identifying predictor rules, full regulatory compliance is still the paradigm that needs to be employed. It is the only safeguard to decrease and/or eliminate false negatives in which additional regulatory non-compliance could occur when full regulatory compliance is attained with the key indicator tool.

The overall key element is that substantial compliance does not replace full compliance in license decision making. It is predominant when it comes to the theory of regulatory compliance but has a back seat when it comes to identifying predictor rules unless an adjustment is made to the 2 x 2 Key Indicator Matrix which has been addressed in previous posts. The use of substantial compliance is also a key measurement component of the Regulatory Compliance Scale which has been introduced as an alternative to licensing violation data. However, full compliance will remain as the goal of any key indicator predictor rule method.

In conclusion, full compliance equates to a healthy and safe environment, but it does not necessarily mean it is of the highest quality. Within a regulatory compliance schema, substantial compliance appears more related to program quality. Risk assessment rules are always in compliance in either one of these scenarios.

The Uncertainty-Certainty Matrix for Licensing Decision Making: Policy and Program Implications

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December 2023

This abstract will take the Confusion Matrix which is a well-known metric in the decision-making research literature and refocus it for regulatory science within the context of the definition of regulatory compliance and licensing measurement. It will also deal with the policy implications of this particular metric. In this abstract, it is proposed that the Uncertainty-Certainty Matrix (UCM) is a fundamental building block to licensing decision making. The 2 x 2 matrix has been written about in several posts in this blog and is the center piece for determining key indicator rules, but it is also a core conceptual framework in licensing measurement and ultimately in program monitoring and reviews.

The reason for selecting this matrix is the nature of licensing data, it is binary or nominal in measurement. Either a rule/regulation is in compliance or out of compliance. Presently most jurisdictions deal with regulatory compliance measurement in this nominal level or binary level. There is to be no gray area, this is a clear distinction in making a licensing decision about regulatory compliance. The UCM also takes the concept of Inter-Rater Reliability (IRR) a step further in introducing an uncertainty dimension that is very important in licensing decision making which is not as critical when calculating IRR. It is moving from an individual metric to a group metric (See Figures 1 & 2) involving regulatory compliance with rules.

The key pieces to the UCM are the following: the decision (D) regarding regulatory compliance and actual state (S) of regulatory compliance. Plus (+) = In-compliance or Minus (-) = Out of compliance. So, let's build the matrix:

Table 1: Uncertainty-Certainty Matrix (UCM) Logic Model

UCM Matrix Logic		**Decision (D) Regarding**	**Regulatory Compliance**
		(+) In Compliance	(-) Not In Compliance
Actual State (S) of	(+) In Compliance	Agreement	Disagreement
Compliance	(-) Not In Compliance	Disagreement	Agreement

The above UCM matrix demonstrates when agreement and disagreement occur which establishes a level of certainty (Agreement Cells) or uncertainty (Disagreement Cells). In a perfect world, there would only be agreements and no disagreements between the decisions made about regulatory compliance and the actual state of regulatory compliance. But from experience, this is not the case based upon reliability testing done in the licensing research field in which a decision is made regarding regulatory compliance with a specific rule or regulation and then that is verified by a second observer who generally is considered the measurement standard.

Disagreements raise concerns in general, but the disagreements are of two types: false positives and false negatives. A false positive is when a decision is made that a rule/regulation is out of compliance when it is in compliance. Not a good thing but its twin disagreement is worse where with false negatives it is decided that a rule/regulation is in compliance when it is out of compliance. False negatives need to be avoided because they place clients at extreme risk, more so than a false positive. False positives should also be avoided but it is more important to deal with the false negatives first before addressing the false positives.

Let's look at this from a mathematical point of view in the following matrix. In order to better understand the above relationships and determine when ameliorative action needs to occur to shore up the differences between the agreements and disagreements, it is easier to do this mathematically than trying to eyeball it.

Table 2: Uncertainty-Certainty Matrix (UCM) Math Model

UCM Matrix Math Model		**Decision (D) Regarding**	**Regulatory Compliance**	**Totals**
		(+) In Compliance	(-) Not In Compliance	
Actual State (S)	(+) In Compliance	A	B	Y
Of Compliance	(-) Not In Compliance	C	D	Z
Totals		W	X	

Formulae based upon above: Agreements = (A)(D); Disagreements = (B)(C); Randomness = sqrt ((W)(X)(Y)(Z))

UCM Coefficient = ((A)(D)) - ((B)(C)) / sqrt ((W)(X)(Y)(Z)) in which a coefficient closer to 1 indicates agreement (certainty) and a coefficient closer to –1 indicates disagreement (uncertainty). A coefficient closer to 0 indicates randomness. Obviously, we want to see (A)(D) being predominant and very little in (B)(C) which are false positives and negatives where decisions and the actual state of regulatory compliance are not matching. If (WXYZ) is predominant then there is just randomness in the data. Also, not an intended result.

The reason for even suggesting this matrix is the high level of dissatisfaction with the levels of reliability in the results of program monitoring reviews as suggested earlier. If it were not so high, it would not be an issue; but with it being so high the field of licensing needs to take a proactive role in determining the best possible way to deal with increasing inter-rater reliability among licensing inspectors. Hopefully, this organizational schema via the UCM Matrix will help to think through this process related to licensing measurement and monitoring systems.

$$\boldsymbol{UCM} = \ll \boldsymbol{A} \times \boldsymbol{D} \gg - \ll \boldsymbol{B} \times \boldsymbol{C} \gg \div \sqrt{\ } \ll \boldsymbol{W} \times \boldsymbol{X} \times \boldsymbol{Y} \times \boldsymbol{Z} \gg$$

The above formula provides a means to calculate when action needs to be taken based upon the respective UCM coefficients. A UCM coefficient from +.25 to +1.00 is in the acceptable range; +.24 to -.24 is due to randomness and needs to be addressed with additional inter-rater reliability training; -.25 to –1.00 indicates a severe disagreement problem that needs to be addressed both in reliability training and a full review of the targeted rules/regulations to determine if the specific rule needs additional clarification.

Table 3: Uncertainty-Certainty Matrix (UCM) Licensing Decision Coefficient Ranges

UCM Coefficient	**Licensing Decision**
+.25 to +1.00	Acceptable, No Action Needed, In or Out of Regulatory Compliance Verified through mostly Agreements. (Generally, 90% of cases)
+.24 to -.24	Random, Agreements + Disagreements, Needs Reliability Training. (Generally, 5% of cases)
-.25 to –1.00	Unacceptable, Mostly Disagreements, Needs Training & Rule/Regulation Revision. (Generally, 5% of cases)

Figure 1: Kappa Coefficient

Observed agreement

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Expected agreement if random judgment

Figure 2: Uncertainty-Certainty Coefficient

$$\phi = \frac{ad - bc}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$$

$$\phi = \sqrt{\frac{\chi^2}{n}}$$

Let's provide an example of how this could work. A standard/rule/regulation that is common is the following:

Do all caregivers/teachers and children wash their hands often, especially before eating and after using the bathroom or changing diapers?

This is obviously an observation item where the licensing staff would observe in a sample of classrooms in a child care center for a set period of time. During their observations, there were several opportunities where the necessary behavior was required, and the staff complied with the rule and washed their hands. So, on the surface this specific rule was in compliance and there would appear to be full compliance with this rule based upon the observation.

A second scenario is where the observation is made, and the licensing staff observes the child care staff not washing their hands on several occasions. Then this specific rule would be out of compliance, and it would be duly noted by the licensing staff. These two scenarios establish a certain level of certainty during this observation session. However, there are other outcomes, for example, possibly one of the classrooms that was not observed had the opposite finding than what was observed in these particular classrooms. If data were being aggregated and a specific percentage was to be used the final decision about this rule could be different. Now we are getting into the uncertainty cells of the matrix where a false positive or negative could be the result. The licensing staff records the rule as being in compliance when in reality it is not = false negative or the rule is recorded as being out of compliance when in reality it is in compliance = false positive.

Another example which involves either Random Clinical Trials (RCT) or the use of abbreviated inspections (AI) and the results from these two interventions. The decision making in both RCT and AI is basically the same. We want to make sure that the results match reality. Every time an abbreviated review is done the following four regulatory compliance results should occur based upon the UCM matrix: 1) no additional random non-compliance is found; 2) there are no false negatives (abbreviated review finds no non-compliance but in reality there is); 3) when there is non-compliance found in abbreviated inspections, other related non-compliance is found; and 4) lastly the level of false positives (abbreviated review finds non-compliance but in reality there are no other related non-compliances) is kept to a minimum. This last result based upon copious research is that it is difficult to obtain but as the regulatory science moves forward hopefully this will become more manageable.

Hopefully these above examples provided some context for how the Uncertainty-Certainty Matrix (UCM) can be used in making specific licensing decisions based upon the regulatory compliance results.

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UCM Matrix: Uncertain-Certainty Matrix

Certain A	*UnCertain* B	*UnCertain* C	*Certain* D	*Random* A+B	*Random* A+C	*Random* B+D	*Random* C+D	*Certain* A*D	*UnCertain* B*C	*Random* SUM	*Random* SQRT	*+/-* SUB	*+/0/-* PHI	*Matrix* *Result*
50	0	0	50	50	50	50	50	2500	0	6250000	2500	**2500**	1	***Certain***
25	25	25	25	50	50	50	50	625	625	6250000	2500	**0**	0	***Random***
0	50	50	0	50	50	50	50	0	2500	6250000	2500	**-2500**	-1	***Uncertain***

UCM Matrix Logic		**Decision Regarding**	**Regulatory Compliance**
		(+) In Compliance	(-) Not In Compliance
Actual State of	(+) In Compliance	Agreement	Disagreement
Compliance	(-) Not In Compliance	Disagreement	Agreement

The Model

UCM Matrix Logic		**Decision Regarding**	**Regulatory Compliance**
		(+) In Compliance	(-) Not In Compliance
Actual State of	(+) In Compliance	50	0
Compliance	(-) Not In Compliance	0	50

Certain Matrix

UCM Matrix Logic		**Decision Regarding**	**Regulatory Compliance**
		(+) In Compliance	(-) Not In Compliance
Actual State of	(+) In Compliance	25	25
Compliance	(-) Not In Compliance	25	25

Random Matrix

UCM Matrix Logic		**Decision Regarding**	**Regulatory Compliance**
		(+) In Compliance	(-) Not In Compliance
Actual State of	(+) In Compliance	0	50
Compliance	(-) Not In Compliance	50	0

Uncertain Matrix

Formula:

$$\phi = \frac{ad - bc}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$$

$$\phi = \sqrt{\frac{\chi^2}{n}}$$

UCM Matrix Math Model		**Decision Regarding**	**Regulatory Compliance**	**Totals**
		(+) In Compliance	(-) Not In Compliance	
Actual State	(+) In Compliance	A	B	Y
Of Compliance	(-) Not In Compliance	C	D	Z
Totals		W	X	

Regulatory Compliance Scales and Instrument Based Program Monitoring, Differential Monitoring, and Integrative Monitoring Systems: Alternative Paradigms for Licensing Decision Making

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January 2024

I have written about this topic in posting to this platform but have also posted a great deal on the Medium Platform regarding the importance of the Theory of Regulatory Compliance and bringing substantial compliance to the fore front of regulatory science. This abstract and technical research note will build upon these previous assertions and expand them into some practical applications that can be utilized within regulatory science as it relates to licensing measurement, regulatory compliance scaling, and monitoring systems paradigms.

Regulatory Compliance has been always approached as an all or none phenomenon, whether a rule is in compliance, or it is not. There is no in-between or shades of gray or partial compliance. This worked when the prevailing paradigm was that full regulatory compliance and program quality were a linear relationship. This was the assumption but not empirically verified until the later 1970's-1980's. When this assumption was put to an empirical test, it did not hold up but rather a curvilinear relationship between regulatory compliance and program quality was discovered. This upset the prevailing paradigm and suggested we needed a new approach to addressing the relationship between regulatory compliance and program quality.

It became clear after these findings in the 1970's-80's and then in the 2010's when replication studies were completed that substantial regulatory compliance could not be ignored based upon this new theory of regulatory compliance in which substantial compliance acted as a "sweet spot" of best outcomes or results when comparing regulatory compliance and program quality scores. The nominal metric needed to be revised and more of an ordinal metric was to be its replacement. Because now it wasn't just being in or out of compliance, but it mattered which rules were in or out of compliance and how they were distributed. This revised application involved aggregate rules and does not apply to individual rule scoring. The studies completed between 1970 and 2010 involved aggregate rules and not individual rules. To determine if the nominal to ordinal metric needs to be revised still needs empirical data to back this change.

The introduction of substantial compliance into the regulatory compliance measurement strategy moved the field from an instrument-based program monitoring into a more differential monitoring approach. With differential monitoring this approach considered which rules and how often reviews should be done. Also, a new Regulatory Compliance Scale was proposed to take into account the importance of substantial compliance based upon the regulatory compliance theory of diminishing returns. As this Regulatory Compliance Scale has evolved within the licensing health and safety field it needs further revision in which program quality can be infused into the decision making related to individual rules. Remember that the original studies were concerned about rules in the aggregate and not individual rules. It has now become apparent that in dealing with the infusion of quality into rule formulation, a return to the individual rule approach makes the most sense.

The next iteration of the Regulatory Compliance Scale will contain the following categories: Exceeding full compliance, Full compliance, Substantial compliance, and Mediocre compliance to adjust for the infusion of the quality element. This differs slightly from the original aggregate rule Regulatory Compliance Scale where the categories were Full compliance, Substantial compliance, Mediocre compliance and Low compliance where only licensing health and safety elements were considered (see the Table below which depicts the regulatory compliance scales and program monitoring systems side by side).

Without the Theory of Regulatory Compliance, differential and integrative monitoring would not be needed because regulatory compliance would have had a linear relationship with program quality and full compliance would have been the ultimate goal. There would have been no need for targeted rule enforcement or reviews because all rules would have had an equal weight when it came to protecting clients and any individual rule would have predicted overall compliance. But it "just ain't so" as it is said. The need to make adjustments is brought about by the theory and it has not been the same ever since.

Regulatory Compliance Scales and Program Monitoring Systems

Scoring Level	**Individual Rule**		**Aggregate Rules**	**Individual Rule**
Scale	**Instrument based**	***Scale***	**Differential**	**Integrated**
7	Full Compliance	7	Full Compliance	Exceeds Compliance
-	---	5	Substantial	Full Compliance
-	---	3	Mediocre	Substantial
1	Out of Compliance	1	Low	Mediocre/Low

The above table attempts to summarize in tabular form the previous paragraphs in describing the relationship between program monitoring and licensing measurement scaling via a proposed regulatory compliance scale. As one can see this moves the paradigm from a nominal to an ordinal measurement rubric and depicts the differences in the measurement focus either at the individual rule or aggregate rules scoring levels. It also considers the significance of substantial compliance given the theory of regulatory compliance in which substantial compliance focus is a "*sweet spot*" phenomenon as identified in the regulatory science research literature. It is hoped that the regulatory science field takes these paradigm shifts into consideration in moving forward with building licensing decision making systems and how licenses are issued to facilities.

As a final footnote, keep in mind that the Theory of Regulatory Compliance applies to the relationship between regulatory compliance and program quality and does not apply to regulatory compliance in and of itself related to health and safety. When dealing with regulatory compliance, full compliance is the ultimate goal with individual rules and in determining which rules are predictive rules. It is the preferred methodology in order to eliminate false negatives and decreasing false positives in making licensing decisions related to regulatory compliance.

These above concepts all relate to the field of regulatory compliance and how to make informed decisions about licensing, particularly in the context of program monitoring. Here's how they connect:

Regulatory Compliance Scales:

These scales move away from a binary "compliant" or "non-compliant" approach to regulations. Instead, they acknowledge degrees of compliance, recognizing that minor deviations may not be as detrimental as major ones.

They provide a framework for evaluating the severity and frequency of non-compliance, allowing for more nuanced licensing decisions.

Instrument Based Program Monitoring (IBPM):

This is the traditional method of monitoring compliance, relying on standardized instruments and checklists to assess adherence to specific rules.

It's a comprehensive approach, but can be time-consuming and inflexible, potentially leading to over-regulation or missing important aspects of program quality.

Differential Monitoring (DM):

This approach takes into account the risk associated with different regulations, focusing monitoring efforts on areas with the highest potential for harm or non-compliance.

It allows for a more efficient use of resources and can be tailored to the specific needs of each program.

DM often utilizes Regulatory Compliance Scales to determine the severity of non-compliance and guide the level of monitoring needed.

Integrative Monitoring Systems (IMS):

These systems go beyond simply checking compliance and aim to assess the overall quality of a program.

They integrate data from various sources, including IBPM, DM, and other program-specific metrics, to provide a holistic picture of performance.

IMS can inform licensing decisions by considering not only compliance but also program effectiveness in achieving its goals.

Here's a simplified analogy to illustrate the relationships:

Think of regulations as traffic rules.

IBPM is like a police officer checking every car for every violation, regardless of severity.

DM is like a police officer focusing on patrolling areas with high accident rates or known reckless drivers.

Regulatory Compliance Scales are like different levels of fines based on the severity of the traffic violation.

IMS is like a traffic management system that collects data on accidents, traffic flow, and road conditions to optimize traffic flow and safety.

Relationships:

RCS forms the foundation for DM and IMS by providing a way to assess degrees of compliance.

IBPM provides data for RCS and can be incorporated (with adaptations) into DM and IMS.

DM builds on RCS and IBPM by differentiating the intensity of monitoring based on risk and compliance.

IMS is the most comprehensive approach, integrating RCS, IBPM, DM, and additional data sources for a deeper understanding of program performance.

Regulatory Compliance Scales can be used within any of the monitoring approaches to provide a more nuanced assessment of compliance.

IBPM can be a starting point for differential monitoring, providing data on rule compliance to inform risk assessments.

Differential monitoring can be integrated into an integrative monitoring system, along with other data sources, to provide a comprehensive picture of program performance.

Here are some additional points to consider:

The choice of the most appropriate approach will depend on the specific context, such as the type of program being regulated and the available resources.

Implementation of these alternative paradigms requires careful planning and training of regulators and program providers.

Ongoing research and evaluation are needed to refine these approaches and ensure their effectiveness.

Conclusion:

These alternative paradigms offer a more flexible and effective approach to licensing decision-making compared to the traditional IBPM approach. They allow for a better understanding of program strengths and weaknesses, optimize resource allocation, and ultimately lead to better regulatory outcomes.

These concepts offer a shift from traditional "one-size-fits-all" compliance models to more flexible and nuanced approaches that consider risk, program quality, and degrees of compliance. This can lead to more efficient and effective regulatory systems that support program improvement while protecting public safety.

Ultimately, these concepts offer alternative paradigms for licensing decision-making, moving away from a rigid "one-size-fits-all" approach to a more nuanced and risk-based system that considers both compliance and program quality.

TRC+: Regulatory Compliance Theory of Diminishing Returns

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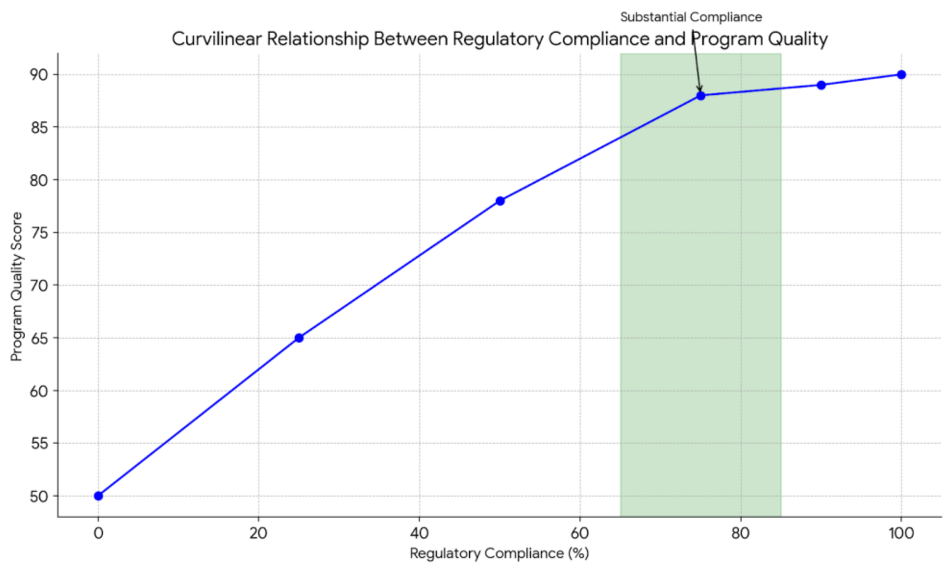
January 2024

This research abstract will update the relationship between regulatory compliance and program quality (depicted in the below graph) using three equations listed below which deal with a simple linear model at the low compliance range, a threshold model at the midpoint compliance range, and a diminishing returns model at the higher compliance range. A fourth model is also proposed which places more emphasis on the program quality side of the equation going beyond compliance levels.



1. Simple Linear Model (Low Compliance Range):

For the lower end of the compliance spectrum, where achieving basic rules leads to improved quality, a simple linear model might be applicable:

Program Quality = a * Regulatory Compliance + b

This assumes a direct positive relationship between compliance (measured as 0-100%) and quality, represented by the slope "a" and baseline quality "b" when no compliance exists.

2. Threshold Model:

Another approach is to introduce a threshold level of compliance, below which there's minimal quality improvement, but exceeding it leads to rapid quality gains:

Program Quality = f(Regulatory Compliance - Threshold)

Here, "f" is a function (potentially non-linear) representing the quality increase based on exceeding the threshold level.

3. Diminishing Returns Model:

The theory emphasizes a "plateau effect" for high compliance levels, where further compliance improvements yield minimal quality gains. This can be captured through models like:

Program Quality = max(Quality_max , min (Regulatory Compliance, Quality_max))

Here, "Quality_max" represents the upper limit of achievable quality, and the equation ensures quality doesn't exceed this limit regardless of compliance exceeding it.

These three equations should help to fine tune the analyses related to TRC+: Regulatory Compliance Theory of Diminishing Returns. A fourth model is also proposed which expands the theory called the Multivariate Model:

4. Multivariate Model:

The theory acknowledges numerous factors influencing the relationship, including program type, regulatory agency, and implementation effectiveness. These can be incorporated into more complex, multivariate models, like:

Program Quality = f1(Regulatory Compliance, Program Type, Agency Effectiveness) + f2(Compliance Implementation)

This example utilizes various functions ("f1", "f2") to account for diverse influences on program quality, going beyond just compliance levels.

Remember, these are just conceptual examples, and the specific equation will depend on the context and chosen factors for analysis. It's crucial to consider the specific research questions and limitations of each model approach when interpreting the results.

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