

Regulatory Compliance Scaling for Decision Making

Richard Fiene, Ph.D.

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There is a lack of empirical demonstrations of regulatory compliance decision making. In the past, I have used the methodologies of key indicators, risk assessment and the resultant differential monitoring techniques of how often and what should be reviewed for decision making. What has not been addressed is decision making based upon comprehensive reviews when all regulations are assessed. This short paper will address how empirical evidence taken from the past 40+ years of establishing and researching a national data base for regulatory compliance can help lead us to a new scaling of regulatory compliance decision making.

In analyzing regulatory compliance data it becomes perfectly clear that the data have very little variance and are terribly skewed in which the majority of programs are in either full or substantial compliance with all the respective regulations. Only a small handful of programs fall in the category of being in low compliance with all the regulations.

The proposed scaling has three major decision points attached to regulatory compliance scores. Either programs are in full or substantial compliance, in low compliance or somewhere in the middle. Full or substantial regulatory compliance is 100% or 99-98% in regulatory compliance. Low regulatory compliance is less than 90% and mid-regulatory compliance is between 97%-90%. These ranges may seem exceptionally tight but based upon the national data base on regulatory compliance that I maintain at the Research Institute for Key Indicators (RIKILLC) these are the ranges that have formed over the past 40 years. These data ranges should not come as a surprise because we are talking about regulatory compliance with health and safety standards. These are not quality standards, these are basic protections for clients. The data are not normally distributed, not even close as is found in quality tools and standards.

What would a **Regulatory Compliance Decision-Making Scale** look like:

| <u>Data</u> | <u>Level</u> | <u>Decision</u> |
|--------------------|-------------------------|----------------------------|
| 100-98% | Full/Substantial | License |
| 97-90% | Mid-Range | Provisional License |
| 89% or less | Low | No-License |

States/Provinces/Jurisdictions may want to adjust these levels and the scaling based upon their actual data distribution. For example, I have found certain jurisdictions to have a very unusually skewed data distributions which means that these ranges need to be tightened even more. If the data distribution is not as skewed as the above scale than these ranges may need to be more forgiving.

This regulatory compliance decision making scale does not take into account if abbreviated methodologies are used, such as risk assessment or key indicator models that are used in a differential monitoring approach. The above scale is to be used if a jurisdiction decides not to use a differential monitoring approach and wants to measure regulatory compliance with all regulations and complete comprehensive reviews.

Richard Fiene, Ph.D., Research Psychologist, Research Institute for Key Indicators (RIKILLC); Professor of Psychology (ret), Penn State University; Senior Research Consultant, National Association for Regulatory Administration (NARA).
<http://RIKInstitute.com>

Regulatory Compliance Scoring System and Scale

Richard Fiene, Ph.D.

Research Institute for Key Indicators and Penn State

National Association for Regulatory Administration

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By using the ECPQIM DB – Early Childhood Program Quality Improvement and Indicator Model Data Base, it is possible to propose developing and using a Regulatory Compliance Scoring System and Scale (RC3S). This new proposed RC3S could be used by state human service agencies to grade facilities as is done in the restaurant arena. Presently, in the human service field, licenses are issued with a Certificate of Compliance but generally it does not indicate what the regulatory compliance level is at. This new proposal would alleviate this problem by providing a scale for depicting the level of regulatory compliance.

The ECPQIM DB is an international data base consisting of a myriad group of data sets drawn from around the USA and Canada. It has been in the making over 40 years as of this writing, so its stability and generalizability have been demonstrated. What follows is the chart depicting the RC3S.

Regulatory Compliance Scoring System and Scale (RC3S)

| Color | Non-Compliance Level | Regulatory Compliance Level |
|--------|----------------------|-----------------------------|
| Blue | 0 | Full Compliance |
| Green | 1-2 | Substantial Compliance |
| Yellow | 3-6 | Mid-Range Compliance |
| Orange | 7-9 | Low Compliance |
| Red | 10-15+ | Very Low Compliance |

It is evident from the above chart that the color goes from blue to red which indicates increasing risk of non-compliance and a lower level of overall regulatory compliance which is not a good thing in the licensing field. Non-compliance levels indicate the number of rules or regulations or standards that are not complied with. And lastly, the regulatory compliance level indicates the movement from full (100% regulatory compliance with all rules) to very low compliance with rules. These ranges for the scaling are based up 40 years of research in understanding and plotting the data distributions around the world related to regulatory compliance in the human services. These results have consistently appeared over this 4-decade time period and show no signs of changing at this point.

Regulatory Compliance & Program Quality Grid Model: Technical Research Note

Richard Fiene, Ph.D.

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Depicted below is a regulatory compliance grid model showing the relationship between regulatory compliance (RC) and program quality (PQ).

An explanation of the below chart will demonstrate how regulatory compliance and program quality in human service facilities interact. The horizontal blue axis depicts the various levels of regulatory compliance while the vertical green axis depicts the various levels of program quality of facilities. It ranges from 1-5 or low to high for each axis. The red "X's" represent the relationship that has been identified in the research literature based upon the theory of regulatory compliance in which there is either a plateau effect or a downturn in quality as regulatory compliance increases. The one italicized "X" is an outlier that has also been identified in the research literature in which sometimes (it does not happen often) low compliant programs really are at a high quality level.

It is proposed in order to mitigate the plateau effect with regulatory compliance and program quality standards because regulatory compliance data distributions are severely skewed which means that many programs that have questionable quality are being included in the full (100%) compliance domain. When regulatory compliance standards are increased in their quality components this will lead to a higher level of overall quality as depicted in the "XX" cell all the way on the lower right. It also helps to mitigate the severe skewness in the regulatory compliance data distribution. The data distribution does not approximate a normally distributed curve which is the case with the program quality data distribution.

Regulatory Compliance x Program Quality Grid Model

| PQ/RC -> | 1 Low | 2 Med | 3 Substantial | 4 Full 100% | 5 Quality Addons |
|----------|-------|-------|---------------|-------------|------------------|
| 1 Low | XXX | | | | |
| 2 | | XX | | | |
| 3 Med | | | XX | XXX | |
| 4 | | | XX | X | |
| 5 High | X | | | | XX |

By utilizing this model, it helps to deal more directly in taking a non-linear relationship and making it linear again when comparing regulatory compliance with program quality. This model provides a theoretical approach supporting what many state licensing administrators are thinking from a policy standpoint: add more quality to health and safety rules/regulations. This grid/matrix also depicts the three regulatory compliance models: Linear, Non-linear, and Stepped.

**RIKI – Research Institute for Key Indicators Data Laboratory Penn State University
Edna Bennett Pierce Prevention Research Center and NARA**

*in strategic partnership with NARA –
National Association for Regulatory
Administration and affiliated with the
Penn State University Edna Bennett
Pierce Prevention Research Center*

Regulatory Compliance Scale

Posted on [January 9, 2022](#) by [Dr Fiene](#)

This blog post will propose a new Regulatory Compliance Scale (RCS)(Fiene, 2022) which should help in making comparisons between regulatory compliance and program quality systems, such as Environmental Rating Scales and Quality Rating & Improvement systems. The proposed scale builds off of a familiar 1-7 Likert scale that has been used a good deal in the early care and education field within program quality instruments/tools. This scale is based upon 40+ years of research into regulatory compliance data distributions which have been reported in this blog (RIKINotes) over the years.

The proposed scale (see **RCS Table** below) has the following structure of full compliance, substantial compliance, mediocre compliance, and low/non-optimal compliance. Numerically it is proposed that full compliance = 0 no rule violations; substantial compliance = 1-3 rule violations; mediocre compliance = 4-9 rule violations; and low/non-optimal compliance = 10+ rule violations. The transformation to a 1-7 Likert scale is as follows: full compliance = 7; substantial compliance = 5; mediocre compliance = 3; and low/non-optimal compliance = 1.

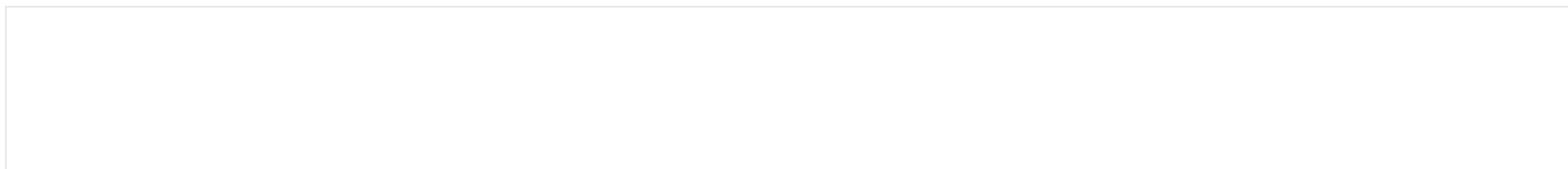
When the above regulatory compliance scale is utilized it substantially reduces the skewness and kurtosis in the regulatory compliance data distribution which is a major problem with all regulatory compliance data

distributions and has been reported repeatedly in the human services licensing research literature. The revised or transformed data distribution begins to approach a more normally distributed data set; albeit, not as normally distributed as the various Environmental Rating Scales but significantly better when straight frequency counts are used in determining regulatory compliance. This has been the preferred means of data recording since the introduction of Instrument-based Program Monitoring (IPM) in the 1980's. It is being proposed that the above Regulatory Compliance Scale (RCS)(Fiene, 2022) be used in place of this frequency based data system.

This newly proposed scale should go a long way in making future analyses in utilizing regulatory compliance data more useful and meaningful when making comparisons with the various program quality initiatives present in the early care and education field, such as the Environmental Rating Scales and Quality Rating & Improvement Systems.

| <u>RCS</u> | <u>Definitions/Levels</u> | <u>Rule Violations</u> |
|-------------------|----------------------------------|-------------------------------|
| 7 | Full 100% Compliance | 0 Violations |
| 5 | Substantial Compliance | 1-3 Violations |
| 3 | Mediocre Compliance | 4-9 Violations |
| 1 | Low/Non-Optimal Compliance | 10+ Violations |

Regulatory Compliance Scale (RCS)(Fiene, 2022)



Introducing the Ceiling Effect/Diminishing Returns, Regulatory Compliance Scale, and the Quality Indicators Scale to Regulatory Science

Richard Fiene PhD

Research Institute for Key Indicators/Prevention Research Center/Penn State University

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The purpose of this short paper/public policy commentary is to introduce three relatively new, recently validated concepts to regulatory science. The first of the concepts (ceiling effect) is one that I have written about a good deal in previous policy commentaries when addressing the theory of regulatory compliance (Fiene, 2019). The other two (regulatory compliance and quality indicator scales (Fiene, 2022, 2023b; NARA, 2023)) have been validated more recently so they are relatively new, but I think will have a similar impact on the regulatory science field based upon the research interest generated worldwide.

The “Ceiling Effect” is a more user-friendly term for the theory of regulatory compliance diminishing returns. I have found in recent webinars and presentations that the notion of a ceiling effect resonates with other regulatory science researchers more so than the theory of regulatory compliance diminishing returns. Scientists can wrap their heads around the ceiling effect much easier than the theory, so I am going to use this new term rather than the older. However, they do mean the same thing, same result, just different terminology. It is similar to what happened with “inferential inspections” (earlier term) and “differential monitoring” (present terminology) (Fiene, 2023a). Same concept, just different terms.

The “ceiling effect” is the same relationship between regulatory compliance and program quality. As regulatory compliance increases from substantial compliance to full 100% compliance, program quality shows either no improvement or diminished improvement over the same course. This is the essence of the theory of regulatory compliance diminishing returns (Fiene, 2019, 2023a, 2023b; NARA, 2023). No change here.

The second concept I want to introduce is the regulatory compliance scale (Fiene, 2022) which appears from recent studies to be a better metric in measuring regulatory compliance than just counting the number of violations that a program has related to their respective rules, regulations, or standards. So how does the regulatory compliance scale work. It essentially puts violations into buckets of regulatory compliance as follows: full compliance (100%) or no violations; substantial compliance (99-98%) or 1-2 violations; mediocre compliance (97-90%) or 3-9 violations; and lastly low/non-optimal compliance (89% or lower) or 10+ violations. Why buckets, because logically it works, it is the way we think about regulatory compliance. It is a

discrete rather than continuous metric and logically fits into these four categories. This is based upon 50 years of research into regulatory compliance data distributions and when the data are moved from frequency counts of violation data into these buckets/categories, the math works very well in identifying the better performing programs.

The last concept to be introduced deals with quality indicators which have been proposed as part of a differential monitoring paradigm but not utilized and validated in specific jurisdictions. Well, that has changed now with a major study completed in the Province of Saskatchewan which has clearly demonstrated in a valid and reliable fashion how quality indicators can be used effectively and efficiently when compared to other program quality scales and regulatory compliance data (NARA, 2023).

All these above results (Fiene, 2023b; NARA, 2023) were part of this Province of Saskatchewan five-year project, and they are all in the early care and education domain, but I think that the results are pertinent to any industry governed by regulatory science principles. One needs to change the content obviously, but the metrics and methodology would hold up because of their base in solid scientific principles of instrument and research design.

References:

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

Richard Fiene PhD

Research Institute for Key Indicators/Penn State University

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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

| <u>Scoring Level</u> | <u>Individual Rule</u> | | <u>Aggregate Rules</u> | <u>Individual Rule</u> |
|----------------------|-------------------------|--------------|------------------------|------------------------|
| <u>Scale</u> | Instrument based | <u>Scale</u> | 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.

Regulatory Compliance Scale Trials and Tribulations (Enhanced Version)

Richard Fiene PhD

Research Institute for Key Indicators Data Lab/Penn State University

January 2024

The Regulatory Compliance Scale (RCS) was introduced several years ago and has been used in a couple of validation studies for differential monitoring and regulatory compliance's ceiling effect phenomenon. RCS buckets or thresholds were statistically generated based upon these studies, but it is time to validate those buckets and thresholds to determine if they are really the best model in creating a regulatory compliance scale. Since proposing the RCS, there has been a great deal of interest from jurisdictions in particular from Asian and African nations. Additional statistically based trials were conducted, and this brief report is the compilation of those trials over the past year.

The data used are from several jurisdictions that are part of the international database maintained at the Research Institute for Key Indicators Data Laboratory at Penn State University focusing on program quality scores and rule violation frequency data. These data from the respective databases were recoded into various thresholds to determine the best model. The jurisdictions were all licensing agencies in the US and Canada geographically dispersed where both regulatory compliance and program quality data was obtained from a sample of early care and education programs.

METHODOLOGY

The following methodology was used starting with the original RCS buckets/thresholds of Full, Substantial, Medium, and Low regulatory compliance:

Table 1: RCS Models used for analyses

| RCS | | | | Models | | | |
|----------------|--------------------|-----------------|----------|----------|----------|----------|----------|
| | | <i>Original</i> | <i>1</i> | <i>2</i> | <i>3</i> | <i>4</i> | <i>5</i> |
| | <i>Full</i> | 100 | 100 | 100 | 100 | 100 | 100 |
| Scaling | <i>Substantial</i> | 99-98 | 99-97 | 99-97 | 99-98 | 99-98 | 99-97 |
| | <i>Medium</i> | 97-90 | 96-90 | 96-93 | 97-95 | 97-85 | 96-85 |
| | <i>Low</i> | 89> | 89> | 92> | 94> | 84> | 84> |

Five alternate models were used to compare the results to the original RCS. The numbers indicate the number of violations subtract from a perfect score of 100. Full regulatory compliance indicates no violations and a score of 100 on the scale. The next bucket of 99-98 indicates that there were 1 or 2

regulatory compliance violations which resulted in a 99-98 score on the scale. This logic continues with each of the models.

The scale score was determined in the following manner: Full Regulatory Compliance = 7; Substantial Regulatory Compliance = 5; Medium Regulatory Compliance = 3; and Low Regulatory Compliance = 1. This rubric is how the original RCS scaling was done on a Likert type scale similar to other ECE program quality scales, such as the Environmental Rating Scales.

RESULTS

The following results are correlations amongst the respective RCS Models from Table 1 compared to the respective jurisdictions program quality tool (Quality1-3): ERS or CLASS Tools.

Table 2: RCS Model Results compared to Quality Scales

| RCS results | Models | Quality1 | Quality2 | Quality3 |
|----------------------|-------------|--------------|--------------|-------------|
| Jurisdiction1 | RCS0 | .26* | .39* | .39* |
| | RCS3 | .21 | .32* | .33* |
| | RCS5 | .20 | .36* | .33* |
| Jurisdiction2 | RCS0 | .76** | .46** | --- |
| | RCS3 | .12 | -.07 | --- |
| | RCS5 | .18 | -.02 | --- |
| | RCSF1 | .55** | .29* | --- |
| | RCSF2 | .63** | .34 | --- |
| Jurisdiction3 | RCS0 | .19 | .18 | .16 |
| | RCS3 | .21 | .21 | .15 |
| | RCS5 | .18 | .16 | .07 |
| | RCSF1 | .17 | .17 | .10 |
| | RCSF2 | .18 | .18 | .19 |
| Jurisdiction4 | RCS0 | .24* | --- | --- |
| | RCS3 | .28* | --- | --- |
| | RCS5 | .30* | --- | --- |
| | RCSF1 | .21 | --- | --- |
| | RCSF2 | .29* | --- | --- |
| Jurisdiction5 | RCS0 | .06 | -.02 | .07 |
| | RCS3 | .06 | -.01 | .05 |
| | RCS5 | .08 | .00 | .09 |
| | RCSF1 | .00 | -.03 | .05 |
| | RCSF2 | .05 | -.03 | .05 |

*Statistically significant .05 level;

**Statistically significant .01 level.

In the above table starting under Jurisdiction2, two new models were introduced based upon the Fibonacci Sequence (Fibonacci1 = RCSF1; Fibonacci2 = RCSF2) and their model structure is in the

following Table 3. The reason for doing this is that the Fibonacci Sequence introduces additional variation into the scaling process.

Table 3: RCS Fibonacci Models

| RCS Fibonacci | | Models | | |
|----------------|--------------------|-----------------|-------------------|-------------------|
| | | <i>Original</i> | <i>Fibonacci1</i> | <i>Fibonacci2</i> |
| | <i>Full</i> | 100 | 100 | 100 |
| Scaling | <i>Substantial</i> | 99-98 | 40 | 90 |
| | <i>Medium</i> | 97-90 | 20 | 20 |
| | <i>Low</i> | 89> | 13 | 13 |

A second series of analyses were completed in comparing the RCS models with program quality (Quality1) by running ANOVAs with the RCS models as the independent variable and program quality as the dependent variable (Table 4). The reason for doing this was the nature of the data distribution in which there was a ceiling effect phenomenon identified which would have had an impact on the correlations in Table 2 above. All results are significant at $p < .05$ level with the exception of Jurisdiction2.

Table 4: ANOVAs Comparing the RCS Models with Program Quality

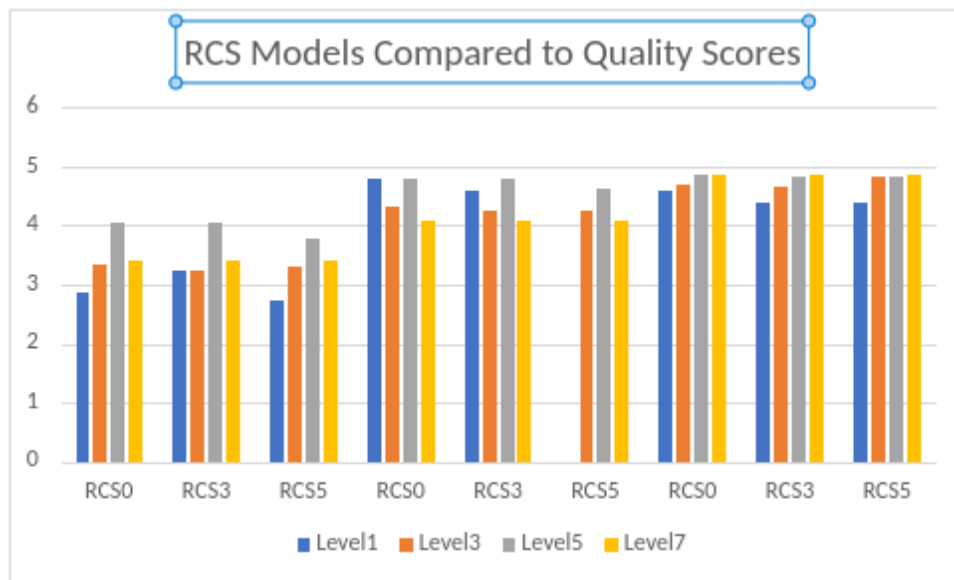
| Jurisdictions | Model | Level 1 | Level 3 | Level 5 | Level 7 |
|---------------|-------------|--------------|--------------|--------------|--------------|
| Jurisdiction1 | RCS0 | 2.85 | 3.34 | 4.05 | 3.40 |
| | RCS3 | 3.24 | 3.23 | 4.05 | 3.40 |
| | RCS5 | 2.73 | 3.32 | 3.77 | 3.40 |
| Jurisdiction2 | RCS0 | 4.81 | 4.31 | 4.80 | 4.10 |
| | RCS3 | 4.59 | 4.25 | 4.80 | 4.10 |
| | RCS5 | --- | 4.26 | 4.64 | 4.10 |
| Jurisdiction3 | RCS0 | 4.59 | 4.68 | 4.86 | 4.87 |
| | RCS3 | 4.38 | 4.67 | 4.83 | 4.87 |
| | RCS5 | 4.38 | 4.83 | 4.83 | 4.87 |
| Jurisdiction4 | RCS0 | 37.81 | 37.01 | 44.28 | 41.96 |
| | RCS3 | 36.57 | 38.60 | 44.28 | 41.96 |
| | RCS5 | 33.46 | 36.53 | 43.10 | 41.96 |
| Jurisdiction5 | RCS0 | 3.93 | 4.17 | 4.28 | 4.07 |
| | RCS3 | 4.02 | 4.24 | 4.28 | 4.07 |
| | RCS5 | 3.75 | 4.13 | 4.26 | 4.07 |

DISCUSSION

Based upon the above results, it appears that the original RCS model proposed in 2021 is still the best model to be used, although the Fibonacci Sequence model is a close second in some of the jurisdictions. This model will need further exploration in determining its efficacy as a replacement or enhancement to the original RCS Model.

The bottom line is that the original RCS Model is as good as any and no other model is consistently better than all the rest. The RCS Model does have a slight edge over Regulatory Compliance Violation RCV frequency counts in some jurisdictions but not in others. It is much easier to interpret the relationship between quality and the RCS models than it is to interpret the results from the quality scores and the RCV data distribution. So, the recommendation would be for licensing agencies to think in terms of using this new scaling technique in one of its model formats in order to determine its efficacy. Pairing up RCS and RCV data side by side by licensing agencies would be important studies to determine which approach is the better approach.

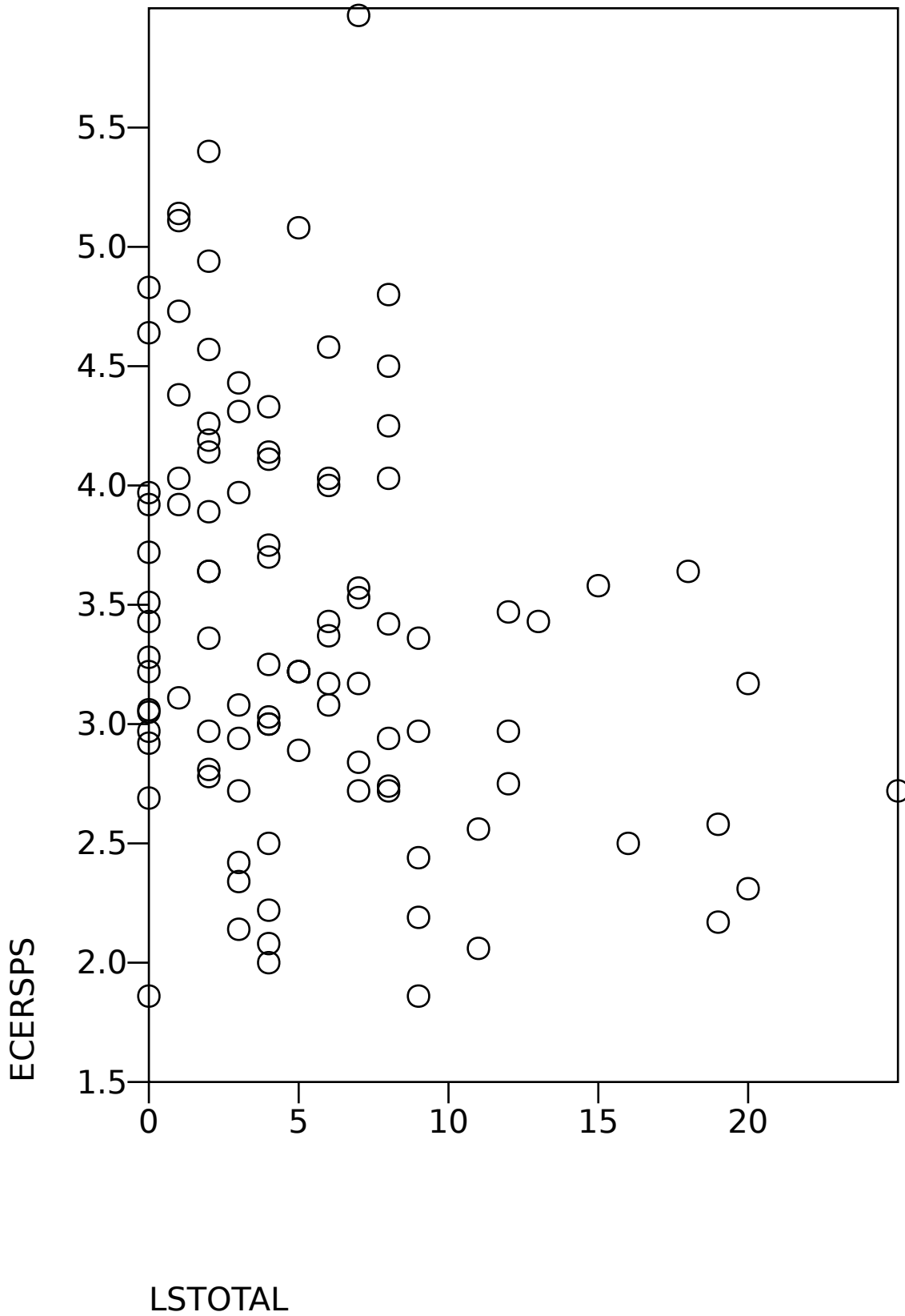
The below graphic depicts the relationship between the RCS Models (0, 3, 5) when compared to the quality scores (1-6) clearly showing the ceiling effect and diminishing returns effect phenomenon so typical of regulatory compliance data when compared to program quality. These graphs are from the first three jurisdictions (1, 2, 3) from the above tables.



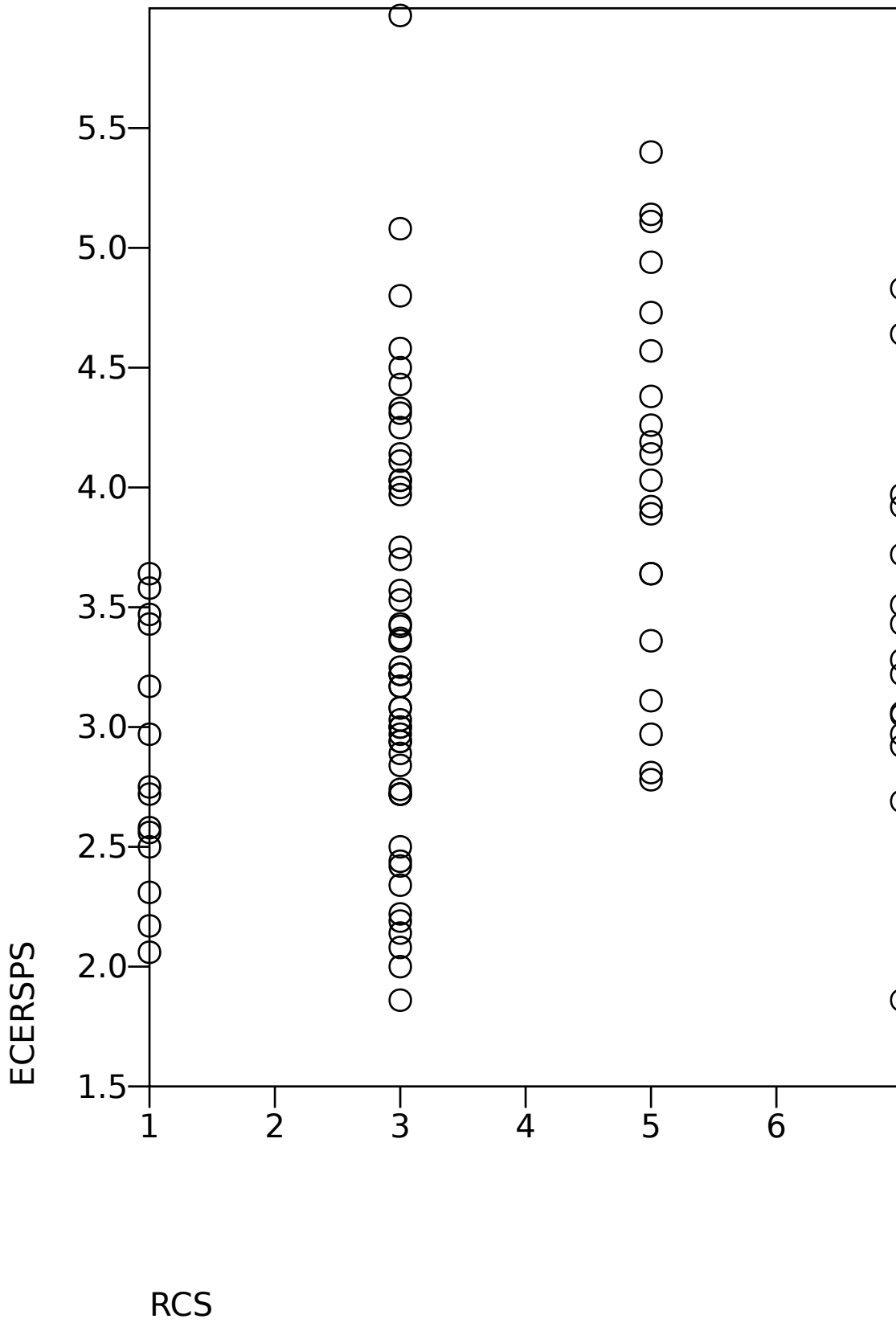
Richard Fiene PhD, Research Psychologist/Regulatory Scientist, Research Institute for Key Indicators Data Laboratory/Penn State University, email: rfiene@rikoinstitute.com websites: <https://rikoinstitute.com> or <https://prevention.psu.edu/person/rick-fiene/>

The below appendices present graphic displays of moving from nominal RCV to ordinal RSC measurement which really captures the differences in how the data are displayed and the ease in which viewing the data becomes in making such a move. Also, basic descriptive statistics are displayed to clearly demonstrate the differences in the various RCS Models.

Scatterplot ECERSPS vs. LSTOTAL



Scatterplot ECERSPS vs. RCS



FREQUENCIES

FREQUENCIES

/VARIABLES= RCS RCS3 RCS5
 /FORMAT=AVALUE TABLE
 /STATISTICS=MEAN STDDEV.

RCS

| <i>Value Label</i> | <i>Value</i> | <i>Frequency</i> | <i>Percent</i> | <i>Valid Percent</i> | <i>Cum Percent</i> |
|--------------------|--------------|------------------|----------------|----------------------|--------------------|
| | 1.00 | 15 | 14.42 | 14.42 | 14.42 |
| | 3.00 | 54 | 51.92 | 51.92 | 66.35 |
| | 5.00 | 20 | 19.23 | 19.23 | 85.58 |
| | 7.00 | 15 | 14.42 | 14.42 | 100.00 |
| <i>Total</i> | | 104 | 100.0 | 100.0 | |

RCS

| | | |
|----------------|----------------|------|
| <i>N</i> | <i>Valid</i> | 104 |
| | <i>Missing</i> | 0 |
| <i>Mean</i> | | 3.67 |
| <i>Std Dev</i> | | 1.80 |

RCS3

| <i>Value Label</i> | <i>Value</i> | <i>Frequency</i> | <i>Percent</i> | <i>Valid Percent</i> | <i>Cum Percent</i> |
|--------------------|--------------|------------------|----------------|----------------------|--------------------|
| | 1.00 | 41 | 39.42 | 39.42 | 39.42 |
| | 3.00 | 28 | 26.92 | 26.92 | 66.35 |
| | 5.00 | 20 | 19.23 | 19.23 | 85.58 |
| | 7.00 | 15 | 14.42 | 14.42 | 100.00 |
| <i>Total</i> | | 104 | 100.0 | 100.0 | |

RCS3

| | | |
|----------------|----------------|------|
| <i>N</i> | <i>Valid</i> | 104 |
| | <i>Missing</i> | 0 |
| <i>Mean</i> | | 3.17 |
| <i>Std Dev</i> | | 2.16 |

RCS5

| <i>Value Label</i> | <i>Value</i> | <i>Frequency</i> | <i>Percent</i> | <i>Valid Percent</i> | <i>Cum Percent</i> |
|--------------------|--------------|------------------|----------------|----------------------|--------------------|
| | 1.00 | 8 | 7.69 | 7.69 | 7.69 |
| | 3.00 | 52 | 50.00 | 50.00 | 57.69 |
| | 5.00 | 29 | 27.88 | 27.88 | 85.58 |
| | 7.00 | 15 | 14.42 | 14.42 | 100.00 |
| <i>Total</i> | | 104 | 100.0 | 100.0 | |

RCS5

| | | |
|----------------|----------------|------|
| <i>N</i> | <i>Valid</i> | 104 |
| | <i>Missing</i> | 0 |
| <i>Mean</i> | | 3.98 |
| <i>Std Dev</i> | | 1.67 |