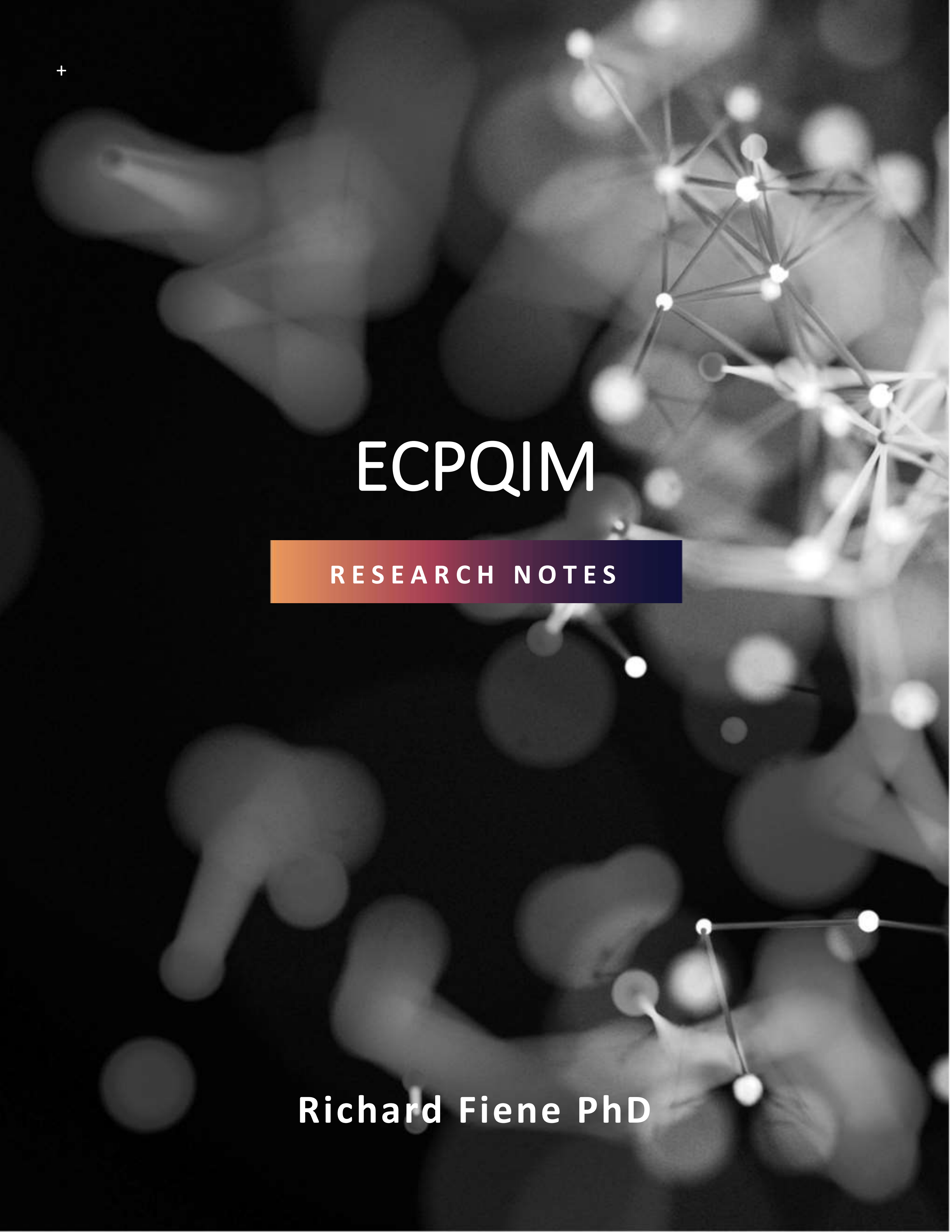


ECPQIM

RESEARCH NOTES

Richard Fiene PhD

Technical Research Notes

Regulatory Science, Differential Monitoring, Licensing Measurement

Richard Fiene, PhD

May 2022

Abstract

This anthology contains technical research notes and abstracts written over the past decade documenting key aspects of regulatory science, differential monitoring and licensing measurement as it relates to early care and education assessment focusing on regulatory compliance. These notes and abstracts complement the articles, papers, chapters, presentations written during this same decade. For the interested reader please go to the following website to view these publications (http://rikinstitute.com/publications/).

This anthology contains enhancements to licensing measurement and differential monitoring, such as how best to deal with skewed data, nominal versus ordinal data measurement, effectiveness and efficiency relationship, relationship of regulatory compliance and program quality.

Research Institute for Key Indicators

Richard Fiene, Ph.D.
Research Psychologist

Theory of Regulatory Compliance Algorithm

September 15, 2019

RIKI Technical Research Note

This technical Research Note will provide the algorithm for the Theory of Regulatory Compliance (TRC) as proposed by Fiene in 2016 and 2019. The algorithm will provide the basic relationship between differential monitoring, comprehensive inspections, program quality, and client outcomes.

The TRC Algorithm

TRC = DM (RA/KI) > CI x PQ/CO

Where:

DM = Differential Monitoring such as weighted risk assessment (RA) or key indicators (KI).

CI = Comprehensive Inspections in which all rules/regulations are reviewed.

PQ = Quality Rating and Improvement Systems or Early Childhood Environment Scales.

CO = Client Outcomes such as child development assessments.

What the Algorithm Means:

The Theory of Regulatory Compliance (TRC) algorithm essentially means that using risk assessment (RA) or key indicators (KI) is both more cost effective and efficient than completing comprehensive inspections (CI) of facilities in correlating with program quality (PQ) or client outcomes (CO). Completing abbreviated/targeted reviews (DM) are better than doing more comprehensive reviews (CI) in which full compliance is the goal. The Theory of Regulatory Compliance indicates that substantial and not full regulatory compliance is in the best interest of the client and produces the highest level of program quality (PQ).

DIFFERENTIAL MONITORING LOGIC MODEL AND ALGORITHM (DMLMA)©: A NEW EARLY CHILDHOOD PROGRAM QUALITY INDICATOR MODEL4 (ECPQIM4)© FOR EARLY CARE AND EDUCATION REGULATORY AGENCIES

Richard Fiene, Ph.D.

This Differential Monitoring Logic Model and Algorithm (DMLMA©) is a 4th generational Early Childhood Program Quality Indicator Model4 (ECPQIM4©) in which the major monitoring systems in early care and education are integrated conceptually so that the overall early care and education system can be assessed and validated. With this new model, it is now possible to compare results obtained from licensing systems, quality rating and improvement systems (QRIS), risk assessment systems, key indicator systems, technical assistance, and child development/early learning outcome systems. The various approaches to validation are interposed within this model and the specific expected correlational thresholds that should be observed amongst the key elements of the model are suggested (see Table 1 and Figures 1 & 2).

The DMLMA© can be used by state agencies (child care, child residential, adult residential (just replace Child Outcomes with Adult Outcomes)), Federal agencies (Head Start, child care, Pre-K), and large provider organizations where an economy of scale is required. This model can be used with state as well as national standards, such as state licensing rules/regulations and *Head Start Performance Standards* or *Caring for Our Children/Stepping Stones.* Most states and Federal agencies have either some or all of the key elements of this model in their overall monitoring systems. The purpose of this model is to alter a one-size fits all monitoring system to one that is targeted, spending more time with problem programs who need additional assistance. This is a cost neutral model that is both cost effective and efficient and re-allocates resources from the compliant programs to the non-compliant programs.

Key Elements (see Figures 1 & 2): **CI** = state or federal standards, usually rules or regulations that measure health and safety - *Caring for Our Children or Head Start Performance* Standards will be applicable here. **PQ** = Quality Rating and Improvement Systems (QRIS) standards at the state level; ERS (ECERS, ITERS, FDCRS), CLASS, or CDPES (Fiene, 2007). **RA** = risk assessment tools/systems in which only the most critical rules/standards are measured. *Stepping Stones* is an example of this approach**.** **KI** = key indicators in which only predictor rules/standards are measured. The *Thirteen Indicators of Quality Child Care* is an example of this approach. **DM** = differential monitoring decision making in which it is determined if a program is in compliance or not and the number of visits/the number of rules/standards are ascertained from a scoring protocol**.** **PD** = technical assistance/training and/or professional development system which provides targeted assistance to the program based upon the **DM** results. **CO** = child outcomes which assesses how well the children are developing which is the ultimate goal of the system.

Once the above key elements are in place, it is then possible to look at the relationships amongst them to determine if the system is operating as it was intended. This is done through a validation (Figure 2) of the overall system and assessing the inter-correlations (Figure 1) to determine that the DM system is improving the health, safety, program quality and ultimately the overall development of the children it serves.

The DMLMA© provides a cross-cutting methodology that can be used in all early care and education delivery systems as well as in other human services. In the past many of these monitoring systems have functioned in silos. The DMLMA© integrates all these various monitoring systems together so that the overall monitoring system can be validated as being cost effective and efficient.

STATE AGENCY PLAN (These Steps can be viewed as an overall plan as outlined in Zellman & Fiene (2012):

The **first step** in utilizing the DMLMA for a state is to take a close look at its Comprehensive Licensing Tool (CI) that it uses to collect violation data on all rules with all facilities in its respective state. If the state does not utilize a tool or checklist or does not review all violation data than it needs to consider these changes because the DMLMA is based upon an Instrument Based Program Monitoring System (IPM) which utilizes tools/checklists to collect data on all rules.

The **second step** for the state is to compare their state's rules with the National *Health and Safety Performance Standards (Caring for Our Children*) to determine the overlap and coverage between the two. This is the first approach to validation which involves Standards review (Zellman & Fiene, 2012).

The **third step** for the state if it utilizes a Risk Assessment (RA) tool is to assess the relationship between this tool and *Stepping Stones* to determine the overlap and coverage between the two. This is a continuation of the first approach to validation which involves Standards review (Zellman & Fiene, 2012).

The **fourth step** for the state is to compare the results from the CI with the RA tools. This step is the second approach to validation which involves Measures (Zellman & Fiene, 2012). The correlation between CI and RA should be at the .50 level or higher (.50+)(see Table 1).

In the **fifth step**, if a state is fortunate enough to have a QRIS – Quality Rating and Improvement System in place and has sufficient program quality (PQ) data available then they will have the ability to compare results from their CI tool with their PQ tool and validate outputs by determining the relationship between compliance with health and safety rules (CI) and program quality (PQ) measures, such as the ERS's, CLASS, CDPES, etc… This is a very important step because very few empirical demonstrations appear in the research literature regarding this relationship. This step is the third approach to validation which involves Outputs (Zellman & Fiene, 2012). It would be expected that lower correlations (.30+) would be found between CI and PQ because these tools are measuring different aspects of quality such as health & safety versus caregiver-child interactions or overall classroom quality.

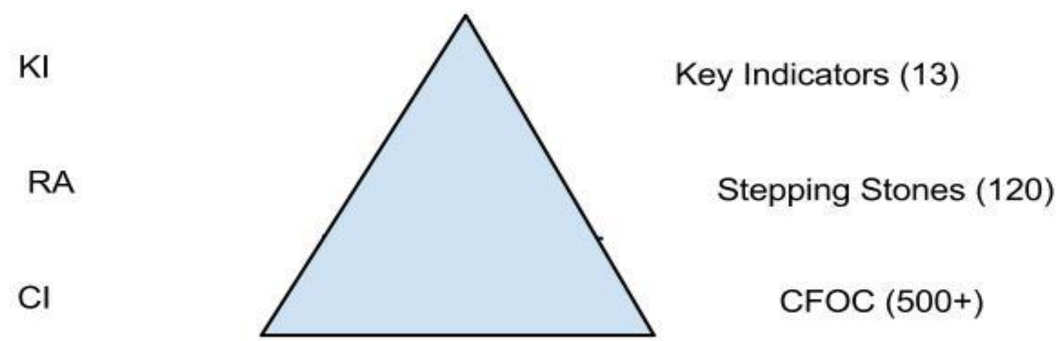
The **sixth step** is for the state to generate a Key Indicator (KI) tool from the CI data base. Please see Fiene & Nixon (1985) and Fiene & Kroh (2000) for a detailed explanation of the methodology for generating a KI tool. This step is also part of the second approach to validation which involves Measures. The correlation between the CI and KI should be very high (.70+) because the KI is a subset of predictor rules taken from the CI data base. If a state did not want to use the KI methodology, a direct comparison could be drawn from The *Thirteen Indicators of Quality Child Care* (Fiene, 2002).

The **seventh step** for the state is to use the RA and KI tools together to determine overall compliance of facilities and how often and which rules will be monitored for future visits. This is the basic component of a Differential Monitoring (DM) approach and continues the second approach to validation (Measures). Also, this step should drive decisions within the technical assistance/training/professional development (PD) system in what resources are allocated to a particular facility. It would be expected that moderate correlations (.50+) would be found amongst RA, KI, DM, and PD.

The **eighth and final step** for the state is to compare the results from the various monitoring tools (CI, PQ, RA, KI) with any child development outcome (CO) data they collect. This is a relatively new area and few, if any, states at this point have this capability on a large scale. However, as Early Learning Networks and Standards are developed, this will become more common place. This step is the forth approach to validation which involves Outcomes (Zellman & Fiene, 2012). The correlations between CI, PQ, RA, KI and CO will be on the lower end (.30+) because there are so many other variables that impact children's development other than child care facilities.

Validation is a continuous approach and is not a once and done process. States should look at their monitoring systems on an on-going basis and make the necessary adjustments as data are collected and compared in order to keep program monitoring as cost effective and efficient.

Relationship of Key Indicators (KI), Stepping Stones (RA), and Caring for Our Children (CFOC)(CI)



The above diagram depicts the relationship amongst KI, RA, and CI in which the full set of rules is represented by CFOC - Caring for Our Children, followed by RA which are the most critical rules represented by Stepping Stones, and finally the predictive rules represented by the 13 Key Quality Indicators.

Table 1: DMLMA© Expected Thresholds

Key Elements	PQ	RA	KI	DM	PD	CO
CI	0.3	0.5	0.7	0.5	0.5	0.3
PQ				0.3	0.3	0.3
RA			0.5	0.5	0.5	0.3
KI				0.5	0.5	0.3
DM					0.5	
PD						0.3

RELATED PUBLICATIONS:

Fiene (2007). Child Development Program Evaluation & Caregiver Observation Scale, in T Halle (Ed.), *Early Care and Education Quality Measures Compendium*, Washington, D.C.: Child Trends.

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Fiene & Kroh (2000). Licensing Measurement and Systems, *NARA Licensing Curriculum*. Washington, D.C.: National Association for Regulatory Administration.

Fiene & Nixon (1985). Instrument based program monitoring and the indicator checklist for child care, *Child Care Quarterly, 14*(3), 198-214.

Griffin & Fiene (1995). *A systematic approach to policy planning and quality improvement for child care: A technical manual for state administrators*. Washington, D.C.: National Center for Clinical Infant Programs-Zero to Three.

Morgan, Stevenson, Fiene, & Stephens (1986). Gaps and excesses in the regulation of child day care, *Reviews of Infectious Diseases--Infectious Diseases in Child Day Care: Management and Prevention, 8*(4), 634-643.

Zellman, G. L. and Fiene, R. (2012). *Validation of Quality Rating and Improvement Systems for Early Care and Education and School-Age Care,* Research-to-Policy, Research-to-Practice Brief OPRE 2012. Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services.

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Figure 1: Differential Monitoring Logic Model & Algorithm (DMLMA)© Thresholds

DMLMA© Expected Thresholds:
High Correlations (.70+) = CI x KI.
Moderate Correlations (.50+) = CI x RA; RA x DM; RA x KI; KI x DM; DM x PD.
Lower Correlations (.30+) = PQ x CI; PQ x CO; PQ x DM; RA x CO; KI x CO; CI x CO.

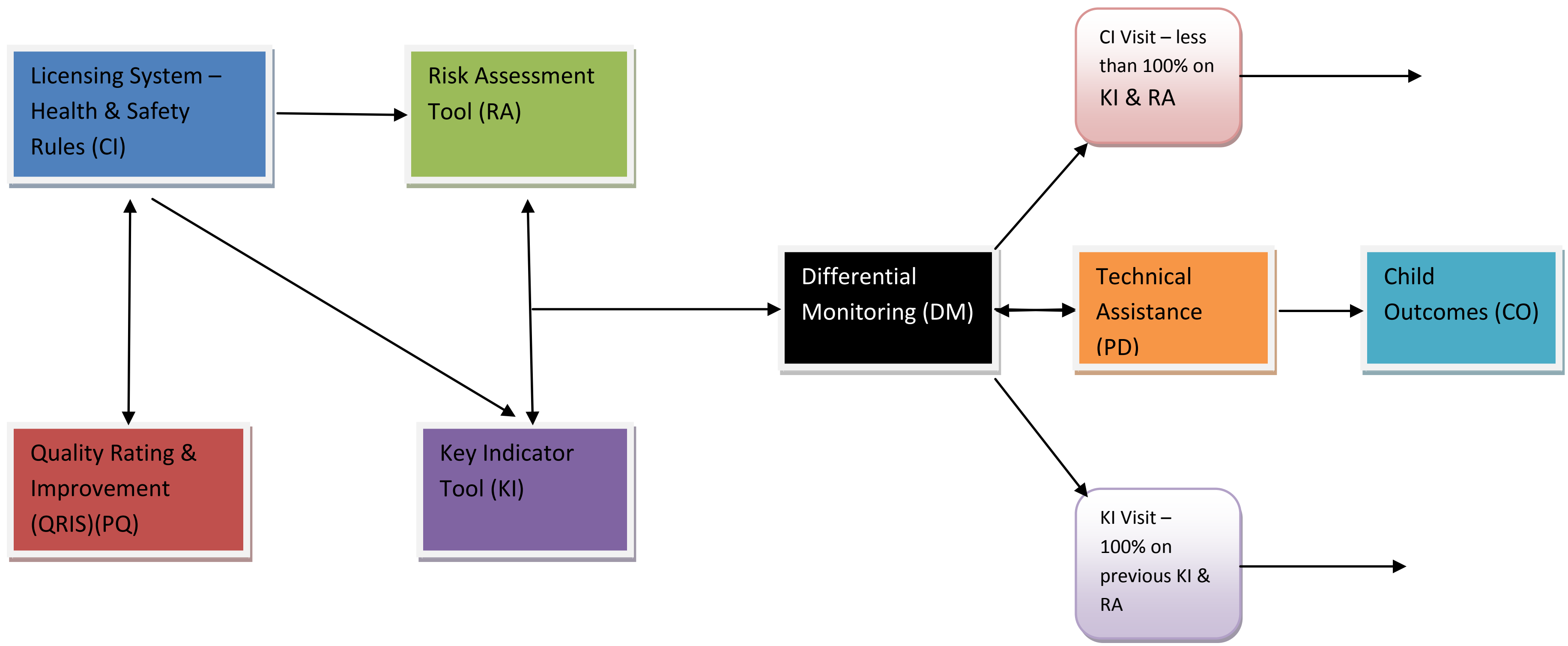
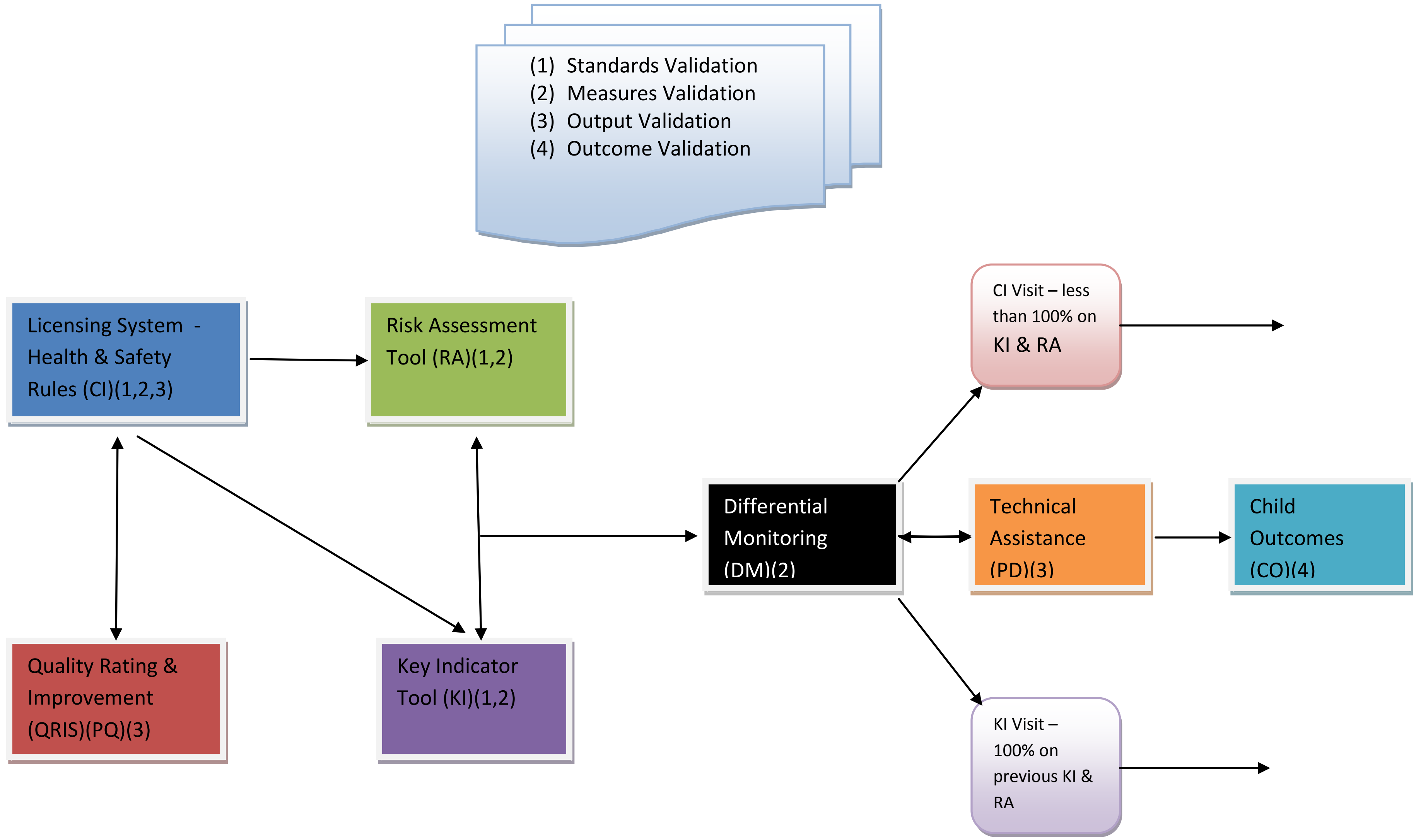


Figure 2: Differential Monitoring Logic Model & Algorithm (DMLMA)© and Validation Approaches (Zellman & Fiene, 2012)

$$\sum CI \times \sum PQ \Rightarrow \sum RA + \sum KI \Rightarrow \sum DM + \sum PD \Rightarrow CO$$



Risk Assessment and Licensing Decision Making Matrices: Taking into Consideration Rule Severity and Regulatory Compliance Prevalence Data

Sonya Stevens, Ed.D. & Richard Fiene, Ph.D.

June 2019

This short paper combines the use of risk assessment and licensing decision making matrices. In the past, risk assessment matrices have been used to determine the frequency of monitoring and licensing visits and scope of reviews based upon individual rule severity, risk factors, or both. Notably, these data were lacking because they had not been aggregated to determine what type of licensing decisions should be made based upon prevalence, probability, or regulatory compliance history data. The approach described here is a proposed solution to that problem.

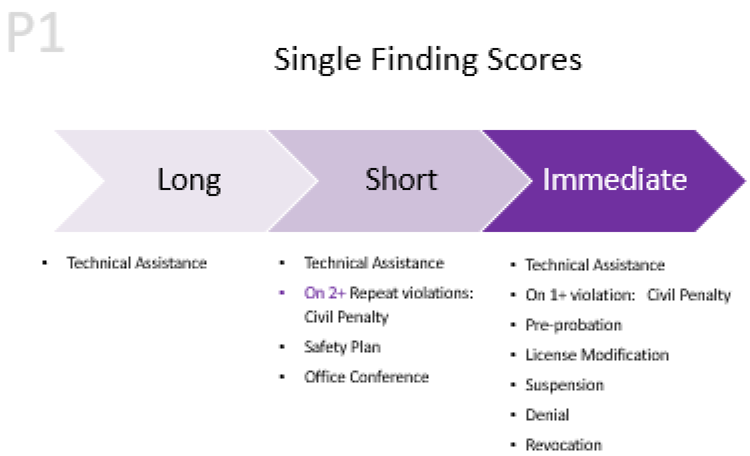
Washington State's HB 1661 (2017) redefined the department's facility licensing compliance agreement (FLCA) process. One feature of this new process is to allow licensed providers to appeal violations noted on the FLCA that do not involve "health and safety standards.[1]" To determine what licensing rules are and are not "health and safety standards" under the new definition, the department worked with community and industry stakeholders, and sought extensive public input, to assignment weights to licensing regulations. These weights were based on each regulation's risk of harm to children. A rule designed to protect against the lowest risk of harm was assigned a "1" and a rule designed to protect against the highest risk of harm was assigned an "8". Weights of "2" through "7" were determined accordingly. These weights were then grouped into three different categories based on risk:

- **Weights 8, 7 and some 6 = immediate concern**
- **Weights 4, 5 and most 6 = short term concern**
- **Weights 1, 2, and 3 = long term concern**

Using the new risk categories, the department developed a two-prong approach that considers both the risk of harm to children at the time a violation is monitored (single findings) and the risk of harm to children arising from violations noted for a given provider over a four year period (historical or overall findings). Used together, the department will assess the single findings and the historical findings to determine appropriate licensing actions, ranging from offering technical assistance to summarily suspending and revoking a child care license. In addition, the department will also note how many times a provider violates the *same* rule, with the severity of a licensing action increasing each time. For example, a violation within the short term concern category could be subject to a civil penalty when violated the second (or potentially the 3rd) time in a four-year period. Whereas, a violation in the immediate concern category could be subject to a civil penalty or more severe action upon the first violation. (See Graphic for Step 1).

[1] Washington law governing child care and early learning defines "health and safety standards" to mean "rules or requirements developed by the department to protect the health and safety of children against substantial risk of bodily injury, illness, or death." RCW 43.216.395(2)(b).

Step 1:



A more difficult task is assigning initial thresholds for the overall finding score. It is this second step (Step 2) where we need to consider probability and severity side by side as depicted in Chart 1 below which is generally considered the standard Risk Assessment Matrix in the licensing research literature:

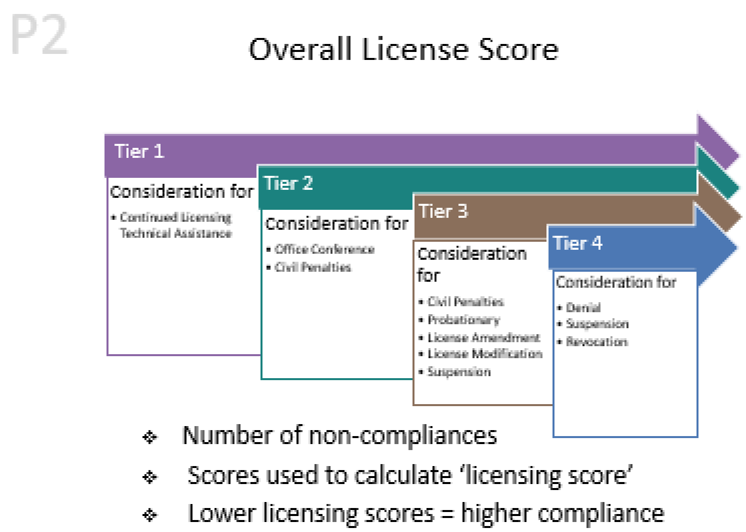
Step 2:

Chart 1 – Risk Assessment Matrix

		Probability/	**Prevalence**		
	Levels	**High**	**Medium**	**Low**	**Weights**
Risk/	**High**	***9***	***8***	***7***	***7-8***
Severity	**Medium**	***6***	***5***	***4***	***4-6***
	Low	***3***	***2***	***1***	***1-3***
	# of Rules	***8 or more***	***3-7***	***2 or fewer***	

The next step (Step 3) is to build in licensing decisions using a graduated Tiered Level system as depicted in the following figure. In many jurisdictions, a graduated Tiered Level system is used to make determinations related to monitoring visits (frequency and scope) and not necessarily for licensing decisions.

Step 3:



Step 4 involves combining steps 1 and 2 into a revised risk assessment matrix as depicted in the following chart:

Step 4:

Risk Assessment (RA) Matrix Revised

	Levels	**High**	**Medium**	**Low**
Risk/Severity	**Immediate**	**9**	**8**	**7**
	Short-term	**6**	**5**	**4**
	Long-term	**3**	**2**	**1**
			Probability	
	Regulatory Compliance (RC): # of Rules out of compliance and In compliance	**8+ rules out of compliance. 92 or less regulatory compliance.**	**3-7 rules out of compliance. 93 – 97 regulatory compliance.**	**2 or fewer rules out of compliance. 98 – 99 regulatory compliance.**

The last step (Step 5) is to take steps 3 and 4 and combine them together into the following charts which will provide guidance for making licensing decisions about individual programs based upon regulatory compliance prevalence, probability, and history as well as rule risk/severity data.

Step 5:

Licensing Decision Making Matrix*

Tier 1 = (1 – 2) RA Matrix Score

Tier 2 = (3) RA Matrix Score
Tier 3 = (4 – 5) RA Matrix Score

Tier 4 = (6 – 9) RA Matrix Score

***Regulatory Compliance (RC)(Prevalence/Probability/History + Risk/Severity Level)**

Tier 1 = ((RC = 93 – 97) + (Low Risk)); ((98 – 99) + (Low Risk)) = Tier 1

Tier 2 = (RC = 92 or less) + (Low Risk) = Tier 2

Tier 3 = ((RC = 93 – 97) + (Medium Risk)); ((98 – 99) + (Medium Risk)) = Tier 3

Tier 4 = (RC = (92 or less) + (Medium Risk)) = Tier 4; ((93 -97) +(High Risk)) = Tier 4; ((98 – 99) + (High Risk)); ((92 or less) + (High Risk)) = Tier 4+

The following algorithms should be followed in moving from the Risk Assessment Matrix (RAM) (Step 4) to the Licensing Decision Making Matrix (Step 5):

1) Σ (Yr1 RC + Yr2 RC + Yr3 RC + Yr4 RC).
2) Identify all rules by high, medium, low, no risk levels. HR, MR, LR, NULL.
3) HR = Tier4.
4) Σ NC Total/# of Years = Average NC.
5) Σ NC by RCH, RCM, and RCL.
6) LR + RCL or LR + RCM = Tier 1.
7) LR + RCH = Tier 2.
8) MR + RCL or MR + RCM = Tier 3.
9) MR + RCH or HR + RCM or HR + RCL = Tier 4.
   HR + RCH = Tier 4+.

Risk Level:
HR = High Risk (7-8 weights)
MR = Medium Risk (4-6 weights)
LR = Low Risk (1-3 weights)
Prevalence Level:
RCH = High Non Compliance (NC) (8+) or Low Regulatory Compliance (RC) (92 or less)
RCM = Medium Non Compliance (3-7) or Medium Regulatory Compliance (93-97)
RCL = Low Non Compliance (1-2) or High Regulatory Compliance (98-99)

A Theory on the Relationship With Professional Development, Program Quality and Regulatory Compliance Predicting Early Childhood Outcomes

Richard Fiene, Ph.D.

July 2019

This abstract is the compilation of 50 years of research into early childhood professional development, program quality indicators and regulatory compliance and their respective impact on early childhood outcomes. Professional development, program quality and regulatory compliance all have impacts on early childhood outcomes (ECO) but if we put them all in the same equation, what are their relative impact on outcomes. That is the purpose of this abstract. Based upon results from the Research Institute for Key indicators (RIKI) Early Childhood Program Quality Improvement and Indicators Model (ECPQIM) data base, it is now possible to ascertain their relative weights.

For purposes of this abstract, professional development (PD) includes any training, coaching or technical assistance which focuses on teaching staff. Program quality (PQ) includes Quality Rating and Improvement Systems (QRIS) standards and their respective observational evaluations (ERS, CLASS). Regulatory compliance (RC) includes licensing health and safety rules and regulations as promulgated and enforced by state agencies. In the past, these systems have been dealt with in silos and there has been very little attempts at combining them in any fashion. One of the results of the ECPQIM data base was and is to attempt combining these various systems into a unified equation or algorithm.

Based on the results of the ECPQIM data base results, the following equation/algorithm can depict this unified relationship:

$$\mathbf{ECO = \Sigma\ (.50PD + .30PQ + .20RC)}$$

In this relationship, the largest impact comes from the PD system, followed by the PQ system and lastly by the RC system. The implications of this relationship are that states may want to reconsider how they are allocating resources based upon this above equation/algorithm. This is a controversial proposal but one that should be considered since it is driven by empirical evidence into the relative impact over the past 50 years of research related to professional development, program quality and regulatory compliance as they relate to early childhood outcomes.

THEORY OF REGULATORY COMPLIANCE

Richard Fiene

October 2016

The Theory of Regulatory Compliance (TRC)[1] *deals with the importance and significance of complying with rules or regulations*. This theory has implications for all rule, regulatory, and standards development throughout human service and economic domains although the research is being drawn from the human services field. The TRC has developed over the past 40 years. It has particular significance now as the need for either more or less oversight has become politically charged. What is important about the TRC is its emphasis on selecting the right rules rather than having more or less rules and the nature of these rules as being significantly predictive of positive outcomes by being in compliance with said rules.

The Theory of Regulatory Compliance was first proposed in the 1970's when the relationship between compliance with rules was compared to compliance with best practice standards and outcome data. From this comparison, it became clear that as facilities were in 100% compliance with all rules, there overall best practice scores and positive outcomes began to drop off. It was also found that there was a "*sweet spot" at a substantial compliance level* where best practice scores and positive outcomes were at their highest levels. In statistical terms, the relationship *was curvilinear rather than linea*r. This initial result has been confirmed many times over the past 40 years in different forms of human service facilities. This result also led to the conclusion that possibly being in *"full" or 100% compliance with all rules* was not necessarily a good policy and that *all rules or regulations are not created equal.*

This led to the development of two methodologies dealing *with risk assessment and key indicators of regulatory compliance*. In both of these methodologies, the focus is on identifying a more targeted group of rules that either statistically predict overall regulatory compliance or reduce risk.

But what is the underlying reason for the TRC. It appears from data collected in various regulatory systems that the nature of the rules themselves may be the real problem. When rules are too minimal to comply with, it is *far more difficult to discriminate between the really good facilities and the mediocre facilities*. This unfortunately is the nature of regulatory data, it is dramatically *skewed data* with the majority of facilities being in compliance with all the rules.

The solution to the above dilemma is not to de-regulate or to over-regulate but to come up with the *"right" balance* of rules or regulations. We do not want to make the mistake of the old proverbial "throwing out the baby with the bathwater". We need to have some form of oversight but it needs to be the right balance of oversight based upon risk and predictive targeting of specific rules or regulations. The statistical methodologies exist to identify these specific risk and predictive rules and regulations.

1. For additional information regarding TRC, please go to the following website: http://RIKInstitute.com/RIKI.

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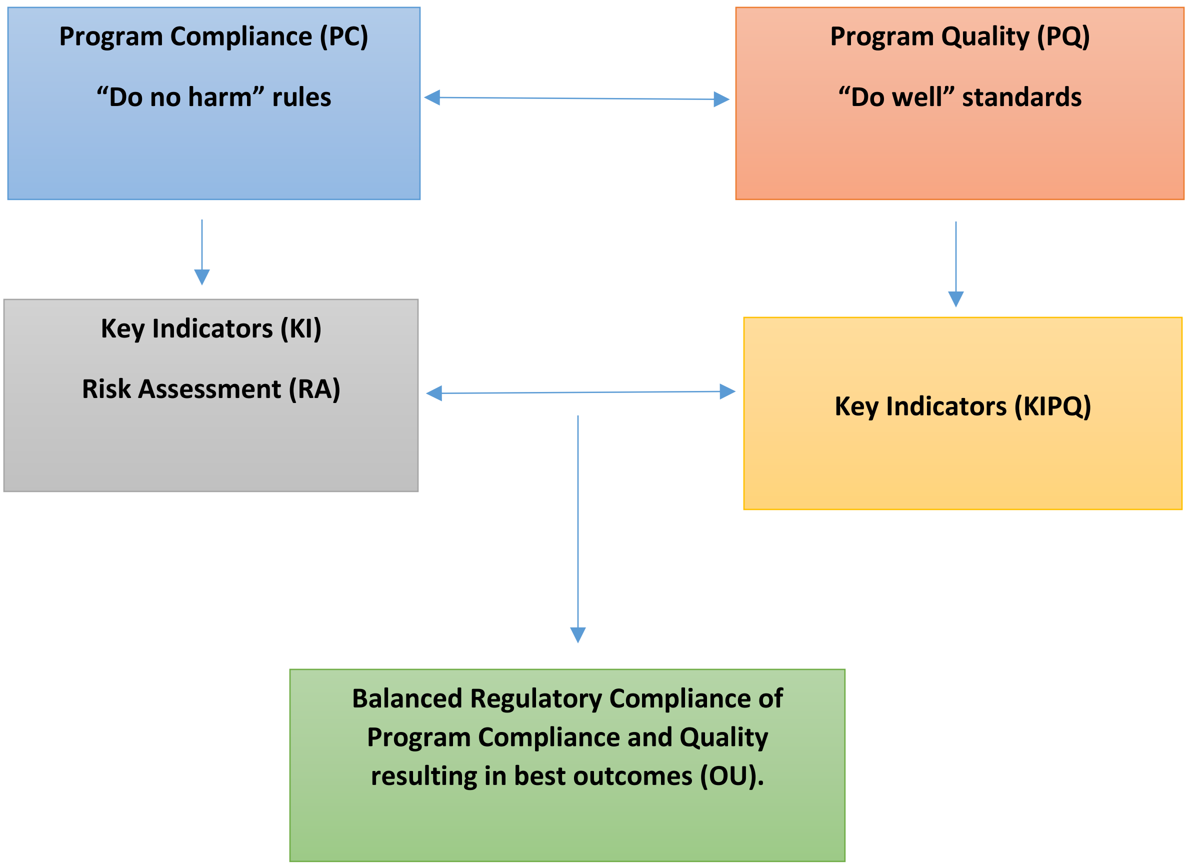
Theory of Regulatory Compliance Algorithm (Fiene, 11/16)



Balance of "do no harm" rules with "best practice" standards selected by risk and ability to predict positive outcomes. The Theory of Regulatory Compliance deals with selecting the "right" rules and standards that have predictive validity and do no harm. It acknowledges that all rules and standards are not created equal and have a differential impact in a monitoring or licensing system. By following a differential monitoring approach of key indicators and risk assessment, the most cost efficient and effective system can be implemented. The Theory of Regulatory Compliance proposes policy based upon substantial but not full compliance (100%) with all rules. The following algorithm summarizes TRC:

(PC < 100) + (PQ = 100) → KI (10-20% PC) + RA (10-20% PC) + KIQP (5-10% of PQ) → OU

Theory of Regulatory Compliance Math Modeling (Fiene, 11/16)

This presentation will provide key definitions, a legend and math modeling concepts related to the Theory of Regulatory Compliance. It builds upon the previous two presentations on an overview and algorithm for the Theory of Regulatory Compliance (TRC).

Legend/Definitions:
R = Rules/Regulations
C = Compliance with rules/regulations
NC = Non-Compliance with rules/regulations
KI = Key Indicators of substantial (99%) compliance with all rules/regulations
CI = Comprehensive Instrument measuring compliance with all rules/regulations
RA = Risk Assessment measuring the relative risk of non-compliance with specific rules/regulations
DM = Differential Monitoring using Key Indicators and/or Risk Assessment

Math Modeling:
ΣR = C
Summation of all rules equals compliance score.

KI > 0 = CI
If KI greater than zero, use comprehensive instrument for measuring compliance with all rules/regulations.

RA (NC%) = CI
If RA has a pre-determined % on non-compliance, use comprehensive instrument for measuring compliance with all rules/regulations.

KI + RA = DM
Key indicators plus Risk Assessment equals a Differential Monitoring Approach.

TRC = 99% + ϕ = 100%
Theory of Regulatory Compliance equals substantial compliance but not full compliance.

NC + C = CI
Non-Compliance plus Compliance with all rules/regulations equals the score on the comprehensive instrument.

(CI < 100) + (CIPQ = 100) --> KI (10-20% CI) + RA (10-20% CI) + KIQP (5-10% of CIPQ) --> OU
Where CI < 100 is substantial compliance with all rules or the 99% rule, CIPQ = 100 maximizing doing well, KI (10-20% CI) is key indicators are generally 10-20% of all rules as well as risk assessment (RA (10-20% CI)), KIQP (5-10% of CIPQ) is the percent of standards taken from program quality that become key indicators of quality, and finally OU are positive outcomes or results.

Theory of Regulatory Compliance Monitoring Paradigms

Richard Fiene

December 2016

This paper provides some key elements to the two dominating paradigms (Relative versus Absolute) for regulatory compliance monitoring based upon the Theory of Regulatory Compliance. See the table below for the key elements summarized for the Monitoring Paradigms followed by a more detailed description of each key element. These key elements are all inter-related and at times are not mutually exclusive.

Regulatory Compliance Monitoring Paradigms

Relative <---> Absolute

Substantial <---> Monolithic
Differential Monitoring <--> One size fits all monitoring
Not all standards are created equal <---------------------------------> All standards are created equal
Do things well <--> Do no harm
Strength based <---> Deficit based
Formative <---> Summative
Program Quality <---> Program Compliance
100-0 scoring <--> 100 or 0 scoring
QRIS <---> Licensing
Non Linear <---> Linear

Relative versus Absolute Regulatory Compliance Paradigm: this is an important key element in how standards/rules/regulations are viewed when it comes to compliance. For example, in an absolute approach to regulatory compliance either a standard/rule/regulation is in full compliance or not in full compliance. There is no middle ground. It is black or white, no shades of gray. It is 100% or zero. In defining and viewing these two paradigms, this dichotomy is the organizational key element for this paper.

Substantial versus Monolithic: in monolithic regulatory compliance monitoring systems, it is one size fits all, everyone gets the same type of review (this is addressed in the next key element below) and is more typical of an absolute paradigm orientation. In a substantial regulatory compliance monitoring system, programs are monitored on the basis of their past compliance history and this is more typical of a relative paradigm orientation. Those with high compliance have fewer and more abbreviated visits/reviews while those with low compliance have more comprehensive visits/reviews.

Differential Monitoring versus One Size Fits All Monitoring: in differential monitoring (Relative Paradigm), more targeted or focused visits are utilized spending more time and resources with those problem programs and less time and resources with those programs that are exceptional. In the One Size Fits All Monitoring (Absolute Paradigm), all programs get the same type/level of review/visit regardless of past performance.

Not all standards are created equal versus All standards are created equal: when looking at standards/rules/regulations it is clear that certain ones have more of an impact on outcomes than others. For example, not having a form signed versus having proper supervision of clients demonstrates this difference. It could be argued that supervision is much more important to the health and safety of clients than if a form isn't signed by a loved one. In a relative paradigm, all standards are not created nor administered equally; while in an absolute paradigm of regulatory compliance, the standards are considered created equally and administered equally.

"Do things well" versus "Do no harm": "doing things well" (Relative Paradigm) focuses on quality of services rather than "doing no harm" (Absolute Paradigm) which focuses on health and safety. Both are important in any regulatory compliance monitoring system but a balance between the two needs to be found. Erring on one side of the equation or the other is not in the best interest of client outcomes. "Doing no harm" focus is on the "least common denominator" – the design and implementation of a monitoring system from the perspective of focusing on only 5% of the non-optimal programs ("doing no harm") rather than the 95% of the programs that are "doing things well".

Strength based versus Deficit based: in a strength based monitoring system, one looks at the glass as "half full" rather than as "half empty" (deficit based monitoring system). Emphasis is on what the programs are doing correctly rather than their non-compliance with standards. A strength based system is non-punitive and is not interested in catching programs not doing well. It is about exemplars, about excellent models where everyone is brought up to a new higher level of quality care.

Formative versus Summative: relative regulatory compliance monitoring systems are formative in nature where there is an emphasis on constant quality improvement and getting better. In absolute regulatory compliance monitoring systems, the emphasis is on being the gate-keeper and making sure that decisions can be made to either grant or deny a license to operate. It is about keeping non-optimal programs from operating.

Program Quality versus Program Compliance: relative regulatory compliance monitoring systems focus is on program quality and quality improvement while in absolute regulatory compliance monitoring systems the focus in on program compliance with rules/regulations with the emphasis on full, 100% compliance.

100 – 0 scoring versus 100 or 0 scoring: in a relative regulatory compliance monitoring system, a 100 through zero (0) scoring can be used where there are gradients in the scoring, such as partial compliance scores. In an absolute regulatory compliance monitoring system, a 100% or zero (0) scoring is used demonstrating that either the standard/rule/regulation is fully complied with or not complied with at all.

QRIS versus Licensing: examples of a relative regulatory compliance monitoring system would be QRIS – Quality Rating and Improvement Systems. Absolute regulatory compliance systems would be state licensing systems.   Many programs talk about the punitive aspects of the present human services licensing and monitoring system and its lack of focus on the program quality aspects in local programs. One should not be surprised by this because in any regulatory compliance system the focus is on "doing no harm" rather than "doing things well". It has been and continues to be the focus of licensing and regulations in the USA. The reason QRIS - Quality Rating and Improvement Systems developed in early care and education was to focus more on "doing things well" rather than "doing no harm".

Non-Linear versus Linear: the assumption in both relative and absolute regulatory compliance monitoring systems is that the data are linear in nature which means that as compliance with standards/rules/regulations increases, positive outcomes for clients increases as well. The problem is the empirical data does not support this conclusion. It appears from the data that the relationship is more non-linear where there is a plateau effect with regulatory compliance in which client outcomes increase until substantial compliance is reached but doesn't continue to increase beyond this level. There appears to be a "sweet spot" or balancing of key standards/rules/regulations that predict client outcomes more effectively than 100% or full compliance with all standards/rules/regulations – this is the essence of the Theory of Regulatory Compliance – substantial compliance with all standards or full compliance with a select group of standards that predict overall substantial compliance and/or positive client outcomes.

As the regulatory administration field continues to think about the appropriate monitoring systems to be designed and implemented, the above structure should help in thinking through what these systems' key elements should be. Both paradigms are important, in particular contexts, but a proper balance between the two is probably the best approach in designing regulatory compliance monitoring systems.

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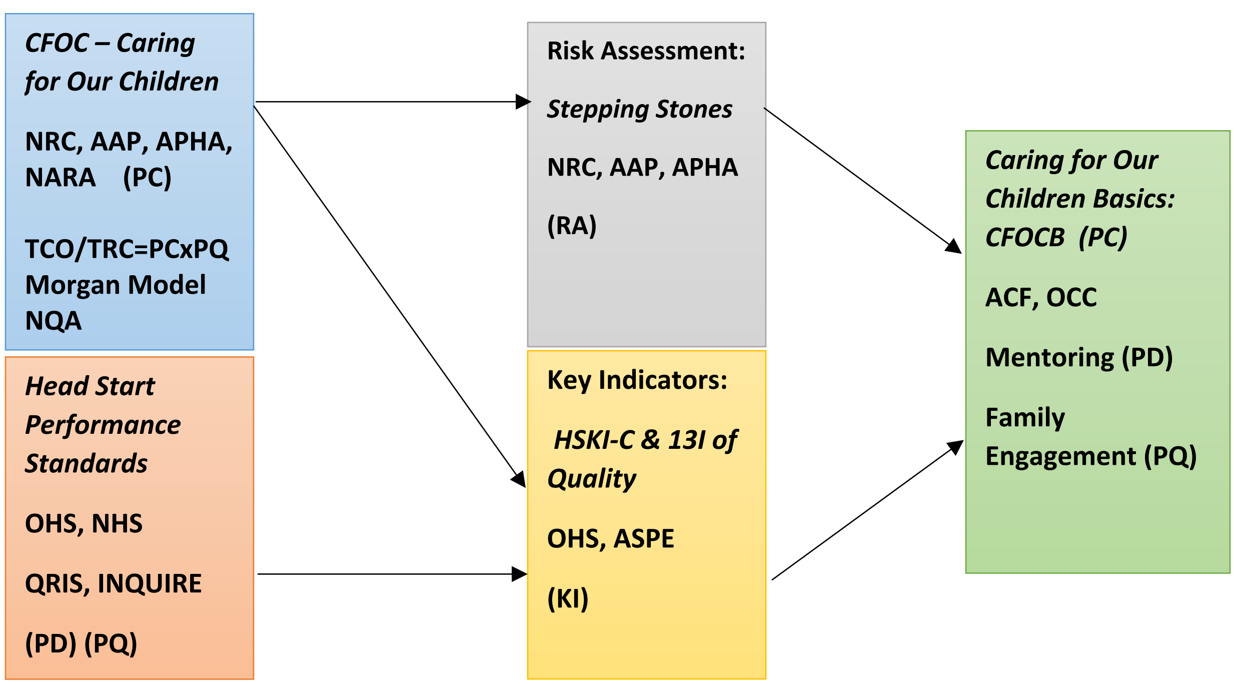
EARLY CHILDHOOD PROGRAM QUALITY IMPROVEMENT/INDICATOR MODEL (ECPQI2M4©) & DIFFERENTIAL MONITORING LOGIC MODEL AND ALGORITHM (DMLMA©) Update (Fiene, 12/12/15)

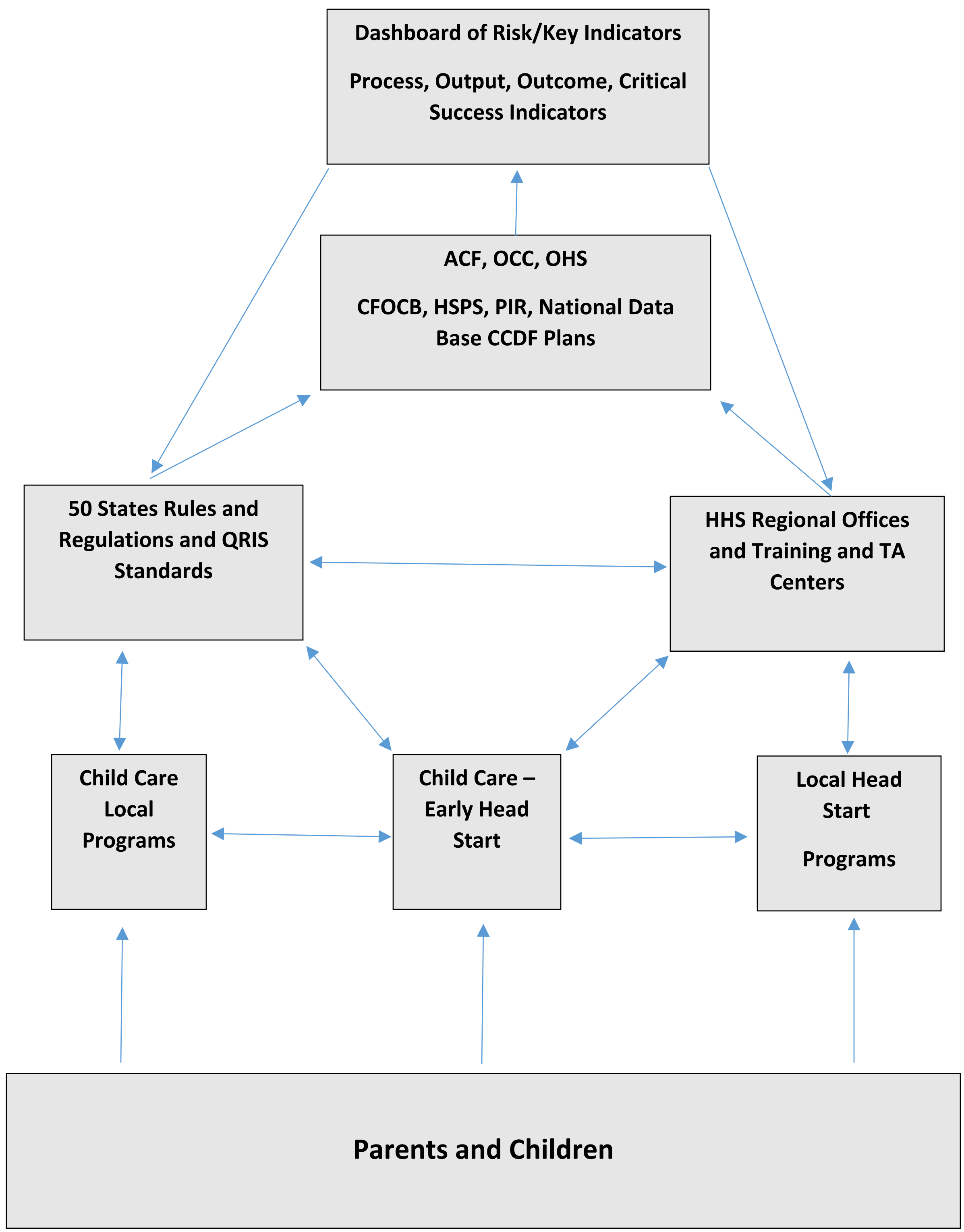
<u>Legend:</u>
NRC = National Resource Center for Health and Safety in Child Care
AAP = American Academy of Pediatrics
APHA = American Public Health Association
OHS = Office of Head Start
ACF = Administration for Children and Families
OCC = Office of Child Care
ASPE = Assistant Secretary's Office for Planning and Evaluation
13I = *Thirteen Indicators of Quality Child Care*, ASPE
HSKI-C = Head Start Key Indicators
Stepping Stones = Stepping Stones to Caring for Our Children, NRC, AAP, APHA
PD = Professional Development, Training, Technical Assistance, Mentoring
PQ = Quality Rating and Improvement Systems (QRIS), Quality Improvements
TCO/TRC = Theory of Regulatory Compliance/Outcomes

Comprehensive Reviews **Abbreviated Reviews** **Differential Monitoring**

Absolute Paradigm ***Relative Paradigm***



National Differential Monitoring Conceptual Framework (Fiene, 2016)



National Differential Monitoring Conceptual Framework Brief Explanation:

The key elements for this conceptual framework is the emphasis on data utilization via key indicators and risk assessment which results in targeted/differential monitoring of programs via a state, regional, and national data base. Data would be collected at the local level in programs (child care (centers, homes, group homes); Head Start programs;child care/early Head Start programs, etc...) and would be monitored at the state and regional levels. The data via monitoring reports, CCDF plans, etc.. would move from the state and regional levels to the national level at ACF to form a national data base. From the national data base, a series of key indicator, risk assessment, process, output, outcome and critical success indicators would be culled (dashboard) from the full comprehensive data base to determine the levels of future reviews and monitoring of states and programs.

These indicators would be fed back to the regional offices and states with states being able to do the same with their respective licensing systems in reviews of local programs. The data from the comprehensive data base would also be fed back to the states, regional offices and the training & technical assistance offices to focus specific training and technical assistance based upon the results of the monitoring reviews. Within this conceptual framework, it is proposed to use a professional development passport within state professional development systems/registries which has badges attached for ongoing training & technical assistance for individual ECE staff. This professional development passport could provide the basis of a document (it would contain all the training received by the individual via a stamp/badge articulation documentation process) that would be transferable from state to state similar to how a regular passport is used as identification in moving from country to country. This could potentially become a national credentialing/licensing system for ECE staff.

This conceptual framework would take into account the collecting and analyzing of data and its subsequent utilization for training & technical assistance. All the components/key elements for such a system have been set up by ACF, now what we need to do is put all the pieces together into a unified monitoring system.

Theory of Regulatory Compliance Algorithm (2/17)

1) ΣR = C
2) Review C history x 3 yrs
3) NC + C = CI
4) If CI = 100 -> KI
5) If KI > 0 -> CI or if C < 100 -> CI
6) If RA (NC% > 0) -> CI
7) KI + RA = DM
8) KI = ((A)(D)) - ((B)(E)) / sqrt ((W)(X)(Y)(Z))
9) RA = ΣR1 + ΣR2 + ΣR3 + ….. ΣRn / N
10) (TRC = 99%) + (ϕ = 100%)
11) (CI < 100) + (CIPQ = 100) -> KI (10% CI) + RA (10-20% CI) + KIQP (5-10% of CIPQ) -> OU

Legend:

R = Rules/Regulations/Standards
C = Compliance with Rules/Regulations/Standards
NC = Non-Compliance with Rules/Regulations/Standards
CI = Comprehensive Instrument for determining Compliance
ϕ = Null
KI = Key Indicators
KI >= .26+ Include
KI <= .25 Null, do not include
RA = Risk Assessment
ΣR1 = Specific Rule on Likert Risk Assessment Scale (1-8; 1 = low risk, 8 = high risk)
N = Number of Stakeholders
DM = Differential Monitoring
TRC = Theory of Regulatory Compliance
CIPQ = Comprehensive Instrument Program Quality
KIPQ = Key Indicators Program Quality
OU = Outcomes
A = High Group + Programs in Compliance on Specific Compliance Measure (R1...Rn).
B = High Group + Programs out of Compliance on Specific Compliance Measure (R1...Rn).
E= Low Group + Programs in Compliance on Specific Compliance Measure (R1...Rn).
D = Low Group + Programs out of Compliance on Specific Compliance Measure (R1...Rn).
W = Total Number of Programs in Compliance on Specific Compliance Measure (R1...Rn).
X = Total Number of Programs out of Compliance on Specific Compliance Measure (R1...Rn).
Y = Total Number of Programs in High Group (ΣR = 98+).
Z = Total Number of Programs in Low Group (ΣR <= 97).
High Group = Top 25% of Programs in Compliance with all Compliance Measures (ΣR).
Low Group = Bottom 25% of Programs in Compliance with all Compliance Measures (ΣR).

Regulatory Compliance Matrices

2 x 2 Matrix (In vs Out of compliance x High vs Low Groups):

A	**B**
C	**D**

(A = In compliance + High Group)(B = In compliance + Low Group)(C = Out of Compliance + High Group)(D = Out of Compliance + Low Group); **B** = false positives; **C = false negatives;** A + D > B + C; B > C; **A + D = + results**.

2 x 3 Matrix (In vs Out of compliance x 100% vs Substantial vs Low Compliance Groups):

A	**B**	**C**
D	**E**	**F**

(A = In compliance + 100% Group)(B = In compliance + Substantial Compliance Group)(C = In compliance + Low Group)(D = Out of compliance + 100% Group)(E = Out of compliance + Substantial Compliance Group)(F = Out of compliance + Low Group); **C** = false positives; **D, E = false negatives;** B > A > C; **B + F = + results.**

3 x 2 Matrix (In vs Partial vs Out of compliance x High vs Low Groups):

A	**B**
C	**D**
E	**F**

(A = In compliance + High Group)(B = In compliance + Low Group)(C = Partial compliance + High Group)(D = Partial compliance + Low Group)(E = Out of compliance + High Group)(F = Out of compliance + Low Group); **B** = false positives; **E = false negatives;** A > C > B > D; **A + F = +results.**

3 x 3 Matix (In vs Partial vs Out of compliance x 100% vs Substantial vs Low Compliance Groups):

A	**B**	**C**
D	**E**	**F**
G	**H**	**I**

(A = In compliance + 100% Group)(B = In compliance + Substantial Compliance Group)(C = In compliance + Low Group)(D = Partial compliance + 100% Group)(E = Partial compliance + Substantial Compliance Group)(F = Partial compliance + Low Group)(G = Out of compliance + 100% Group)(H = Out of compliance + Substantial Compliance Group)(I = Out of compliance + Low Group); **C** = false positives; **G, H = false negatives**; B > A > D > E > C > F; **B + D + I = + results.**

Theory of Regulatory Compliance and Regulatory Compliance Monitoring Paradigm Matrix Notes (Fiene, 2-12-17)

Outline:

- 2x2 absolute vs 3x3+ relative matrices.
- 2x2 In or Out x 100% or 0%.
- 3x3 100%, Substantial, Low x In, Partial, Out.
- TRC proposes 3x2 = 100%, Substantial, Low x In, Out.
- KI 2x2 or 3x2; RA 3x3 matrices.
- Normally distributed curve 3x3+ vs Skewed data 2x2 - visualize a normally distributed curve over the cells vs a very skewed curve over the 2 cells.
- ERS as 7x7 potential matrix.
- Use these matrices to explain RCMP and potential data analyses.
- Better analytical techniques for analyzing these matrices.
- Problem with 2x2 are the false negatives.
- Does a 3x3+ reduce the false negatives. Key question.
- What I have found over my 40+years is that I have as many questions as I have answers at this point, not sure that 2x2 or 3x2 are best matrices. What happens if we expand to a 7x7 matrix.
- Phi to Chi-square as the preferred statistic?
- Would Matrix Algebra be more appropriate.
- First time tying KI and RA together via 2x2 and 3x3 matrices. Common analytical framework.

Research Questions:

What are the differences between a 2x2 vs 2x3 vs 3x3 matrices? This will account for absolute, relative and substantial compliance ranges.

What is the impact of having 2x2, 2x3, and 3x3 on false negatives?

What are the results with 100% vs 99-98% and low compliance groups?

What are the differences between samples and full data sets?

Relationship between PC and PQ? Linear or non-linear

Matrices:

A	**B**
C	D

2 x 2 = I/O x H/L (I = In compliance)(O = Out of compliance)(H = High Group)(L = Low Group)
A + D = positive+ results, to be expected
B = false positives
C = false negatives
A + D > B + C
B > C
Class ARC Matrix

A	**B**	**C**
D	E	F

3 x 2 = H/S/L x I/O (S = Substantial Compliance) or 3 x 3 with I/P/O where P = Partial.
A = 100% compliance
B = Substantial compliance
C = Low compliance
C = false positives
D = false negatives
B > A > C
B + F = + results, to be expected
Fiene TRC Matrix

A	**B**	**C**
D	**E**	**F**
G	**H**	**I**

3 X 3+ = H/M/L x H/M/L
A = Low probability + low risk
E= Medium probability + medium risk
I= High probability + high risk
A > B > C > D > E > F > G > H > I
Fiene RA Matrix

Classification Matrix & Sensitivity Analysis for Validating Licensing Key indicator Systems
Technical Research Note (Fiene, 2017)

	1	*2*	*3*	*5*	*7*	*8*	*10*	*Comments*
A	1.00	1.00	1.00	0.00	0.00	1.00	1.00	Perfect
B	0.52	0.52	0.52	0.48	0.48	0.52	0.04	Random
C	0.71	0.96	0.94	0.04	0.29	0.84	0.70	False (-)
D	0.94	0.78	0.71	0.22	0.06	0.81	0.70	False (+)
E	------	0.00	0.00	1.00	------	0.00	------	False +100%
F	0.00	0.00	0.00	1.00	1.00	0.00	-1.00	False+-100
H	0.45	0.46	0.40	0.54	0.55	0.46	-0.08	Random

Measures:
1 = Sensitivity *TPR = TP / (TP + FN)*
2 = Specificity *SPC = TN / (FP + TN)*
3 = Precision *PPV = TP / (TP + FP)*
5 = False Positive *FPR = FP / (FP + TN)*
7 = False Negative *FNR = FN / (FN + TP)*
8 = Accuracy *ACC = (TP +TN) (P + N)*
10 = Correlation *((TP)(TN)) - ((FP)(FN)) / SQRT((TP + FP)(TP + FN)(TN + FP)(TN + FN))*

PP = Predicted Positive = CI+
PN = Predicted Negaive = CI-
TP= True Positive = KI+
TN = True Negative =KI-

	TRUE POSITIVE (TP)(KI+)	*TRUE NEGATIVE (TN)(KI-)*
PREDICTED POSITIVE (PP)(CI+)	++	+-
PREDICTED NEGATIVE (PN)(CI-)	-+	--

CI+/CI-/KI+/KI-
A = 25/0/0/25 – Perfect match between CI and KI.
B = 13/12/12/13 – Random matching between CI and KI.
C = 17/7/1/25 – KI+ x CI- (False-)
D = 17/1/7/25 – KI- x CI+ (False+)
E = 0/0/50/0 – KI- x CI+ unlikely
F = 0/25/25/0 - False + & - 100% unlikely
H = 20/24/30/26 – Random matching between CI and KI.

Technical Detail Notes: Validation Updates to the Fiene Key Indicator Systems

January 2015

These notes will provide guidance on validating existing Key Indicator Licensing Systems. These notes are based upon the last three years of research and data analysis in determining the best means for conducting these validation studies.

These notes are based upon existing Key Indicator Systems in which data can be drawn from an already present data base which contains the comprehensive instrument (total compliance data) and the key indicator instrument (key indicator rule data). When this is in place and it can be determined how licensing decisions are made: full compliance with all rules or substantial compliance with all rules to receive a license, then the following matrix can be used to begin the analyses (see Figure 1):

Figure 1	***Providers who fail the Key Indicator review***	***Providers who pass the Key Indicator review***	***Row Totals***
Providers who fail the Comprehensive review	***W***	***X***	
Providers who pass the Comprehensive Review	**Y**	**Z**	
Column Totals			***Grand Total***

A couple of annotations regarding Figure 1.

W + Z = the number of agreements in which the provider passed the Key Indicator review and also passed the Comprehensive review.

X = the number of providers who passed the Key Indicator review but failed the Comprehensive review. This is something that should not happen, but there is always the possibility this could occur because the Key Indicator Methodology is based on statistical methods and probabilities. We will call these False Negatives (FN).

Y = the number of providers who failed the Key Indicator review but passed the Comprehensive review. Again, this can happen but is not as much of a concern as with "**X**". We will call these False Positives (FP).

Figure 2 provides an example with actual data from a national organization that utilizes a Key Indicator System. It is taken from 50 of its program providers.

Figure 2	***Providers who fail the Key Indicator review***	***Providers who pass the Key Indicator review***	***Row Total***
Providers who fail the Comprehensive review	***25***	***1***	***26***
Providers who pass the Comprehensive Review	**7**	**17**	***24***
Column Total	***32***	***18***	***50***

To determine the agreement ratio, we use the following formula:

$$\frac{A}{A + D}$$

Where A = Agreements and D = Disagreements.

Based upon Figure 2, A + D = 42 which is the number of agreements; while the number of disagreements is represented by B = 1 and C = 7 for a total of 8 disagreements. Putting the numbers into the above formula:

$$\frac{42}{42 + 8}$$

Or

.84 = Agreement Ratio

The False Positives (FP) ratio is .14 and the False Negatives (FN) ratio is .02. Once we have all the ratios we can use the ranges in Figure 3 to determine if we can validate the Key Indicator System. The FP ratio is not used in Figure 3 but is part of the Agreement Ratio.

Figure 3 – Thresholds for Validating the Fiene Key Indicators for Licensing Rules

Agreement Ratio Range	False Negative Range	Decision
(1.00) – (.90)	.05+	Validated
(.89) – (.85)	.10 - .06	Borderline
(.84) – (.00)	.11 or more	Not Validated

RESOURCES AND NOTES

For those readers who are interested in finding out more about the Key Indicator Methodology and the more recent technical updates as applied in this paper in actual state examples, please see the following publication:

Fiene (2014). *ECPQIM4©: Early Childhood Program Quality Indicator Model4*, Middletown: PA; Research Institute for Key Indicators LLC (RIKI). (http://drfiene.wordpress.com/riki-reports-dmlma-ecpqim4/)

In this book of readings/presentations are examples and information about differential monitoring, risk assessment, key indicators, validation, measurement, statistical dichotomization of data, and regulatory paradigms. This publication delineates the research projects, studies, presentations, & reports completed during 2013-14 in which these updates are drawn from.

For those readers interested in a historical perspective to the development of the Key Indicator methodology and licensing measurement, please see the following publications (most of these publications are available at the following website (http://rikinstitute.wikispaces.com/home):

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RIKI LLC

KEY INDICATOR TECHNICAL NOTES (12-8-15) RJF (this note updates a previous technical note from earlier in 2015 regarding this same topic):

Each state/jurisdication will be different when applying the Key Indicator Methodology but there are some guiding principles that should be used:

1) Sample size should be around 100-200 programs. Less than 100 may not produce significant results and indicators will be missed. Over 200 programs will provide too many indicators reaching significance.

2) Set the p value to .01 ($p < .01$). $P < .05$ is too lenient and $p < .001$ is too stringent. $P < .01$ gives a proper balance for the number of indicators a state/jurisdiction will need.

3) The best model to use is the 100% for the high group (100-99% can also be used) with the middle programs not being used and the bottom 25% being used for the low group. The worse model to use is 100% as the high group and 99% or less as the low group. Too much error variance in the programs is introduced with an increase in making false negatives and the phi and Pearson correlations drop off significantly.

4) Select a moderate number of key indicators, don't select too few. It is more reliable to go with a few additional indicators than using too few.

5) Minimize false negatives by using the model described in #3 above.

Validation of the Key Indicator Methodology: Two Examples

Richard Fiene, Ph.D.

June 2015

Introduction

The purpose of this paper is to address the validation of the key indicator methodology as suggested in the *ASPE White Paper on ECE Monitoring* (2015). It was so accurately pointed out in this *White Paper* regarding the need to continue to access and validate differential monitoring which generally consists of the key indicator and risk assessment methods.

Over the past 35 years various aspects of differential monitoring have been assessed and validated. For example, studies by Kontos and Fiene (1987) and Fiene (2000) demonstrated the relationship between key indicators and child development outcomes. In 2002, another *ASPE White Paper on the Thirteen Indicators of Quality Child Care: A Research Update* summarized the research over the previous 20 years in demonstrating a core set of key indicator risk assessment standards. More recently, a study completed in Georgia (Fiene, 2014) validated the use of core rules in a risk assessment and differential monitoring approach. And in 2012, a study was done in California which demonstrated the time savings in using a key indicator approach. And finally, in 2013-14, a study was done in the national Head Start program in which their key indicator approach (Head Start Key Indicators (HSKI)) validated the decision making ability of key indicators in which an 84% - 91% agreement was found between the HSKI and Full Compliance Reviews. The focus of this paper will be on the latest findings from Head Start since these findings have not been published to date.

The National Child Care Licensing Study (2011) and the National Center for Child Care Quality Improvement (2014) have reported the significant use of differential monitoring, key indicators and risk assessment methods by many states throughout the country. And with the reauthorization of CCDBG (2014) and the increased emphasis on ECE program monitoring there is an increased need to validate these approaches. This paper is the beginning attempt to begin this process focusing on the key indicator method.

Methodology

This validation method is based upon existing Key Indicator Systems in which data can be drawn from an already present data base which contains the comprehensive instrument (total compliance data) and the key indicator instrument (key indicator rule data). When this is in place and it can be determined how licensing decisions are made: full compliance with all rules or substantial compliance with all rules to receive a license, then the following matrix can be used to begin the analyses (see Figure 1):

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Or

.84 = Agreement Ratio

The False Positives (FP) ratio is .14 and the False Negatives (FN) ratio is .02. Once we have all the ratios we can use the ranges in Figure 3 to determine if we can validate the Key Indicator System. The FP ratio is not used in Figure 3 but is part of the Agreement Ratio.

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Agreement Ratio Range	**False Negative Range**	**Decision**
(1.00) – (.90)	**.05+**	**Validated**
(.89) – (.85)	**.10 - .06**	**Borderline**
(.84) – (.00)	**.11 or more**	**Not Validated**

Results

The following results are from a study completed in 2014 using Head Start data where HSKI reviews were compared with comprehensive reviews to make certain that additional non-compliance was not found when HSKI tools were administered to programs.

There was an 84% - 91% (see Table 1) agreement between the HSKI and Comprehensive Reviews which would indicate that the HSKI method was validated in Head Start based upon Figure 3 above in the Methodology section.

FY 2015 HSKI Agreement Table 1

FY 2015 HSKI Agreement Tables with Combined OHSMS Data from FYs 2012, 2013, and 2014

	% agreement	**Sensitivity**
FIS	91%	63%
GOV/SYS	84%	63%
SR	87%	52%

Fiscal (5)

- FIS1.1 - Effective financial management systems (D, I, T)
- FIS2.1 - Timely and complete financial records (D)
- FIS4.1 - Signed and approved time records (T)
- FIS5.3 - NFS contributions are necessary and reasonable (D)
- FIS6.2 - Complete and accurate equipment records (D, T)

SR (9)

- CDE1.2 - System to track, use, and report on SR goals (I)
- CDE2.1 - Evidenced-based curriculum (I)
- CDE3.1 – Individualizing (I)
- CDE3.4 - Child access to mental health services (I)
- CDE4.1 - Teacher qualifications (S)
- CHS1.5 - Health services tracking system (I)
- CHS2.2 - Referrals for children with disabilities to LEA or Part C Agency
- FCE2.3 - Access to mental health services (I)
- FCE5.3 - Coordination with LEAs and Part C Agencies

GOV/SYS (9)

- GOV2.1 - Training and Technical Assistance for GB and PC (I)
- GOV2.2 - GB responsibilities regarding program administration and operations (I)
- GOV3.1 - Reporting to GB and PC (I)
- GOV2.4 - PC submits program activity decisions to GB (I)
- SYS1.2 - Annual Self-Assessment (I)

- SYS4.1 - Communication mechanisms (I)
- SYS5.2 - Publication and availability of an Annual Report (I)
- SYS2.1 - Ongoing Monitoring (I)
- SYS5.1 - Record–keeping (I)

I = Interview
D = Document Review
T = Transaction Review
S = Staff files

Discussion

This paper presents a validation methodology to validate the differential monitoring approach that utilizes key indicators. This is an area that needs additional research as many more states began to think about employing the various approaches for differential monitoring involving risk assessment and key indicators.

The results from this paper are very encouraging in that they clearly demonstrate that a very large delivery system, the national Head Start program, can utilize key indicators (HSKI – Head Start Key Indicators) for a differential monitoring approach (Aligned Monitoring System).

For additional information regarding this paper:

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Appendix

A more recent validation study has been completed in the Province of Ontario, Canada where they compared three sets of Key Indicators over three calendar years in a similar fashion to the Head Start study reported above. Below are the results of these analyses.

Validation Summary

Year	Key Indicators	Agreement Ratio
2014	29 Indicators	0.90
	35 Indicators	0.92
	41 Indicators	0.94
2013	29 Indicators	0.90
	35 Indicators	0.92
	41 Indicators	0.93
2012	29 Indicators	0.91
	35 Indicators	0.93
	41 Indicators	0.94

Note. The key indicators are validated when the agreement ratio is 0.90 or above.

Technical Detail Updates to the Fiene Key Indicator Methodology

January 2015

The Key Indicator Methodology has recently been highlighted in a very significant Federal Office of Child Care publication series on Contemporary Licensing Highlights. In that Brief the Key Indicator Methodology is described as part of a differential monitoring approach along with the risk assessment methodology. Because of the potential increased interest in the Key Indicator Methodology, a brief update regarding the technical details of the methodology is warranted. For those readers who are interested in the historical development of Key Indicators I would suggest they download the resources available at the end of the paper.

This brief paper provides the technical and statistical updates for the key indicator methodology based upon the latest research in the field related to licensing and quality rating & improvement systems (QRIS). The examples will be drawn from the licensing research but all the reader needs to do is substitute “rule” for “standard” and the methodology holds for QRIS.

Before proceeding with the technical updates, let me review the purpose and conceptual underpinning of the Key Indicator Methodology. Key Indicators generated from the methodology are not the rules that have the highest levels of non-compliance nor are they the rules that place children most at risk of mortality or morbidity. Key Indicators are generally somewhere in the middle of the pack when it comes to non-compliance and risk assessment. The other important conceptual difference between Key Indicators and risk assessment is that only Key Indicators statistically predict or are predictor rules of overall compliance with all the rules for a particular service type. Risk assessment rules do not predict anything other than a group of experts has rated these rules as high risk for children’s mortality/morbidity if not complied with.

Something that both Key Indicators and risk assessment have in common is through their use one will save time in their monitoring reviews because you will be looking at substantially fewer rules. But it is only with Key Indicators that you can statistically predict additional compliance or non-compliance; this is not the case with risk assessment in which one is only looking at those rules which are a state’s high risk rules. And this is where differential monitoring comes into play by determining which programs are entitled to either Key Indicators and/or risk assessment for more abbreviated monitoring reviews rather than full licensing reviews (the interested reader should see the *Contemporary Licensing Series on Differential Monitoring, Risk Assessment and Key Indicators* published by the Office of Child Care.

Technical and Statistical Framework

One of the first steps in the Key Indicator Methodology is to sort the licensing data into high and low groups, generally the highest and lowest licensing compliance with all the rules can be used for this sorting. Frequency data will be obtained on those programs in the top level (usually top 20-25%) and the bottom level (usually the bottom 20-25%). The middle levels are not used for the purposes of these analyses. These two groups (top level & the bottom level) are then compared to how each program scored on each child care rule (see Figure 1). In some cases, especially where there is very high compliance with the rules and the data are extremely skewed, it may be necessary to use all those programs that are in full (100%) compliance with all the rules as the high group. The next step is to look at each rule and determine if it is in compliance or out of compliance with the rule. This result is cross-referenced with the High Group and the Low Group as depicted in Figure 1.

Figure 1	***Providers In Compliance on Rule***	***Programs Out Of Compliance on Rule***	***Row Total***
Highest level (top 20-25%)	***A***	***B***	***Y***
Lowest level (bottom 20-25%)	**C**	**D**	***Z***
Column Total	***W***	***X***	***Grand Total***

Once the data are sorted in the above matrix, the following formula (Figure 2) is used to determine if the rule is a key indicator or not by calculating its respective Key Indicator coefficient. Please refer back to Figure 1 for the actual placement within the cells. The legend (Figure 3) below the formula shows how the cells are defined.

Figure 2 – Formula for Fiene Key Indicator Coefficient

$$\phi = (A)(D)-(B)(C) \div \sqrt{(W)(X)(Y)(Z)}$$

Figure 3 – Legend for the Cells within the Fiene Key Indicator Coefficient

A = High Group + Programs in Compliance on Specific Rule.
B = High Group + Programs out of Compliance on Specific Rule.
C = Low Group + Programs in Compliance on Specific Rule.
D = Low Group + Programs out of Compliance on Specific Rule.

W = Total Number of Programs in Compliance on Specific Rule.
X = Total Number of Programs out of Compliance on Specific Rule.
Y = Total Number of Programs in High Group.
Z = Total Number of Programs in Low Group.

Once the data are run through the formula in Figure 2, the following chart (Figure 4) can be used to make the final determination of including or not including the rule as a key indicator. Based upon the chart in Figure 4, it is best to have a Key Indicator Coefficient approaching +1.00 however that is rarely attained with licensing data but has occurred in more normally distributed data.

Continuing with the chart in Figure 4, if the Key Indicator Coefficient is between +.25 and -.25, this indicates that the indicator rule is unpredictable in being able to predict overall compliance with the full set of rules. Either a false positive in which the indicator appears too often in the low group as being in compliance, or a false negative in which the indicator appears too often in the high group as being out of compliance. This can occur with Key Indicator Coefficients above +.25 but it becomes unlikely as we approach +1.00 although there is always the possibility that other rules could be found out of compliance. Another solution is to increase the number of key indicator rules to be reviewed but this will cut down on the efficiency which is desirable and the purpose of the key indicators.

The last possible outcome with the Key Indicator Coefficient is if it is between -.26 and -1.00, this indicates that the indicator is a terrible predictor because it is doing just the opposite of the decision we want to make. The indicator rule would predominantly be in compliance with the low group rather than the high group so it would be statistically predicting overall non-compliance. This is obviously something we do not want to occur.

Figure 5 gives the results and decisions for a QRIS system. The thresholds in a QRIS system are increased dramatically because QRIS standard data are less skewed than licensing data and a more stringent criterion needs to be applied in order to include particular standards as Key Indicators.

Figure 4 – Thresholds for the Fiene Key Indicators for Licensing Rules

Key Indicator Range	Characteristic of Indicator	Decision
(+1.00) – (+.26)	Good Predictor	Include
(+.25) – (-.25)	Unpredictable	Do not Include
(-.26) – (-1.00)	Terrible Predictor	Do not Include

Figure 5 – Thresholds for the Fiene Key Indicators for QRIS Standards

Key Indicator Range	Characteristic of Indicator	Decision
(+1.00) – (+.76)	Good Predictor	Include
(+.75) – (-.25)	Unpredictable	Do not Include
(-.26) – (-1.00)	Terrible Predictor	Do not Include

RESOURCES AND NOTES

For those readers who are interested in finding out more about the Key Indicator Methodology and the more recent technical updates as applied in this paper in actual state examples, please see the following publication:
Fiene (2014). *ECPQIM4©: Early Childhood Program Quality Indicator Model4*, Middletown: PA; Research Institute for Key Indicators LLC (RIKI). (http://drfiene.wordpress.com/riki-reports-dmlma-ecpqim4/)
In this book of readings/presentations are examples and information about differential monitoring, risk assessment, key indicators, validation, measurement, statistical dichotomization of data, and regulatory paradigms. This publication delineates the research projects, studies, presentations, & reports completed during 2013-14 in which these updates are drawn from.

For those readers interested in a historical perspective to the development of the Key Indicator methodology and licensing measurement, please see the following publications (most of these publications are available at the following website (http://rikinstitute.wikispaces.com/home):

Lahti, Elicker, Zellman, & Fiene (2014). Approaches to validating child care quality rating and improvement systems (QRIS): Results from two states with similar QRIS type designs, *Early Childhood Research Quarterly*, available online 9 June 2014, doi:10.1016/j.ecresq.2014.04.005.

Fiene (2013**)**. A Comparison of International Child Care and US Child Care Using the Child Care Aware – NACCRRA (National Association of Child Care Resource and Referral Agencies) Child Care Benchmarks, *International Journal of Child Care and Education Policy, 7(1),* 1-15.

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Fiene KIM Technical Updates 2015

Key Indicator Methodology Technical Note(2): The Dichotomization and Bi-Polarization of the Matrix Data Base

Richard Fiene, Ph.D.

June 2015

This latest technical note updates the thresholds for the high and low groups within the key indicator matrix. This technical note is based upon the latest studies during the early 2015 time frame in which very large data distributions were available to test certain criteria with the key indicator methodology. Because of the extreme skewness present in licensing/regulatory data, certain statistical adjustments need to be made so that the analyses performed reflect the distribution of data. One of these statistical adjustments is the dichotomization of data which is generally not suggested with the exception of very skewed data. Since licensing data are so skewed, this adjustment has been used throughout the key indicator methodology. However, an additional adjustment is now warranted given not only the skewness of data but also because of the data being nominal in nature. This additional adjustment I am calling the bi-polarization of data in order to accentuate the differences between the high and low groups within the key indicator matrix.

I have tested several data sets utilizing bi-polarization and found that the results are more significant with its use than without its use. Please keep in mind that licensing data is very different from other forms of data found in the early care and education (ECE) research literature. It is not like the ERS or CLASS data which is more normally distributed and lends itself to more parametric statistical analyses. Licensing data are nominal in nature and always very skewed which means that more non-parametric methods are warranted, such as phi coefficient and dichotomization of data. An example of how this actually works may help.

Licensing data are measured as either being in or out of compliance. There is no middle ground, it is not measured on a Likert scale. Therefore it is nominal in nature, either it is all there or it is not. Licensing data are also measured in the sense that all rules are created equally, in other words, they all have the same weight or importance, such as 1 = compliance; 0 = non-compliance. Being in full 100% compliance which means 0 violations is the goal of a regulatory/licensing system. One does not want to see many violations of the rules because this will place children at risk of harm and the purpose of an early care and education (ECE) licensing/regulatory system is to reduce the potential harm to children. In the licensing measurement literature, this 100% compliant group is generally labeled or considered the high compliant group. With some licensing laws which allow substantial but not full 100% compliance with the full set of rules, it would then be allowable to have possibly 1 or 2 violations and still be considered in this high compliant group. The low compliant group has been generally any program that had any non-compliance or had 2 or more violations. When these two groups were compared to each individual rule utilizing the phi coefficient formula it was found that a more accurate approach was to accentuate or increase the difference between the high and low groups by eliminating the intervening violations in following manner: high group of 0 violations; 1-4 violations being eliminated; 5+ violations defined as the low group. This additional bi-polarization of data helped to accentuate the differences in calculating the phi coefficient and provided a more sensitive key indicator tool.

Another data distribution issue that should be addressed here that justifies the above cutoffs is that there is very little variance in licensing/regulatory data. Generally the frequency distribution is 20 or less and the average set of rules is over 200 rules. So the frequency distribution is extremely skewed within less than 10% of the potential data distribution. Also, the majority of programs are 100% in compliance with all the rules. And an additional complication is that the scoring of each rule is scored as if it had an equal risk value when in reality the rules can place children at either great risk to relatively little risk if found non-compliant. These measurement issues are very different than in other measurement systems such as ERS or CLASS. The important message to take from this is that rules are not a ruler, they do not measure things equally and cannot be analyzed or compared to other measurement systems that are more normally distributed.

Although licensing is part of the program quality continuum in establishing basic health and safety standards for children, it is a system with measurement limitations that can only be compared on a nominal basis making several statistical adjustments as suggested above necessary.

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Problem Solving Coaching = Online Pinging: How to Make Coaching Both Effective and Efficient and Some Additional Individual Learning Advantages

Richard Fiene, PhD & Benjamin Levi, MD, PhD
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September 2017

The purpose of this short paper is to introduce a potentially new technology that can impact the professional development field as well as learning in general. It is presented for its heuristic value to get us thinking about the possibilities of this new technology as a new online delivery system.

We know that problem solving coaching is an effective quality improvement/professional development intervention (Training, Technical Assistance, and Quality Rating and Improvement Systems) but one that is not particularly efficient. It is very time intensive which drives up cost but it is so much more effective than run of the mill professional development interventions that revolve around workshop or lecture type delivery. (***Mathematical Policy Research (2011) has completed a comprehensive review of coaching and its impacts***). Many states want to use coaching throughout their technical assistance and quality improvement initiatives but it is not sustainable.

In order to deal with these problems of efficiency, a new technology called "Pinging" has been devised where training/professional development segments can be sent directly to a cell phone/tablet/computer based upon learning algorithms and where no face-to-face interaction is necessary. Everything occurs online with "pings" tied to an assessment of knowledge and/or behaviors that may be lacking which are then reinforced to become more positive. This is a new approach to coaching which is being monitored and evaluated as part of an NIH R01 grant (***iLookOut Child Abuse Prevention Training Program, B. Levi, PI***) to determine its efficacy, effectiveness, and efficiency.

Going beyond the professional development field there are some direct applications to learning and instruction in general. For example, could pinging be used as a means to individualize instruction and learning to help solve McVicker-Hunt's "Problem of the Match" or to address Vygotsky's "Zone of Proximal Development" via a skilled tutor? Could pinging be used as an individualized text for a learner in which based upon an assessment, only content relevant to the learner's strengths and weaknesses are presented to the learner's electronic device (laptop computer, tablet, smartphone). Rather than having standardized textbooks that reach maybe

50% of the students, let's have individualized texts that reach 100%; but doing it electronically rather than hard copy. Suddenly this technology could be efficient enough to make this happen. Having individualized texts as hard copy is not cost efficient and could never be sustained, but doing it electronically could be a game changer. It is differential learning rather than one-size-fits-all learning.

Conceptually, think of a bulls-eye with learning opportunities and content spread out all over the bulls-eye but few in the center of the bulls-eye. Now enter pinging where the learning opportunities and content can be targeted to just hit the center of the bulls-eye. This way we can optimize learning opportunities making them relevant to the specific learner which might not be the same learning opportunities for another learner who has a different profile of learning needs.

So what does pinging look like?

Think of the last time you took an exam and did really well on certain aspects of the exam but bombed others. Generally the instructor reviews all the right answers so you get the feedback on what you did wrong but that's where it ends. With pinging, you get an additional learning opportunity to extend learning about what you did not really understand with additional positive reinforcement giving you opportunities to test your knowledge further.

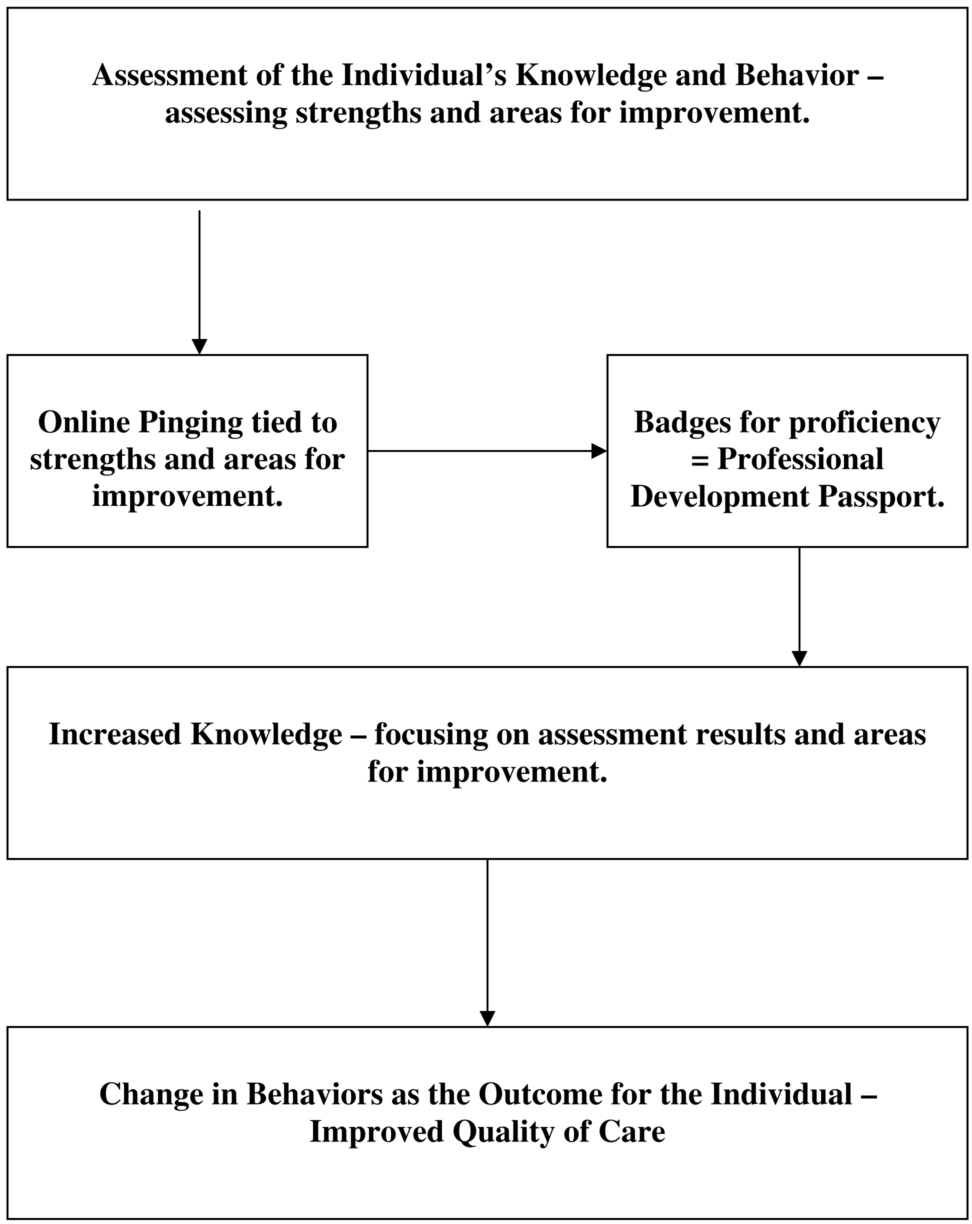
Algorithms are written that tie additional content to every exam question with additional supportive feedback which can be used to reinforce gaps in learning. These algorithms are activated based on the learner's test score. By doing this, we tie assessment to learning via pinging to give the individual learner the opportunity to enhance their learning beyond the assessment. In fact the assessment becomes the driver for additional learning via pinging rather than the assessment becoming the end goal. So rather than learn --> assessment we are changing the paradigm to learn --> assessment --> learn via pinging via multiple path ways. We are creating a learning - assessment - learning continuum. Here is the simple algorithm from the iLookOut program:

Pre-Assessment --> iLookOut Learning Online Program --> Post-Assessment --> Pings sent
(A1, A2, A3, A4..) (B1, B2, B3, B4..) (C1, C2, C3, C4..) (D1, D2, D3..

All this additional pinging occurs electronically sent to devices in a gamification format which becomes fun for the learner. It is cost efficient because the content is sent to a device without the need for a coach or instructor to follow up although that is always a possibility for a learner having a great deal of difficulty. An assessment can be done again after the pinging has occurred to determine the change in the learner's knowledge base. Other assessments could be used to see if behavior changes as well as knowledge changes have occurred depending on the content. For example, the NIH R01 grant we mentioned earlier is looking at just that, how knowledge changed about child abuse reporting, but also how it changed actual behaviors in reporting of child abuse, did it make for better reporting where false negatives and positives have decreased?

As we said at the beginning, this short paper or abstract is presented for its heuristic value to get us thinking about this new pinging technology as both a learning and coaching enhancement. The learning principles have been with us for some time, what is different now, is the available technology which could make a costly intervention more cost efficient. We have more questions about the technology than we have answers at this point. It has tremendous potential but we need to determine if it can live up to its billing as an effective and efficient enhancement.

Problem Solving Coaching Equaling Online Pinging: Making Coaching Both Effective and Efficient (Fiene & Levi, 2017)



Pinging Grant	Year 1 8/1/16-7/31/18	Year 2 8/1/17-7/31/18	Year 3 8/1/18-7/31/19	Year 4 8/1/19-7/31/20	Year 5 8/1/20-7/31/21
iLookOut	COMPLETE: Research study infrastructure Content for iLookOut Instrument validation Filming/editing Recruitment materials Pinging & badging plan IRB approvals	Sequential pings 1-52	Sequential pings 53-104	Sequential pings 105-156	Sequential pings (1-54) + Scenarios + Feedback (if optimal) + Leader Board (if optimal)
Standard		∅	Pings + Scenarios +/- Feedback Measure impact on: Judgment & Motivation	Pings + Scenarios + Feedback (Cross-over design) Measure impact on: Judgment & Motivation	
Control		∅	∅	Pings +/- Leader Board (No vs. Yes Person vs. Group) Measure impact on learner achievement	
State-wide		∅	∅	∅	

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Better Kid Care Coaching + Online Modules ITERS Statistical Design

Richard Fiene

September 2017

The purpose of this technical research note is to outline the statistical design for evaluating the effectiveness of a coaching intervention and determining the specific relationships between key module content and ITERS indicators. The statistical design has two components: 1) t-tests to determine equivalency (pre-test) of two groups (Coaching and Comparison) and their subsequent sub-scale scores on a post-test after the coaching intervention has been administered. The comparison group will only receive the normal online modules that are readily available to all child care providers.

	Pre-Test	Post-Test
Coaching	C1	C2
Comparison	C3	C4

C1 + C3 should show non-significant differences on the ITERS scores. C1 -> C2 should show significant differences on the ITERS based on the coaching intervention. C3 -> C4 should show some significant differences on the ITERS but not as much as C1 -> C2. And lastly, C2 <-> C4 should show significant differences on the ITERS with C2 being significantly higher.

The second component of the statistical design is as follows: 2) correlations will be conducted between the specific online modules and the ITERS indicators (n = 420). Patterns or paths in the data will be determined to ascertain any relationships between how well classrooms did on the ITERS and what specific online module course content was taken.

	ITERS Indicators						
	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.1.6	1.1.n.........
Modules							
1	sign	ns	ns				
2				sign	ns		
3	sign						
4	ns	ns	ns	ns	ns		

By using the above statistical design, one can determine the effectiveness of the coaching intervention and specifically what modules were most effective.

FUTURE ANALYSES AND RESEARCH RELATED TO DIFFERENTIAL MONITORING, KEY INDICATORS, AND RISK ASSESSMENT METHODOLOGIES UTILIZING PREDICTIVE ANALYTICS

Richard Fiene

January 2015

This short paper addresses what I see as the key future analyses and research related to differential monitoring, key indicators, and risk assessment methodologies. Most of these analyses can most likely be performed via predictive analytics.

Research Questions:

1…There is the need to address the point system within the Differential Monitoring Scoring Protocol (DMSP©) by looking at the probability that the various key elements will occur based upon the research literature. For example, PC x PQ is .5 based upon NQI data because 50% of the states have QRIS systems. This is how all the algorithms would play out if a probability assessment is used rather than the scoring protocol I developed. The scoring protocol mirrors the probability figures as follows:

PC + PQ = .50P/4PTS

KI + RA --> DM= .50P/4PTS

PC + KI --> DM = .25P/2PTS

PC + RA --> DM = .25P/2PTS

2…There is the need to show how KI and RA are integrated mathematically or via an algorithm.

3…With the effectiveness and efficiency relationship curves (see my DMLMA Powerpoint slides). The effectiveness and efficiency lines are curvilinear rather than linear and cross each other at a substantial compliance level rather than earlier which is more typical with linear data.

4…HSKI as the best case example which incorporates all components. Full data sets, report, training slides, validation data, promotional slides, web site, most details and national DB. This needs to be documented fully and written up as a case study.

5…Run phi correlation against Logit regression, compare results.

6…2 x 2 phi to a 2 x 3 chi square. High/Low frequency matrix to Full/Substantial/Low frequency matrix.

7…ECPQIM/PAM/Measures = DM/Clustering/DMSP//KI/Classification/Matrix//RA/clustering/Likert. There needs to be a paper written on the relationship between ECPQIM, predictive analytics modeling (PAM), and the actual measures used for each ECPQIM Key Element. I started this paper but it needs to be fully developed (see DATA File Folder).

8…Try different cut offs and see how results are impacted. I started to do this with the GA data base. The more the indicators, the higher the correlation between IC and CI. KI8 --> KI15. The question becomes what is the best level? KI10, KI9, KI13??? This analysis ties back to the efficiency and effectiveness relationship because as one increases the number of indicators, the effectiveness increases but the efficiency of the model drops off. The opposite is also true.

9…Use HS/KS/IL/GA data bases to run the various analyses. These data bases are available for doing all these analyses.

10…DM = YES OR NO, BASED UPON COMPLIANCE HISTORY; H = YES (100-98); L = NO (97-); YES = KI AND/OR RA (ABBREVIATED INSPECTION); NO = CI (FULL INSPECTION); CLUSTERING OR CLASSIFICATION. These are the various key elements of ECPQIM and the types of analyses within predictive analytics modeling (clustering or classification analysis).

11…DMSP – 0-10; CLUSTERING (0,2,4,6,8,10). DMSP – Differential Monitoring Scoring Protocol is an example of clustering analysis via predictive analytics modeling.

12…KI -- .25+; CLASSIFICATION; either it is included or not. KI – Key Indicators is an example of classification analysis via predictive analytics modeling.

13…RA – 9 OUT OF 10 (9+); HIGH RISK; CLASSIFICATION; either it is included or not. RA – Risk Assessment is an example of classification analysis via predictive analytics modeling.

Regulatory Compliance Scaling for Decision Making

Richard Fiene, Ph.D.

June 2018

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:

Data	**Level**	**Decision**
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 tighten 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.

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The Evolution of Differential Monitoring With the Risk Assessment and Key Indicator Methodologies

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December 2018

The use of differential monitoring by states and Canadian Provinces has evolved very interestingly over the past decade into two parallel approaches which help to inform other interested jurisdictions as they consider a differential monitoring approach.

Differential monitoring is a more targeted or abbreviated form of monitoring facilities or programs based upon "what is reviewed/depth of the review" and "how often/frequent do we review". Two specific methodologies have been used by states to design and implement a differential monitoring approach: risk assessment and key indicators.

It was originally conceived that risk assessment and key indicator methodologies would be used in tandem and not used separately. Over the past decade, a real dichotomy has developed in which risk assessment has developed very independently of key indicators and risk assessment has become the predominant methodology used, while the key indicator methodology has lagged behind in development and implementation.

In this separate development and implementation, risk assessment has driven the "how frequent" visits in a differential monitoring approach while key indicators has driven "what is reviewed" when it comes to rules/regulations/standards.

The other development with both methodologies are the data matrices developed to analyze the data and to make decisions about frequency and depth of reviews. For risk assessment, the standard matrix used is a 3 x 3 matrix similar to the one presented below.

Risk Assessment with Probability along the vertical axis and Risk along the horizontal axis

A	**B**	**C**
D	**E**	**F**
G	**H**	**I**

In the above 3 x 3 Risk Assessment Matrix, (A) indicates a very high risk rule/regulation/standard with a high likelihood that it will occur, while (I) indicates a very low or no risk rule/regulation/standard with a low likelihood that it will occur. (B) through (H) indicate various degrees of risk and probability based upon their position within the Matrix.

The decision making relationship of more frequent visits to the facility or program is made on the following algorithm:

If I > E + F + H > B + C + D + G > A, than more frequent reviews are completed

Just as Risk Assessment utilizes a 3 x 3 Matrix, Key Indicators utilizes a 2 x 2 Matrix in order to analyze the data and make decisions about what is reviewed. Below is an example of a 2 x 2 Matrix that has been used.

Key Indicator with Compliance/Non-Compliance listed vertically and High vs Low Grouping listed hortizontally

A	**B**
C	**D**

In the above 2 x 2 Key Indicator Matrix, (A) indicates a rule/regulation/standard that is in compliance and in the high compliant group, while (D) indicates a rule/regulation/standard that in out of compliance and in the low compliant group. (B) and (C) indicate false positives and negatives.

The decision making relationship of more rules to be reviewed is made on the following algorithm:

If A + D > B + C, than a more comprehensive review is completed

Given the interest in utilizing differential monitoring for doing monitoring review, having this decade's long review of how the risk assessment and key indicator methodologies have evolved is an important consideration.

Is it still possible to combine the risk assessment and key indicator methodologies? It is by combining the 3 x 3 and 2 x 2 Matrices above where the focus of utilizing the Key Indicator methodology is (I) cell of the 3 x 3 Matrix. It is only here that the Key Indicator methodology can be used when combined with the Risk Assessment methodology.

Key Indicator and Risk Assessment Methodologies Used in Tandem

A	**B**	**C**
D	**E**	**F**
G	**H**	**Only Use Key Indicators here**

By utilizing the two methodologies in tandem, both frequency of reviews and what is reviewed are dealt with at the same time which makes the differential monitoring approach more effective and efficient.

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Theory of Regulatory Compliance: Quadratic Regressions

Richard Fiene, Ph.D.

December 2018

The Theory of Regulatory Compliance has been described mathematically as a quadratic formula which captured the non-linear, U-shaped curve relating regulatory compliance and program quality. The form of the equation followed the typical quadratic:

$$Y = ax2 + bx + c$$

The problem in the use of the quadratic formula was that it was not particularly sensitive to false positives and negatives which in the regulatory compliance decision making was very problematic. Most recently, an alternative mathematical approach has been introduced by Simonsohn (2018) in his article: *Two Lines: A Valid Alternative to the Invalid Testing of U-Shaped Relationships With Quadratic Regressions:*

y = a + bxlow + cxhigh + d * high + ZBZ, (1)
where xlow = x – xc if x < xc and 0 otherwise, xhigh = x – xc if x ≥ xc and 0 otherwise, and high = 1 if x ≥ xc and 0 otherwise.
Z is the (optional) matrix with covariates, and BZ is its vector of coefficients.

This article appeared in ***Advances in Methods and Practices in Psychological Science, Vol.1(4) 538–555, DOI: 10.1177/2515245918805755, www.psychologicalscience.org/AMPPS***. This alternative approach is provided to better explain and detail the Theory of Regulatory Compliance. This very brief RIKIllc technical research note is provided for licensing and regulatory science researchers to consider as they make comparisons with their regulatory compliance data. Additional details will be provided as this alternative to quadratic regressions is applied to the ECPQI2M – Early Childhood Program Quality Improvement and Indicator Model International Data Base maintained at the Research Institute for Key Indicators (RIKIllc).

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For additional information about the Theory of Regulatory Compliance and the Early Childhood Program Quality Improvement and Indicator Model, please go to http://RIKInstitute.com

What is the Relationship between Regulatory Compliance and Complaints in a Human Services Licensing System? RIKIllc Technical Research Note

Richard Fiene, Ph.D.

January 2019

Within licensing measurement and the validation of licensing systems it is particularly difficult to have specific outcome metrics that can be measured within a human services licensing system. The purpose of this technical research note is to propose a potential solution to this problem.

Probably the most accurate measures of licensing outcomes focuses on improvements in the health and safety of clients within human services licensed facilities, such as: fewer injuries (safety) or higher levels of immunizations (health). Another measure related to client satisfaction is the number of complaints reported about a licensed facility by clients and the general public. The advantage of using complaints is that this form of monitoring is generally always part of an overall licensing system. In other words, the state/provincial licensing agency is already collecting these data. It is just a matter of utilizing these data in comparing the number of complaints to overall regulatory compliance.

The author had the opportunity to have access to these data, complaint and regulatory compliance data in a mid-Western state which will be reported within this technical research note. There are few empirical demonstrations of this relationship within the licensing research literature. The following results are based upon a very large sample of family child care homes (N = 2000+) over a full year of licensing reviews.

The results of comparing the number of complaints and the respective regulatory compliance levels proved to show a rather significant relationship ($r = .47$; $p < .0001$). This result is the first step in attempting to understand this relationship as well as developing a methodology and analysis schema since directionality (e.g., did the complaint occur before or after the regulatory compliance data collection?) can play a key role in the relationship (this will be developed more fully in a future technical research note). The focus of this research note was to determine if any relationship existed between regulatory compliance and complaint data and if it is worth pursuing.

It appears that looking more closely at the relationship between complaint and regulatory compliance data is warranted. It may provide another means of validating the fourth level of validation studies as proposed by Zellman and Fiene's OPRE Research Brief (*Zellman, G. L. & Fiene, R. (2012). Validation of Quality Rating and Improvement Systems for Early Care and Education and School-Age Care, Research-to-Policy, Research-to-Practice Brief OPRE 2012-29. Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services)* in which four approaches to validation are delineated for Quality Rating and Improvement Systems (QRIS). This author has taken this framework and applied it to licensing systems (*Fiene (2014). Validation of Georgia's Core Rule Monitoring System, Georgia Department of Early Care and Learning*) and more recently proposed as the framework for Washington State's Research Agenda (*Stevens & Fiene (2018). Validation of the Washington State's Licensing and Monitoring System, Washington Department of Children, Youth, and Families*).

For additional information regarding the above studies, the interested reader should go to http://RIKInstitute.com.

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Some Technical Considerations in Using Complaint Data and Regulatory Compliance Data: RIKIllc Technical Research Note #66

Richard Fiene, Ph.D.

January 2019

As promised in RIKIllc Technical Research Note #65, this Note will provide details on the methodology and analytical considerations when using complaint and regulatory compliance data together. As pointed out in the previous technical research note, using complaint data as a potential outcome appears to have merit and should be explored in greater detail. However, with that said there are some parameters that the methodology has that should be explored in order to make the analyses more meaningful.

When looking at regulatory compliance and complaint data there are four possibilities: 1) the facility is in full compliance and has no complaints; 2) the facility is in full compliance but has complaint(s); 3) the facility has some non-compliance and has no complaints; and 4) the facility has some non-compliance and has complaint(s). These four possibilities can be depicted in the following 2 x 2 matrix:

Complaints	***Regulatory Compliance Full (0)***	***Regulatory Compliance Non-Compliance (1)***
No (0)	***00 = Full & No Cell C = Expected***	***10 = Non-Compliance & No Cell B = False Positive***
Yes (1)	***01 = Full & Yes Cell A = False Negative***	***11 = Non-Compliance & Yes Cell D = Expected***

In the above 2 x 2 matrix, we would want to see cell C and cell D as the predominant cells and cell A and B as the less dominant cells, especially cell A because this represents a false negative result.

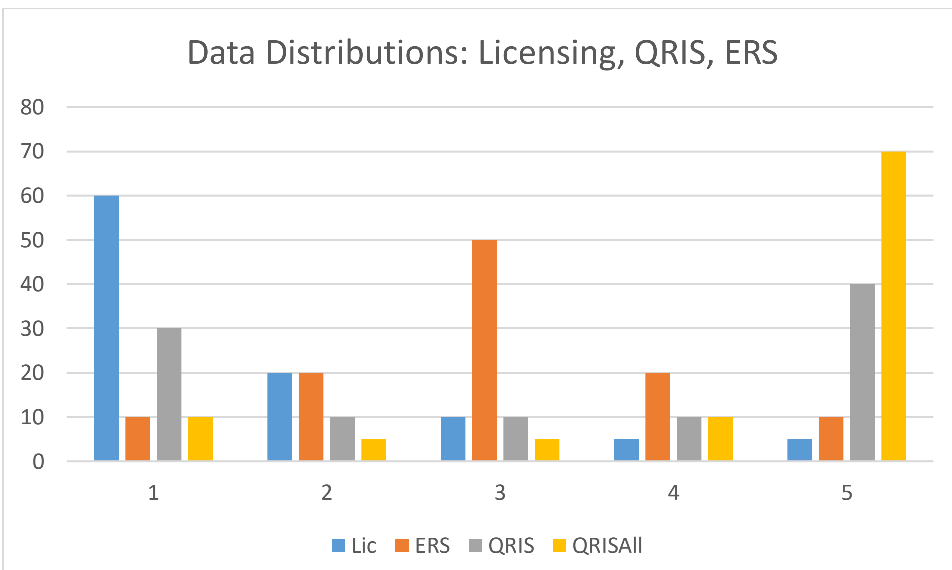
However, there are a couple of limitations to the above matrix that need to be taken into account. One, are the complaints substantiated or not. Any complaint must be substantiated to be counted in the model. If it is unsubstantiated, than it is not counted in the matrix. Two, there is the problem with directionality that needs to be addressed. For example, does the complaint occur before or after the full inspection in order to determine regulatory compliance. The 2 x 2 matrix and the modeling for these analyses is based on the complaint occurring after the full inspection and that is the reason for cell A being labeled a false negative. If the directionality is reversed and the full inspection occurs after a complaint, cell A is no longer a false negative.

Licensing, QRIS, and ERS Data Distributions

Richard Fiene, Ph.D.

January 2019

The frequency or data distributions for licensing (lic), quality rating and improvement systems (QRIS), and environmental rating scales (ERS) are very different. ECE programs obtain very different scores in each of these assessment paradigms. This should not come as a surprise since the three assessments measure very different aspects of an ECE program: Licensing = health and safety standards; QRIS = quality standards; ERS = environmental quality. However, the statistical implications are important given these differences. The distributions are depicted in the graphic below (Data Distributions: Licensing, QRIS, ERS).



Additional notes regarding the above graphic. The licensing distribution clearly shows a highly skewed data distribution, while the ERS distribution is normally distributed, while the QRIS is bi-modal and the QRISAll which represents all providers in a state who are part of the QRIS and those who are not is highly skewed. One (1) = higher scores; 5 = lower scores.

The hope is that the above graphic will assist licensing researchers as they think about analyzing data from each of these respective systems when it comes to parametric and non-parametric statistics.

The Relationship between Early Care & Education Quality Initiatives and Regulatory Compliance: RIKIllc Technical Research Note #67

Richard Fiene, Ph.D.

February 2019

Over the past couple of decades there has been many early care and education initiatives, such as Quality Rating and Improvement Systems (QRIS), Professional Development, Training, Technical Assistance, Accreditation, and Pre-K programs to just name a few. Validation and evaluation studies have begun to appear in the research literature, but in these studies there has been few empirical demonstrations of the relationship between these various quality initiatives and their impact on regulatory compliance or a comparison to their respective regulatory compliance. This brief technical research note will provide examples of these comparisons taken from the Early Childhood Program Quality Improvement and Indicator Model (ECPQI2M) Data Base maintained at the Research Institute for Key Indicators (RIKIllc).

I have written about this back in 2014 (Fiene, 2014) in how the various quality initiatives were having a positive impact on the early care and education delivery system but at that point regulatory compliance data were not available. Today, in 2019, with many changes and developments in state data systems, this is no longer the case. Now it is possible to explore the relationships between data from the various quality initiatives and licensing. Several states in multiple service delivery systems have provided replicable findings in which I feel comfortable reporting out about the relationships across the data systems.

What we now know is that there is a positive and statistically significant relationship between regulatory compliance and moving up the QRIS Quality Levels. In other words, facilities have higher compliance in the higher QRIS Quality Levels and lower compliance in the lower QRIS Levels or if they do not participate in their state's respective QRIS ($F = 5.047 – 8.694$; $p < .0001$).

Other quality initiatives, such as being accredited, shows higher compliance with licensing rules than those facilities that are not accredited ($t = 2.799 - 3.853$; $p < .005 - .0001$).

This is a very important result clearly demonstrating the positive relationship between regulatory compliance and quality initiatives. I have some additional state data sets that I will add to the ECPQI2M data base and will continue to analyze these relationships.

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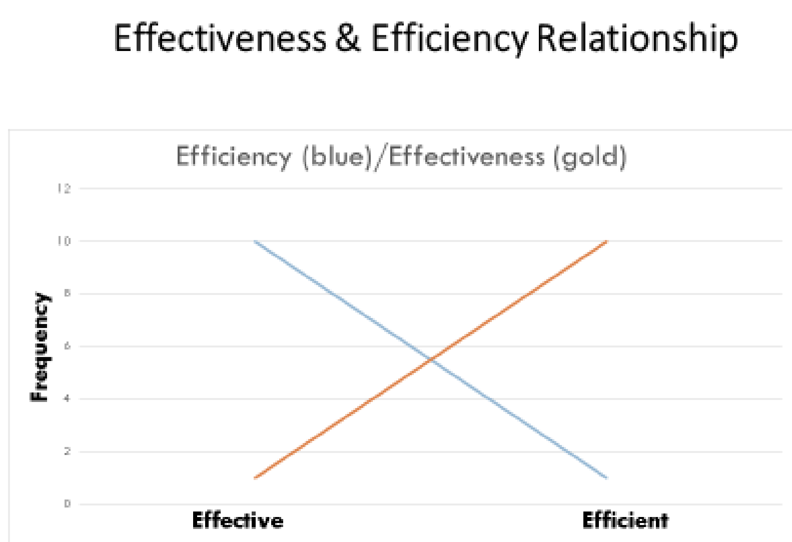
Effectiveness and Efficiency Relationship Leading to Cost Benefit

Richard Fiene, Ph.D.

March 2019

In management science and economic theory in general, the relationship between effectiveness and efficiency has been delineated in terms of two mutually exclusive processes in which you have one but not the other. This brief technical research note will outline an approach which mirrors the relationship in economics between supply and demand and how effectiveness and efficiency can be thought of as images of each other giving way to cost benefit analysis in order to have the proper balance between the two.

The proposed relationship between effectiveness and efficiency is that as one increases the other decreases in a corresponding and proportionate way as depicted in the graphic below. This relationship is drawn from my work in regulatory compliance/licensing systems in comparing data collected in comprehensive licensing reviews and abbreviated licensing reviews where only a select group of rules/regulations are measured. When comprehensive reviews are completed these reviews tend to be more effective but not very efficient use of resources. When abbreviated reviews are completed these reviews tend to be more efficient but are not as effective if too few rules are measured for compliance.



Effectiveness deals with the quality of outputs while efficiency deals with input of resources expended. The Theory of Regulatory Compliance is finding the right balance between effectiveness and efficiency in the above graphic. Where is the balanced "sweet" spot of inputs to produce high quality outputs. As one can see where the effectiveness line is at the highest point and efficiency is at the lowest point, this is a very costly system that is totally out of balance. But the same is true where efficiency is at the highest point and effectiveness is at the lowest point, this is a very cheap system that is totally out of balance producing low quality. The key to this relationship and the theory of regulatory compliance is finding that middle ground where effectiveness and efficiency are balanced and produce the best results for cost and quality and leads us directly to cost benefit analysis.

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Research Institute for Key Indicators (RIKIllc) Technical Research Note #70.

Relationship of the Theory of Regulatory Compliance, Key Indicators, & Risk Assessment Rules with Weights and Compliance Data

Richard Fiene, Ph.D.

April 2019

There is a relationship between general regulatory compliance levels, weights and how these work within the risk assessment and key indicator differential monitoring approaches. What generally happens is that there are high compliance levels with high risk assessment/weighted rules and with moderate weighted rules and low compliance levels with more low weighted rules which led to the Theory of Regulatory Compliance and an emphasis on substantial regulatory compliance. This is a general pattern and there are exceptions to every rule. Please see the chart below which depicts this relationship.

The reason for pointing this relationship out is for policy makers and researchers to be cognizant of these relationships and to be alert for when certain rules do not follow this pattern. Regulatory compliance data are very quirky data and because of its non-parametric characteristics can be difficult to analyze. I know that these results and relationships may seem self-evident, but they need emphasis because it is easy to overlook the obvious and to miss "the forest in looking at the trees".

Compliance	Weights	Approach	Violation of Approach
High	High	Risk Assessment Rules	Low Compliance with Rule
High - Medium	Medium	Key Indicator Rules	False Negatives
Medium	Low	Substantial Compliance	100% Compliance with all Rules

Let's walk through this chart.

High compliance means being in compliance with all or a substantial number of rules, but always keep in mind that when we are discussing regulatory compliance, being in high compliance means 100% - 99% in compliance with all rules. This is a very high standard and most programs can achieve these levels.

Medium compliance is still rather high regulatory compliance (98% - 97%) and is generally considered a high enough level for issuing a full license with a brief plan of correction. This is a level that is considered legally to be in substantial compliance with all rules. This regulatory result of substantial compliance led to the Theory of Regulatory Compliance and the public policy suggestion that substantial and not full (100%) regulatory compliance is in the best interests of clients. Low regulatory compliance, although not part of the chart above, happens very rarely. Programs that do not meet basic health and safety rules are issued cease and desist orders and are put out of business.

High weights are rules that place clients at greatest risk and should never be out of compliance. These are the Risk Assessment Rules that are always reviewed when a licensing inspection is completed, either when a full or abbreviated/differential monitoring visit is conducted. A licensing inspector does not want to leave a facility without having checked these rules.

Medium weights are rules that are very important but do not place clients at greatest risk. They generally add to the well-being of the client but will not jeopardize their health or safety. Generally, but not always, we find these rules as part of a licensing key indicator abbreviated inspection in a differential monitoring visit. For whatever, reason, facilities in high compliance generally have these in compliance and facilities in low compliance generally have these out of compliance or not in compliance. These are our predictor rules that statistically predict overall regulatory compliance.

Low weights are rules that do not have a real risk impact on the client. They are generally paper oriented rules, record keeping type rules. A lot of times they make it into the Key Indicator Rule list because it has to do with attention to detail and at times this will distinguish a high performing provider from one that is not doing as well. However, it can also have the opposite effect and these rules can "muddy the waters" when it comes to distinguishing between really high performing facilities and facilities that are just mediocre by contributing to data distributions that are highly skewed and difficult to find the "best of the best". Licensing researchers and policymakers need to pay attention to this dichotomy.

Risk assessment rules are those rules which have been identified as the most critical in providing the safeguards for clients when in out of home facilities. These rules are very heavily weighted and usually always in compliance. A violation of this approach is finding low compliance with specific risk assessment rules. These rules constitute approximately 10-20% of all rules.

Key indicator rules are those rules which statistically predict overall compliance with all rules. There is a small number of key indicator rules that are identified, generally less than 10% of all rules. These rules are in the mid-range when it comes to their weights or risk factor. And the rules are generally in high to substantial compliance. A violation of this approach is finding a facility in compliance with the key indicator rules but finding other rules out of compliance or the facility in the low group. (Please go to the following website for additional information http://RIKInstitute.com)

Substantial compliance is when the majority of the rules are in compliance with only a couple/few rules being out of compliance which are generally low weighted rules, such as paper driven rules. These rules are in the low-range when it comes to their weights or risk factor. Nice to have in place in being able to say we have "crossed every 't' and dotted every 'i'" but not critical in protecting the health, safety and well-being of the client. A violation of substantial compliance would be requiring full (100%) compliance with all rules.

This short RIKI Technical Research Note (#71) provides some additional guidance and interpretation of how particular patterns of licensing data impact and relate to each other. It is provided because of the nuances of regulatory compliance/licensing data which have limitations from an analytical perspective (Please see the RIKINotes blog on the RIKInstitute.com website).

Here is another way of looking at the chart presented on page 1 which incorporates all the elements elaborated in the chart: **Compliance, Weights, Approach, and Violation of the Approach (V).**

			Weights	
		High Risk	**Medium Risk**	**Low Risk**
Non-	**High NC**	**VRA**	**False Negative**	**TRC**
Compliance	**Medium NC**		**Key Indicators**	
(NC)	**Low NC**	**Risk Assessment**	**False Positive**	**VTRC**

VRA = Violation of Risk Assessment; VTRC = Violation of Theory of Regulatory Compliance.

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Risk Assessment Matrix (RAM) for the State of Washington

Richard Fiene, Ph.D.

May 2019

Risk Assessment Matrices (RAM) are potential decision making tools developed as part of the weighting/risk assessment methodology for licensing and regulatory compliance. Most matrices have two major foci, risk/severity and prevalence/probability components. Each is rank ordered from low to medium to high risk/severity or prevalence/probability. To date there has not been much empirical data used to determine the various levels of low, medium and high that has been shared in the research literature. I am hoping to change this with this short paper.

The data drawn for this paper is taken from the National Licensing, Differential Monitoring, Key Indicator and Risk Assessment Data Base maintained at the Research Institute for Key Indicators (RIKIllc). This data base has been in existence for over 40 years and contains data from many states, provinces and national programs.

In order to determine the relative risk level of specific rules/regulations, generally a weighting system is used where a group of stakeholders in a specific state make assessments to the potential risk for clients if a specific rule is out of compliance. Usually the weighting scale is a Likert type scale going from low risk (1) to high risk (8). Medium risk usually is around a 4.

Prevalence/probability data are not as well determined in the literature and focuses more on the individual rule. However, for the purposes of this paper, I want to use prevalence/probability data drawn from regulatory compliance histories and move beyond individual rules so that the Risk Assessment Matrix (RAM) can be used more effectively for making monitoring decisions. Regulatory compliance histories will provide an overall picture of how well the program has complied with rules over time. The number of rules in Chart 1 are rules that are out of compliance in any monitoring review conducted. Based upon the National Licensing, Differential Monitoring, Key Indicator and Risk Assessment Data Base, these are the averages across jurisdictions and have become the standard thresholds for determining low, medium and high regulatory compliance.

Chart 1 – Risk Assessment Matrix

		Probability/	**Prevalence**		
	Levels	**High**	**Medium**	**Low**	**Weights**
Risk/	**High**	***9***	***8***	***7***	***7-8***
Severity	**Medium**	***6***	***5***	***4***	***4-6***
	Low	***3***	***2***	***1***	***1-3***
	# of Rules	***8 or more***	***3-7***	***2 or fewer***	

The resulting numeric scale from 1-9 provides a rank ordering when Severity/Risk and Prevalence/Probability are cross-referenced. In this rank ordering 9 = High Risk/Severity (Weight = 7-8) and High Prevalence/Probability (8 rules or more are out of compliance) while a 1 = Low Risk/Severity (Weight = 1-3) and Low Prevalence/Probability (2 rules or fewer are out of compliance). A 5 = Medium Risk/Severity (Weight = 4-6) and Medium Prevalence/Probability (3-7 rules are out of compliance).

Utilizing the data from the above Chart 1, a Monitoring Decision Making Matrix (MD2M) can be constructed for the various Licensing Tiers which will assist in determining further targeted monitoring as depicted in Chart 2 below.

Chart 2 – Monitoring Decision Making Matrix

Tier 1	**1,2**	**Potentially eligible for abbreviated reviews & differential monitoring + Technical Assistance (TA) being available.**
Tier 2/3	**3,4,5,6**	**Comprehensive review + required TA + potentially more frequent reviews.**
Tier 4	**7,8,9**	**Comprehensive review + required TA + Potential Sanctions that could lead to licensing revocation.**

Chart 2 takes the data from Chart 1 and transposes the 1-9 Severity/Prevalence data (column 2) to a Tiered Decision Making Scale (Column 1) regarding targeted monitoring and technical assistance (column 3). This chart could be taken further and decisions regarding the status of the license could be made such as Tier 1 would result in a full license, Tier 2/3 would result in a provisional license, and Tier 4 would result in the removal of a license.

In the past, these decisions were generally driven by general guidance with a lack of data driving the decisions. By utilizing data from the National Licensing, Differential Monitoring, Key Indicator and Risk Assessment Data Base it is now possible to make these decisions more objective and data driven. Also, the focus of RAM's in the past has been at the individual rule/regulation level for both risk/severity and prevalence/probability. This presentation moves this level of analysis to a broader focus which looks at the program in general by incorporating regulatory compliance histories in determining prevalence/probability data.

Performance Assessment, Regulatory Compliance and the Use of Weighting to Enhance Standard or Rule Based Licensing Systems

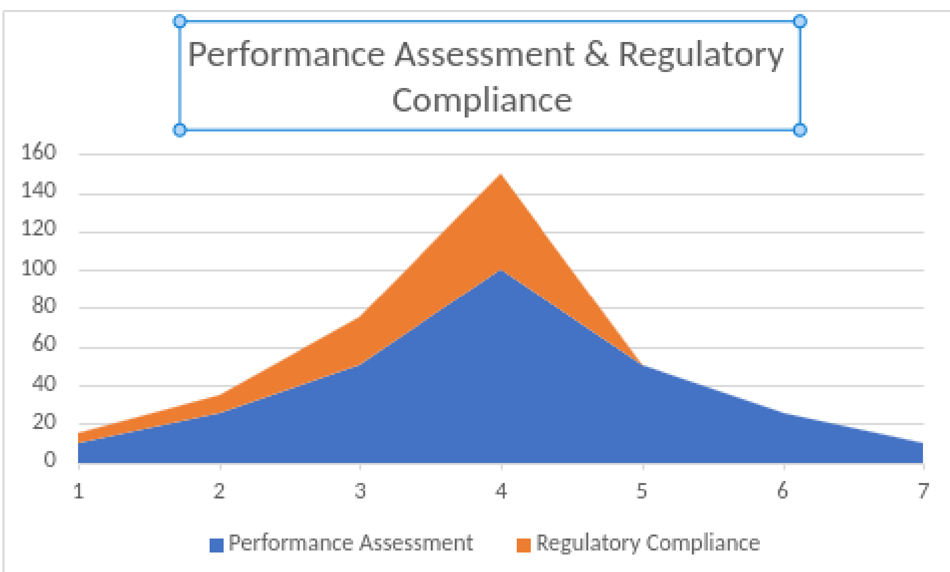
Richard Fiene, Ph.D.

May 2021

The purpose of this short paper is to delineate the commonalities and differences between performance assessment and regulatory compliance. In presenting performance assessments and regulatory compliance side by side it has the potential of introducing a new licensing measurement paradigm which goes beyond basic compliance with rules and standards. This paper builds upon previous technical research notes that are available at http://rikinstitute.com/blog/ which deal with the measurement issues related to licensing and regulatory compliance.

Whenever we think about performance assessments in the Environmental Rating Scales, CLASS, Accreditation Programs, or Quality Rating and Improvement Systems (QRIS), we find more normally distributed curves or distributions where skewness and kurtosis being very low. With regulatory compliance, the same type of normally distributed scores is not the case; the data are very skewed in a positive fashion which means that the majority of the programs are in full compliance (100%) with all the rules or standards. The resulting skewness and kurtosis are much higher which clearly indicates the non-parametric characteristics of the distribution. See the following Table.

Table 1: Data Distributions for Performance Assessment and Regulatory Compliance



Let's walk through Table 1 and discuss the commonalities and differences between performance assessment and regulatory compliance. The vertical axis is a frequency count, the number of programs meeting the particular scores on the horizontal axis. The horizontal axis runs from 1 = Deficient to 7 =

Exemplary. Four (4) = Compliant or Average. These scores represent how well a program meets the rules or standards that are being applied. Anything measured at a 4 or lower would be measured as a risk mitigation while anything above a 4 would measure performance above a specific compliance with the rule standard which is a score of 4. It is suggested that in order to increase the variance in the scoring protocol, weights be applied which measure relative risk or relative performance above or below the average score of 4. In the licensing research literature these would equate to a Risk Assessment Matrix (RAM) or a Performance Assessment Matrix (PAM).

An important discerning characteristic of the two distributions is the continuous nature of the performance assessment scores and the truncated nature of the regulatory compliance scores. The regulatory compliance scores essentially go up to a score of 4 on the Table 1 graphic which indicates full compliance with the rule/standard. It does not continue on as the performance assessment scores do.

The above graphic depiction is presented as a potential licensing measurement paradigm shift in how to think about the relationship between regulatory compliance and performance assessments. Generally, in the past, these two measurement systems have had their own silos and have not been looked at side by side. This paper is suggesting that we alter our vantage point and begin to see these two measurement systems along a continuum one building on the other in a stepped type of model.

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

April 2021

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.

Regulatory Compliance, Licensing, and Monitoring Measurement Principles: Rule Compliance Versus Rule Performance

Richard Fiene, Ph.D.

January 2021

The purpose of this short paper is to delineate the parameters of regulatory compliance, licensing and monitoring measurement principles (throughout this paper the term "regulatory compliance" will be used to encompass these principles). Regulatory compliance is very unique when it comes to measuring it because it is very different from other measurement systems and this impacts how one uses various statistical analyses. In this paper, the limitations of the measurement system will be highlighted with potential solutions that have been devised over the past several decades. Hopefully this paper will add to the measurement and statistical analysis licensing research literature. It is meant for those agency staff who are responsible for designing regulatory compliance, licensing and monitoring systems. Its focus is the human services but the basic principles can be applied to any standards-based system that is based upon a compliance or performance model.

The organization of this paper is as follows. First, let's introduce what is included when we talk about measurement principles for regulatory compliance, licensing and monitoring systems. Second, provide examples that should be familiar to most individuals who have been involved in the human services, in particular the early care and education field. Third, what are the limitations of these various systems that have been identified in the research literature. Fourth, what are some potential solutions to these limitations. And, fifth, what are the next steps and where do we go to build reliable and valid measurement systems dealing with regulatory compliance, licensing, and program monitoring as these relate to the human services delivery system.

So, what is included in this approach. I can be any rule, regulation, or standard based measurement system. Generally, these systems are focused on a nominally based system, sometimes they will be ordinally based. By a nominally based system, either the facility being assessed is in compliance with a particular set of rules, regulations, or standards or it is not. In an ordinally based system, a facility may attain a score on a Likert scale, such as 1 through 5 where 1 is non-optimal and 5 is excellent. These types of measurement scales involve a performance component and are not limited to more of a compliance focus as is the case with a nominally based system. These distinctions are important as one will see later in this paper when it comes to the selection of the appropriate statistics to measure data distributions and the subsequent analyses that can be undertaken.

What are examples of these types of systems? For nominally based systems, just about all the licensing systems in the USA, Canada and beyond employ this type of measurement strategy. As has been said in the previous paragraph, either there is compliance or there is not. It is very black or white, there are not shades of gray. For ordinally based systems, these systems are a bit more diverse. Accreditation, Quality Rating and Improvement Systems (QRIS), the new Head Start Grantee Performance Management System (GPMS), the Environmental Rating Scales, and the CLASS are all examples of ordinally based systems based upon a Likert type measurement system. There are many others, but as a research psychologist whose total career (50 years) has been spent in early care and education, this has been the focus of my research.

The limitations of the above systems are numerous and, in some ways, are difficult to find solutions. In the past, these measurement systems have focused more on the descriptive aspects of data distributions rather than attempting to be predictive or inferential. The first major limitation of the data from regulatory compliance systems is the fact that the data distribution is markedly skewed. What does skew data mean? Most data distributions are normally distributed with very few occurrences at the extremes with the majority of the cases in the middle section of the measurement scale. IQ is an example of a normally distributed data distribution. In a skew data distribution, the majority of data are at one end of the data distribution, either at the positive end or the negative end of the distribution. With regulatory compliance data, it is at the positive end with the majority of facilities being in full or 100% compliance with the rules. Very few of the facilities are at the negative end of the distribution.

What is the big deal? The big deal is that statistically we are limited in what we can do with the data analyses because the data are not normally distributed which is an assumption when selecting certain statistical tests. Basically, we need to employ non-parametric statistical analyses to deal with the data. The other real limitation is in the data distribution itself. It is very difficult to distinguish between high and mediocre facilities. It is very easy to distinguish between high and low performing facilities because of the variance between the high performing facilities and the low performing facilities. However, that is not the case between high and mediocre preforming facilities. Since the majority of facilities are either in full or substantial compliance with the rules, they are all co-mingled in a very tight band with little data variance. This makes it very difficult to distinguish differences in the facilities. And this only occurs with regulatory compliance data distributions. As will be pointed later in this paper, this is not the case with the second measurement system to be addressed dealing with ordinal measurement systems.

There is also a confounding factor in the regulatory compliance data distributions which has been termed the theory of regulatory compliance or the law of regulatory compliance diminishing returns. In this theory/law, when regulatory compliance data are compared to program quality data, a non-linear relationship occurs where either the facilities scoring at the substantial compliance level score better than the fully compliant facilities or there is a plateau effect and there is no significant difference between the two groups: substantial or fully compliant facilities when they are measured on a program quality scale. From a public policy stand point, this result really complicates how best to promulgate compliance with rules. This result has been found repeatedly in early care and education programs as well as in other human service delivery systems. It is conjectured that the same result will be found in any regulatory compliance system.

Another limitation of regulatory compliance data is the fact that it is measured at a nominal level. There is no interval scale of measurement and usually not even an ordinal level of measurement. As mentioned above, either a facility is in compliance or not. From a statistical analytical view, again this limits what can be done with the data. In fact, it is probably one of the barriers for researchers who would like to conduct analyses on these data but are concerned about the robustness of the data and their resulting distributions.

Let’s turn our attention to potential solutions to the above limitations in dealing with regulatory compliance data.

One potential solution and this is based upon the theory of regulatory compliance in which substantial compliance is the threshold for a facility to be issued a license or certificate of compliance. When this public policy determination is allowed, it opens up a couple of alternate strategies for program monitoring and licensing reviews. Because of the theory of regulatory compliance/law of regulatory compliance diminishing returns, abbreviated or targeted monitoring reviews are possible, differential monitoring or inferential monitoring as it has been documented in the literature. This research literature on differential monitoring has been dominated by two approaches: licensing key indicators and weighted risk assessments.

A second solution to the above limitations deals with how we handle the data distribution. Generally, it is not suggested to dichotomize data distributions. However, when the data distribution is significantly skewed as it is with regulatory compliance, it is an appropriate adjustment to the data. By essentially having two groups, those facilities that are in full compliance and those facilities that are not in full compliance with the rules. In some cases, the fully compliant group can be combined with those facilities that are in substantial compliance but this should only be employed when there are not sufficient fully compliant facilities which is hardly never the case since population data and not sampled data are available from most jurisdictions. When data samples were drawn and the total number of facilities were much smaller, substantial compliant facilities were used as part of the grouping strategy. The problem in including them was that it increased the false negative results. With them not being included, it is possible to decrease and eliminate false negatives. An additional methodological twist is also to eliminate and not use the substantial compliant facilities at all in the subsequent analyses which again helps to accentuate the difference scores between the two groups of highly compliant and low compliant scoring facilities.

The next steps for building valid and reliable regulatory compliance systems are drawing upon what has been learned from more ordinally based measurement systems and applying this measurement structure to regulatory compliance systems. As such, the move would be away from a strict nominally based measurement to more ordinal in which more of a program quality element is built into each rule. By utilizing this paradigm shift, additional variance should be built into the measurement structure. So rather than having a Yes/No result, there would be a gradual Likert type (1-5) scale built in to measure "rule performance" rather than "rule compliance" where a "1" indicates non-compliance or a violation of the specific rule. A "5" would indicate excellent performance as it relates to the specific rule. A "3" would indicate compliance with the specific rule meeting the specifics of the rule but not exceeding it in any way.

This paradigm shift has led to the creation of Quality Rating and Improvement Systems (QRIS) throughout the USA because of a frustration to move licensing systems to more quality focused. The suggestion being made here is to make this movement based upon the very recent developments in designing such systems as is the case with Head Start monitoring. Head Start GPMS is developing an innovative Likert based ordinal system which incorporates compliance and performance into their monitoring system. Other jurisdictions can learn from this development. It is not being suggested as a replacement for QRIS or accreditation or ERS/CLASS assessments but as a more seamless transition from licensing to these various assessments. As indicated by the theory of regulatory compliance and the law of regulatory compliance diminishing returns, this relationship between licensing and program quality is not linear. By having this monitoring system approach in place, it may be able to reintroduce more of a linear relationship between licensing and program quality.

Regulatory Compliance & Program Quality Grid Model: Technical Research Note

Richard Fiene, Ph.D.

December 2020

Depicted below if 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 italized "***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%**	**5QualityAddons**
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.

Regulatory Compliance and Program Quality

Richard Fiene, Ph.D

Research Institute for Key Indicators & Penn State University

January 2020

Four technical research notes follow this brief introduction which will provide a blueprint for integrating data analysis within licensing and the various program quality interventions available in the early care and education field, such as quality rating and improvement systems, accreditation, professional development, pre-k programs, and such standards drawn from *Caring for Our Children*.

The four technical research notes are the following:

- *The Cumulative Effect of Standards on Early Care and Education Quality 2020,*
- *Regulatory Compliance Law of Diminishing Returns 2020,*
- *Theory of Early Childhood Outcomes 2019,*
- *Theory of Regulatory Compliance Models 2018.*

These technical research notes when taken together will provide licensing researchers and other researchers interested in the relationship between regulatory compliance and quality a roadmap for doing this type of data analysis. Particular limitations and parameters are pointed out in the technical research notes. These technical research notes were written between the summer of 2018 to the winter of 2019-20.

These technical research notes build upon the regulatory science research literature in the human services over the past 50 years (for the interested reader, additional information can be found at the following website – http://RIKInstitute.com.

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Cumulative Effect of Standards on Early Care and Education Quality

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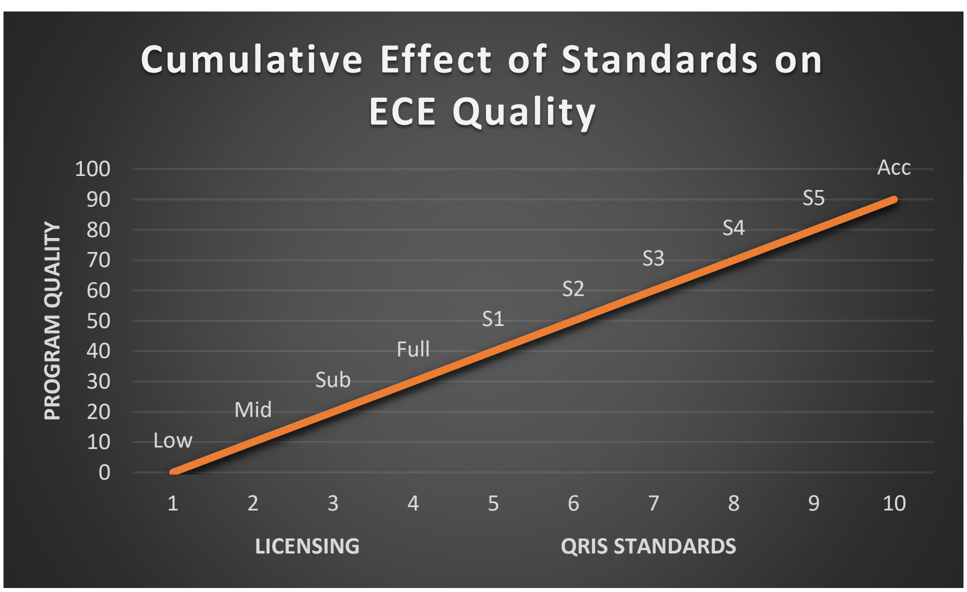
January 2020

The purpose of this technical research note is to extend an early childhood program quality model first proposed by Gwen Morgan (1979). In that model, regulatory and non-regulatory interventions were proposed that would influence the overall quality of early childhood programs. This research note will only focus on the regulatory side, but it will attempt to depict the relationships amongst these interventions in mathematical and graphic terms (see Figure 1).

The advantage in this approach is to begin to tie the empirical data being generated by jurisdictions as they collect and analyze the data from licensing, quality initiatives, QRIS systems, accreditation, and *Caring for Our Children* standards. Although the graphic below and the relationship between the various standards are depicted in a linear fashion, it has been demonstrated that this linear relationship is not as smooth as it appears. The *Regulatory Compliance Law of Diminishing Returns* is an example of the non-linear relationship between licensing and program quality (Fiene, 2020).

The idea that possibly a step wise progression in moving from licensing to QRIS to accreditation may be more appropriate. Only with the use of the new empirical evidence emerging from these systems will we be able to confirm such a model. For now, what we know is that the move from licensing to QRIS in a linear fashion may not be as smooth as depicted in figure 1. In order to ensure a smooth transition as depicted in figure 1, additional standards, such as from a Pre-K program may need to be introduced.

Figure 1: The Cumulative Effect of Standards on Early Care & Education Quality



In figure 1 above, licensing is broken down into the major categories of low, mid, substantial (sub), and full regulatory compliance levels. This progression is depicted as a linear relationship with program quality; however, based upon the Regulatory Compliance Law of Diminishing Returns this is not usually the case. The progression is linear in moving from low to mid to substantial but it decreases or plateaus in moving from substantial to full. QRIS is depicted as a five star system (S1, S2, S3, S4, S5) but in some jurisdictions it may only be a four star system. And lastly is accreditation (acc) which is usually tied to the highest QRIS star level.

Three other program quality interventions need to be considered in this depiction: 1) professional development, 2) Pre-K programs, and 3) *Caring for Our Children* standards. All these quality interventions have a value added, strengthening effect on the relationship depicted in figure 1.

Regulatory Compliance Law of Diminishing Returns

Richard Fiene, Ph.D.

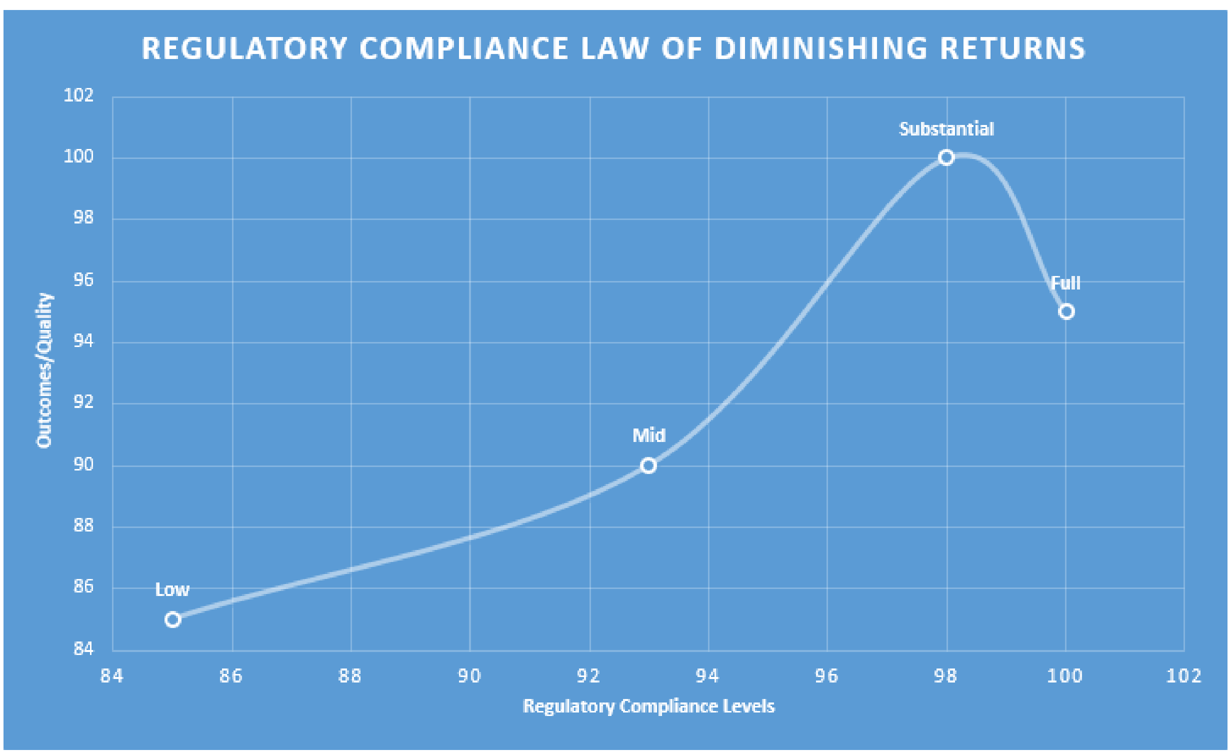
Research Institute for Key Indicators and Penn State University

January 2020

This brief technical research note will provide an update regarding the relationship between regulatory compliance and program quality/outcomes. Based upon the most recent research from studies with the national Head Start program, early care and education programs in Georgia and Washington, it is possible now to begin to address the limitations of full regulatory compliance and its lack of support for program quality/outcomes. The following figure (Figure 1) provides a graphic display of the relationship between these variables from the above-mentioned studies.

For sake of presentation, the data have been smooth-out so that it presents a clearer picture of the relationship. The important aspect of this relationship is not moving from low compliance to mid and substantial compliance. The relationship holds up as it should in demonstrating a consistent linear distribution. The most important aspect is in moving from substantial to full regulatory compliance in which the linear relationship breaks down and there is at least a plateau effect and in many cases a statistically significant drop off in quality outcomes (see Chart 1).

Figure 1: Relationship Between Regulatory Compliance and Program Quality/Outcomes



Based upon the empirical evidence from the above-mentioned studies (see Chart 1), it provides support in demonstrating the need to re-think how we approach regulatory compliance. It would appear to be more cost effective and efficient to determine which rules/regulations have the greatest impact on quality outcomes rather than looking at all rules/regulations as being equal in importance. So does regulatory compliance follow the economic rules of the law of diminishing returns in providing a healthy and safe setting for our clients. And do these findings in human services generalize to other services in the private economic sectors?

The following chart (Chart 1) provides data distributions from states and a national organization showing the relationship between specific program quality tools (ERS and CLASS) and regulatory compliance (RC) data. The last row gives the result as either the data dropping off or plateauing.

Chart 1: Data Distributions for ERS and CLASS from Selected States

RC	**ERS1**	**ERS2**	**CLASS1**	**CLASS2**	**CLASS3**	**CLASS4**	**CLASS5**
Full	3.84	3.40	5.91	2.55	3.03	5.99	5.59
Subst	4.26	3.77	6.22	2.77	3.15	5.93	5.50
Medium	4.18	3.26	-----	-----	2.87	5.85	5.37
Low1	3.92	2.51	6.14	2.55	2.65	5.71	5.32
Low2	-----	-----	-----	-----	2.56	5.52	4.93
Result	Drop Off	Drop Off	Drop Off	Drop Off	Drop Off	Plateau	Plateau
P values	.03	.001	n.s.	n.s.	.001	.001	.003

It is evident from the above data displays in Chart 1 that there is a plateau effect (n = 2) or in 5 cases the average quality scores showed a statistically significant decrease in moving from substantial (Subst) regulatory compliance to full regulatory compliance (Full).

Regulatory Compliance Decision Making Using the Key Indicator Methodology

Richard Fiene, Ph.D.

April 2018

The purpose of this paper is to provide guidance to regulatory administrators in decision making regarding the Key Indicator Methodology. A 2 x 2 Matrix will be used to demonstrate the key decisions that need to be made with various caveats and examples. Key Indicator Systems for Licensing have been used in states for many years now; this paper hopefully will provide a framework for the difficult decision making when it comes to moving from an abbreviated monitoring inspection to a full comprehensive monitoring inspection.

The basic *KIS Decision Making 2 x 2 Matrix* to be employed throughout this paper is the following format:

KIS Decision Making Matrix	**Overall Low Compliance (L)**	**Overall High Compliance (H)**
KI Rule is Not In-Compliance (NC)	L+NC = Desirable	H+NC = False Negative
KI Rule is In-Compliance (C)	L+C = False Positive	H+C = Desirable

The above 2 x 2 Matrix provides the basic decision making in a licensing key indicator system. We want to find a rule that statistically predicts overall high compliance when it is in-compliance (H+C) and when it is not in-compliance it predicts overall low compliance with all rules (L+NC). Less favorable are rules that are in- compliance but predict overall low compliance (L+C) and worse of all is when the rule is not in-compliance but statistically predicts high overall compliance with all rules (H+NC). In the KIS Decision Making Matrix we should always find (L+NC) + (H+C) > (H+NC) + (L+C). (H+NC) should be zero (0) or as close to zero. Both (L+NC) and (H+C) should be the highest populated cells in the matrix. Generally because of the nature of rules, (L+C) is usually well populated as well which is not necessarily a bad thing but it can lead to inefficiencies which will help to defeat the purpose of the Key Indicator Methodology's cost efficiency.

Examples of the above may help to make this more straightforward for decision making:

Example 1:

KIS Decision Making Matrix	**Overall Low Compliance**	**Overall High Compliance**
KI Rule is Not In-Compliance	1	0
KI Rule is In-Compliance	59	44

Example 1 demonstrates a non-significant relationship within the KIS Decision Making Matrix where there is no relationship between this particular rule and its ability to predict overall regulatory compliance. It would not be recommended as a Key Indicator Rule.

Example 2:

KIS Decision Making Matrix	**Overall Low Compliance**	**Overall High Compliance**
KI Rule is Not In-Compliance	5	0
KI Rule is In-Compliance	55	44

In Example 2, this rule reaches significance (phi = .19; $p < .05$) in being able to predict overall compliance because now when the rule is not In-Compliance it predicts overall low compliance, and continues when the rule is In-Compliance to predict overall high compliance. However, there are still a number of False Positives (n = 55) where when the Rule is In-Compliance it is predicting overall low compliance. This can lead to monitoring additional programs that don't necessarily need additional in-depth monitoring which goes counter to the purposed of the Key Indicator Methodology. But this is a fact of life with licensing data, most programs are in compliance with the majority of their rules.

Example 3:

KIS Decision Making Matrix	**Overall Low Compliance**	**Overall High Compliance**
KI Rule is Not In-Compliance	21	3
KI Rule is In-Compliance	39	41

Example 3 provides an interesting dilemma in that it is more highly significant (phi = .33; $p < .001$) than Example 2, but introduces three 3 False Negatives where the program is in the High Compliance Group but the specific Rule is Not In-Compliance.

Example 4:

KIS Decision Making Matrix	**Overall Low Compliance**	**Overall High Compliance**
KI Rule is Not In-Compliance	60	0
KI Rule is In-Compliance	0	44

Example 4 provides a perfect relationship (phi = 1.00; $p < .0001$) between the KI rule and the overall compliance level. The KI rule is always not In-Compliance with the overall low compliance programs and always In-Compliance with the overall high compliance programs. The problem is this KI rule just does not exist in the licensing field. It does in the program quality (QRIS) arena utilizing ERS data but not in licensing and regulatory administration.

So where does this leave the regulatory licensing administrator in making decisions with the Key Indicator Methodology. When should one move from an abbreviated monitoring inspection to a full monitoring inspection? When should a rule become a key indicator? The answer depends on the tolerance for false negatives I feel. Any licensing administrator must be concerned when the false negatives are beginning to populate the matrix.

The purpose of this paper is to help regulatory licensing administrators decide when to use Key Indicators/Abbreviated Inspections and when to use Comprehensive Monitoring Inspections. In the past, phi coefficients were used as the determining factor without regard for False Negatives. Based on the past 40 years of research into Key indicators' Methodology, I think a closer look at the Matrix data is warranted rather than a strict threshold determination using phi coefficients.

Based upon this need to look more closely at the False Positives and Negatives, it is highly recommended to use a top 25% and a bottom 25% for the High and Low Compliance Groups rather than a 50%/50% separation. The 25%/25% breakout is a much better model. And lastly, once the Key Indicators (KI) are in place, run a correlation and scatterplot of the KI with the Comprehensive Instrument (CI) to see how the data display. A very high correlation (r = .75+) should be observed in the comparison of KI and CI. This is the last step in order to validate the use of the KI as an efficient and effective abbreviated instrument that statistically predicts overall compliance via the Comprehensive Instrument (CI).

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Three Things We Have Learned about Key Indicators, Risk Assessments, and Differential Monitoring

Richard Fiene, Ph.D.

April 2018

After 40+ years of research regarding the Key indicator, Risk Assessment and Differential Monitoring methodologies in human service regulatory administration, there are certain consistencies that have been noted over the years. I have highlighted some of these in Technical Research Notes (please see http://RIKInstitute.com) in the past but there are three that I feel are so significant that I wanted to review them here together.

One, in creating the data base for Key Indicators, the best model for sorting the program licensing scores is to compare the top 25% to the bottom 25% while eliminating the middle 50% of the programs that fall within this range. Some states have used the top 50% and the bottom 50% as the sorting schema. In making comparisons utilizing the various data sorting models, the 25%/25% model always performed the best.

Two, in most studies that involved both program compliance data and program quality data, Key indicator and Risk Assessment Rules correlated significantly with ERS and CLASS scores. This is an important finding because one of the reasons for doing abbreviated monitoring inspections such as Key Indicator or Risk Assessment Reviews is to establish a balance between program compliance as measured via licensing and program quality as measured via ERS or CLASS usually within a QRIS protocol.

Three, there appears to be little to no significance to the number of rules within a Key Indicator Tool. It performs well with fewer than 10 rules as well as in cases where there are more rules present in the tool. It is more important what the Key Indicator Rules are than the number. However, with that said, obviously the more rules one has the less efficient the process becomes because you are reviewing more rules than may be warranted.

I thought it important to share these three short thoughts with you regarding the trends I have noticed over the past 40+ years of doing research into Key Indicator, Risk Assessment and Differential Monitoring within human services and early care and education regulatory compliance, licensing, program quality and professional development systems.

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The Basic Tenets of an Effective and Efficient Monitoring System for Regulatory Compliance

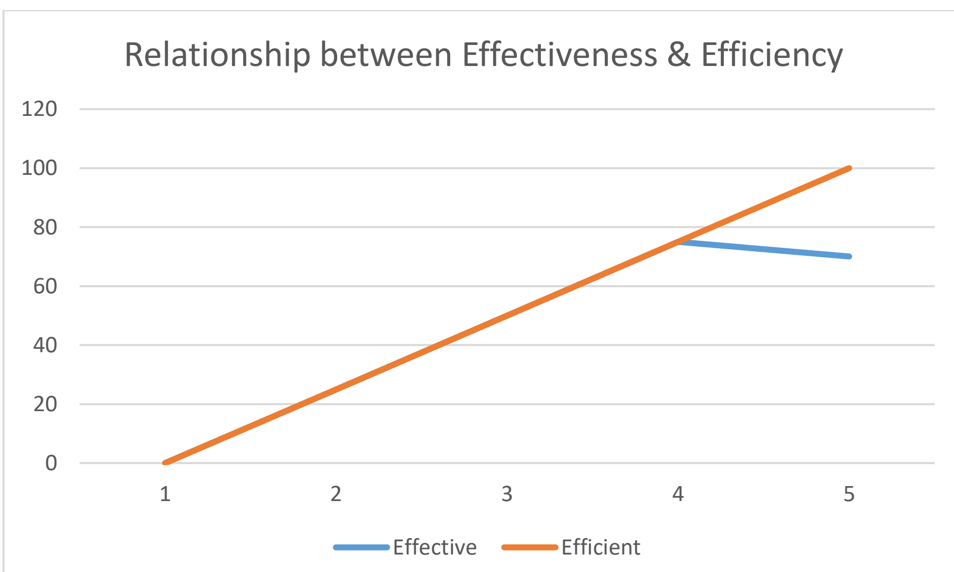
Richard Fiene, PhD.

April 2018

This paper will describe the essential elements of building an effective and efficient monitoring system for regulatory compliance. There is a balancing of both effectiveness and efficiency that need to be conjoined as state administrators think about how best to monitor human services. A basic assumption of this paper is that effectiveness and efficiency are tied together in a deep structure and are not two independent values.

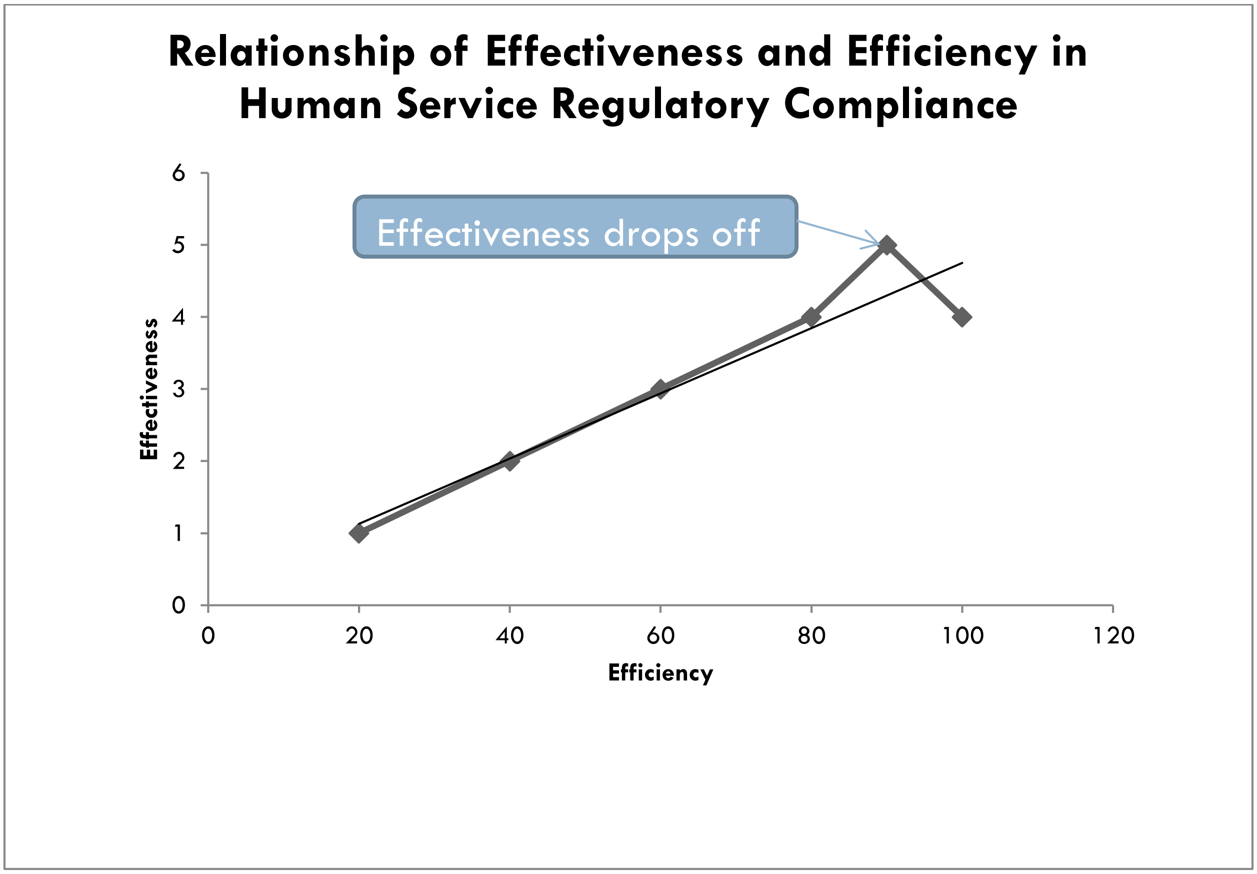
The prevailing theory of the relationship of effective and efficient monitoring systems is based upon a linear relationship between the two. The best monitoring system is one that is both effective and efficient. And this is true up to a point. An alternate theory or paradigm for thinking about this relationship is that as one moves up the efficiency scale, effectiveness will begin to slide as we move from highly efficient systems to the most efficient systems where very few rules are reviewed (see the below figure 1 for a depiction of this relationship). Within the human service regulatory administration and compliance field is the move to more abbreviated inspections in which fewer rules are reviewed. These abbreviated inspections are based upon risk assessment and key indicator methodologies.

Figure 1 – The NonLinear Relationship between Effectiveness and Efficiency



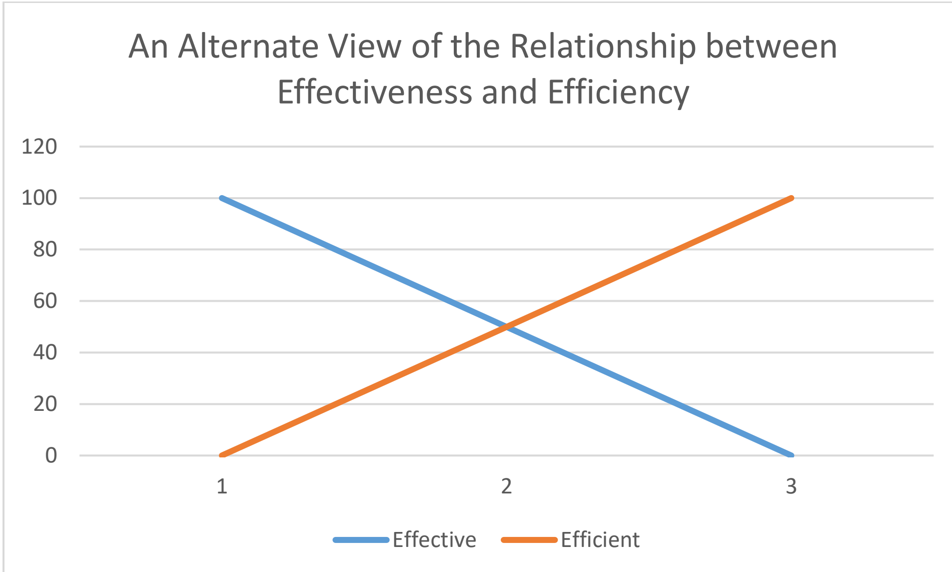
As state administrators of regulatory compliance systems there is the need to find the “sweet spot”, the balance between having both an effective and efficient monitoring system. Finding the correct number of rules to monitor is a difficult decision. Especially in the present focus on de-regulation. We need to be careful to "not throw the baby out with the bath water", so to speak, in public policy terms. The above relationship as depicted in Figure 1 has been discovered in repeated studies by the author in all forms of human service licensing and regulatory administration and compliance studies, such as child residential , adult residential, and early care and education (see Figure 2 below).

Figure 2 – Study Results from Several Human Service Regulatory Administration & Compliance Studies



An alternate way of looking at effectiveness and efficiency is depicted in Figure 3 below. In this depiction, both values are placed within the same graphic in order to determine how they interact with each other. The key to this Intersection of Effectiveness and Efficiency is determining the balance point where one can find the most effective and efficient monitoring system. For state administrators responsible for regulatory administration, it is always difficult to find the correct balance of oversight in a system that is operated with limited resources. There is always pressure to make the most out of limited resources. But with that said, everyone needs to be certain that in the quest for efficiencies we do not really begin to jeopardize effectiveness.

Figure 3 – The Intersection of Effectiveness and Efficiency



The purpose of this paper is to demonstrate an alternate paradigm in thinking about the relationship between effectiveness and efficiency as it relates to program monitoring within a regulatory administration and compliance setting. What are some of the key tenets in deciding upon a monitoring system that will meet the needs of all clients who are receiving various human services without jeopardizing their overall health and safety which is the essence of effectiveness.

Richard Fiene, Ph.D., Senior Research Psychologist, Research Institute for Key Indicators (RIKILLC), Professor of Psychology (ret), Penn State University, & Senior Consultant, National Association for Regulatory Administration (NARA). Contact Dr Fiene at Fiene@RIKInstitute.com or RFiene@NARALicensing.org or rjf8@psu.edu

The Implications in Regulatory Compliance Measurement When Moving from Nominal to Ordinal Scaling

Richard Fiene, Ph.D.

May 2018

The purpose of this paper is to provide an alternate paradigm for regulatory compliance measurement in moving from a nominal to an ordinal scale measurement strategy. Regulatory compliance measurement is dominated by a nominal scale measurement system in which rules are either in compliance or out of compliance. There are no gradients for measurement within the present licensing measurement paradigm. It is very absolute. Either a rule is in full compliance to the letter of the law or the essence of the regulation or it is not. An alternate paradigm borrowing from accreditation and other program quality systems is to establish an ordinal scale measurement system which takes various gradients of compliance into account. With this alternate paradigm, it offers an opportunity to begin to introduce a quality element into the measurement schema. It also allows to take into consideration both risk and prevalence data which are important in rank ordering specific rules.

So how would this look from a licensing decision making vantage point. Presently, in licensing measurement, licensing decisions are made at the rule level in which each rule is either in or out of compliance in the prevailing paradigm. Licensing summaries with corrective actions are generated from the regulatory compliance review. It is a nominal measurement system being based upon Yes/No responses. The alternate measurement paradigm I am suggesting in this paper is one that is more ordinal in nature where we expand the Yes/No response to include gradients of the particular rule. In the next paragraph, I provide an example of a rule that could be measured in moving from a nominal to ordinal scale measurement schema.

Rather than only measuring a rule in an all or none fashion, this alternate paradigm provides a more relative mode of measurement at an ordinal level. For example, with a professional development or training rule in a particular state which requires, let's say, 6 hours of training for each staff person. Rather than having this only be 6 hours in compliance and anything less than this is out of compliance, let's have this rule be on a relative gradient in which any amount of hours above the 6 hours falls into a program quality level and anything less than the 6 hours falls out of compliance but at a more severe level depending on how far below the 6 hours and how many staff do not meet the requirement (prevalence). Also throw in a specific weight which adds in a risk factor and we have a paradigm that is more relative rather than absolute in nature.

From a math modeling perspective, the 1 or 0 format for a Yes or No response becomes -2, -1, 0, +1, +2 format. This is more similar to what is used in accreditation systems where 0 equals Compliance and -1 and -2 equals various levels of Non-Compliance in terms of severity and/or prevalence. The +1 and +2 levels equal value added to the Compliance level by introducing a Quality Indicator. This new formatting builds upon the compliance vs non-compliance dichotomy (C/NC) but now adds a quality indicator (QI) element. By adding this quality element, we may be able to eliminate or at least lessen the non-linear relationship between regulatory compliance with rules and program quality scores as measured by the

Environmental Rating Scales (ERS) and CLASS which is the essence of the Theory of Regulatory Compliance (TRC). It could potentially make this a more linear relationship by not having the data as skewed as it has been in the past.

By employing this alternate paradigm, it is a first demonstration of the use of the Key Indicator Methodology in both licensing and quality domains. The Key Indicator Methodology has been utilized a great deal in licensing but in few instances in the program quality domain. For example, over the past five years, I have worked with approximately 10 states in designing Licensing Key Indicators but only one state with Quality Key Indicators from their QRIS – Quality Rating and Improvement System. This new paradigm would combine the use in both. It also takes advantage of the full ECPQI2M – Early Childhood Program Quality Improvement and Indicator Model by blending regulatory compliance with program quality standards.

A major implication in moving from a nominal to an ordinal regulatory compliance measurement system is that it presents the possibility of combining licensing and quality rating and improvement systems into one system via the Key Indicator Methodology. By having licensing indicators and now quality indicators that could be both measured by licensing inspectors, there would be no need to have two separate systems but rather one that applies to everyone and becomes mandated rather than voluntary. It could help to balance both effectiveness and efficiency by only including those standards and rules that statistically predict regulatory compliance and quality and balancing risk assessment by adding high risk rules.

I will continue to develop this scale measurement paradigm shift in future papers but wanted to get this idea out to the regulatory administration field for consideration and debate. This will be a very controversial proposal since state regulatory agencies have spent a great deal of resources on developing free standing QRIS which build upon licensing systems. This alternate paradigm builds off my Theory of Regulatory Compliance's key element of relative vs absolute measurement and linear vs non-linear relationships. Look for additional information about this on my website RIKI Institute Blog - https://rikinstitute.com/blog/.

Richard Fiene, Ph.D., Senior Research Psychologist, Research Institute for Key Indicators; Professor of Psychology (retired), Penn State University; and NARA Senior Research Consultant. Rjf8@psu.edu. http://RIKInstitute.com.

Fiene Algorithm for Generating Regulatory Compliance Key Indicators (RCKI)

1. Add up regulatory non-compliances for all programs, agencies, jurisdictions, etc...
2. Review Regulatory Compliance history sorted from high to low
3. Nominal (Compliance(1)/Non-Compliance(0)) or ordinal measurement (Gradient(1-5)) scaling
4. Take Risk Assessment Weighting (1-9) into account and apply to nominal or ordinal scaling.
5. Top 25% (High Group) and bottom 25% (Low Group) of regulatory compliance scores
6. Drop out the middle 50% of regulatory compliance scores
7. Develop a 2 x 2 matrix which includes each regulation by the High Group and Low Group
8. Cells of the Matrix: A = High Group + Programs in Compliance on Specific Regulation
9. B = High Group + Programs out of Compliance on Specific Regulation
10. C = Low Group + Programs in Compliance on Specific Regulation
11. D = Low Group + Programs out of Compliance on Specific Regulation
12. W = Total Number of Programs in Compliance on Specific Regulation
13. X = Total Number of Programs out of Compliance on Specific Regulation
14. Y = Total Number of Programs in High Group.
15. Z = Total Number of Programs in Low Group
16. Use the following formula: ((A)(D)) – ((B)(C)) / sqrt ((W)(X)(Y)(Z)) = RCKI
17. Result will range from –1 to +1
18. +.5 to +1.0 will be included as Regulatory Compliance Key Indicators (RCKI). All other regulations will not be included.

Regulatory Compliance Skewness

Richard Fiene, Ph.D.

June 2018

In dealing with regulatory compliance data distributions, one is always impressed with the skewness of the data distribution. This is a major disadvantage of working with these data distributions because it eliminates utilizing parametric statistics. These short comings have been dealt with in the past by using non-parametric statistics, the dichotomization of data distributions, moving from a nominal to ordinal scaling, and risk assessment/weighting. These adjustments have been successful in helping to analyze the data but are not ideal and will never approach a normally distributed curve. However, that is not the intent of regulatory compliance data, the data distribution should demonstrate a good deal of skewness because these data are demonstrating protections for clients and not quality services. One would not want the data to be normally distributed.

This short paper/technical research note delineates the state of the art with an international regulatory compliance data base that has been created over the past 40 years at the Research Institute for Key Indicators (RIKILLC). In it, I provide basic descriptive statistics to demonstrate to other researchers the nature of the data distributions so that they can be aware of the shortcomings of the data when it comes to statistical analyses. I have employed various scaling methods to help with the skewness of the data but it still does not approximate normally distributed data. This will be self-evident in the data displays.

	KI	PQ	RC	PQ 1-5	RC 1-5
Mean	**1.68**	**3.42**	**5.51**	**2.96**	**3.48**
SD	**1.61**	**0.86**	**5.26**	**0.90**	**1.43**
Sum	**175**	**348**	**573**	**302**	**362**
Variance	**3.61**	**0.74**	**27.63**	**0.81**	**2.06**
Range	**6.00**	**4.11**	**25.00**	**4.00**	**4.00**
Minimum	**0**	**1.86**	**0**	**1.00**	**1.00**
Maximum	**6.00**	**5.97**	**25.00**	**5.00**	**5.00**
SE Mean	**0.16**	**0.09**	**0.52**	**0.09**	**0.14**
Kurtosis	**0.073**	**-0.134**	**2.112**	**-0.388**	**-1.097**
Skewness	**0.898**	**0.467**	**1.468**	**0.327**	**-0.494**

Legend:

KI = Key Indicators

PQ = Program Quality (ERS Scale)

RC = Regulatory Compliance (State Comprehensive Review Checklist)

PQ 1-5 = Program Quality using 1-5 scale

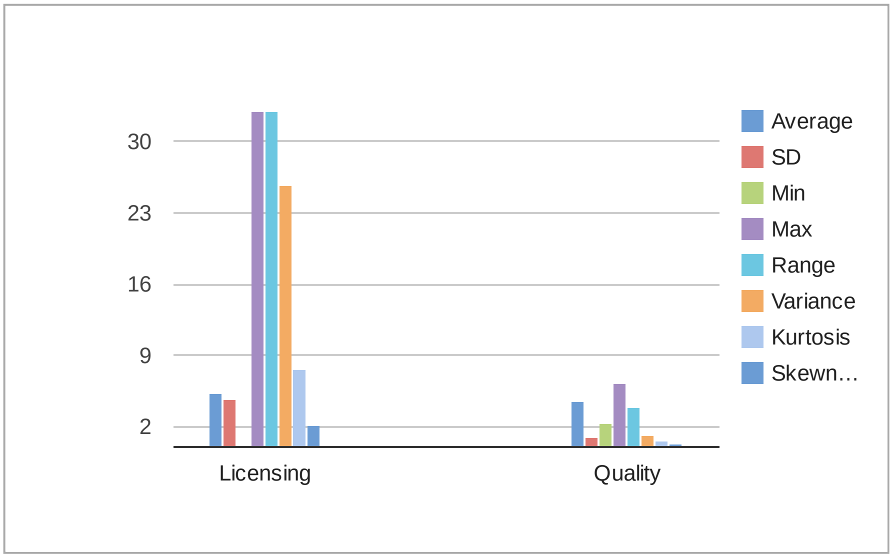
RC 1-5 = Regulatory Compliance using 1-5 scale (1 = Low RC; 2-4 = Med Level RC; 5 = High/Substantial RC)

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)

This display presents descriptive statistics for licensing and quality studies averaged from several states and national data
The data are displayed in both chart and graphic forms.
It clearly demonstrates the differences between licensing and quality data in which licensing data are much more skewed

Licensing and Quality Descriptive Statistics

	Average	**SD**	**Min**	**Max**	**Range**	**Variance**	**Kurtosis**	**Skewnes**	**Programs**
Licensing	**5.35**	**4.76**	**0**	**33**	**33**	**25.66**	**7.72**	**2.22**	**3452**
Quality	**4.58**	**1.07**	**2.32**	**6.33**	**4.01**	**1.17**	**0.67**	**0.26**	**1371**



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Data Distributions for Licensing and Quality Data

Richard Fiene, Ph.D.

November 2017

This technical research note contains examples from various states and nationally of data distributions (frequencies and histograms) depicting how licensing and program quality (ERS, CLASS) data compare to each other.

The data distributions clearly demonstrate how skewed licensing data (s = 2.22) are in comparison to program quality data as represented by the ERS and CLASS scales (s = .26). These data are presented for their historical and descriptive research significance. Each of the data sets were part of larger studies comparing licensing and quality of various child care center and home based programs across the country.

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	4	38	9.00	9.00	72.99
	5	29	6.87	6.87	79.86
	6	23	5.45	5.45	85.31
	7	14	3.32	3.32	88.63
	8	15	3.55	3.55	92.18
	9	8	1.90	1.90	94.08
	10	3	.71	.71	94.79
	11	4	.95	.95	95.73
	12	1	.24	.24	95.97
	13	5	1.18	1.18	97.16
	14	2	.47	.47	97.63
	15	3	.71	.71	98.34
	16	1	.24	.24	98.58
	17	2	.47	.47	99.05
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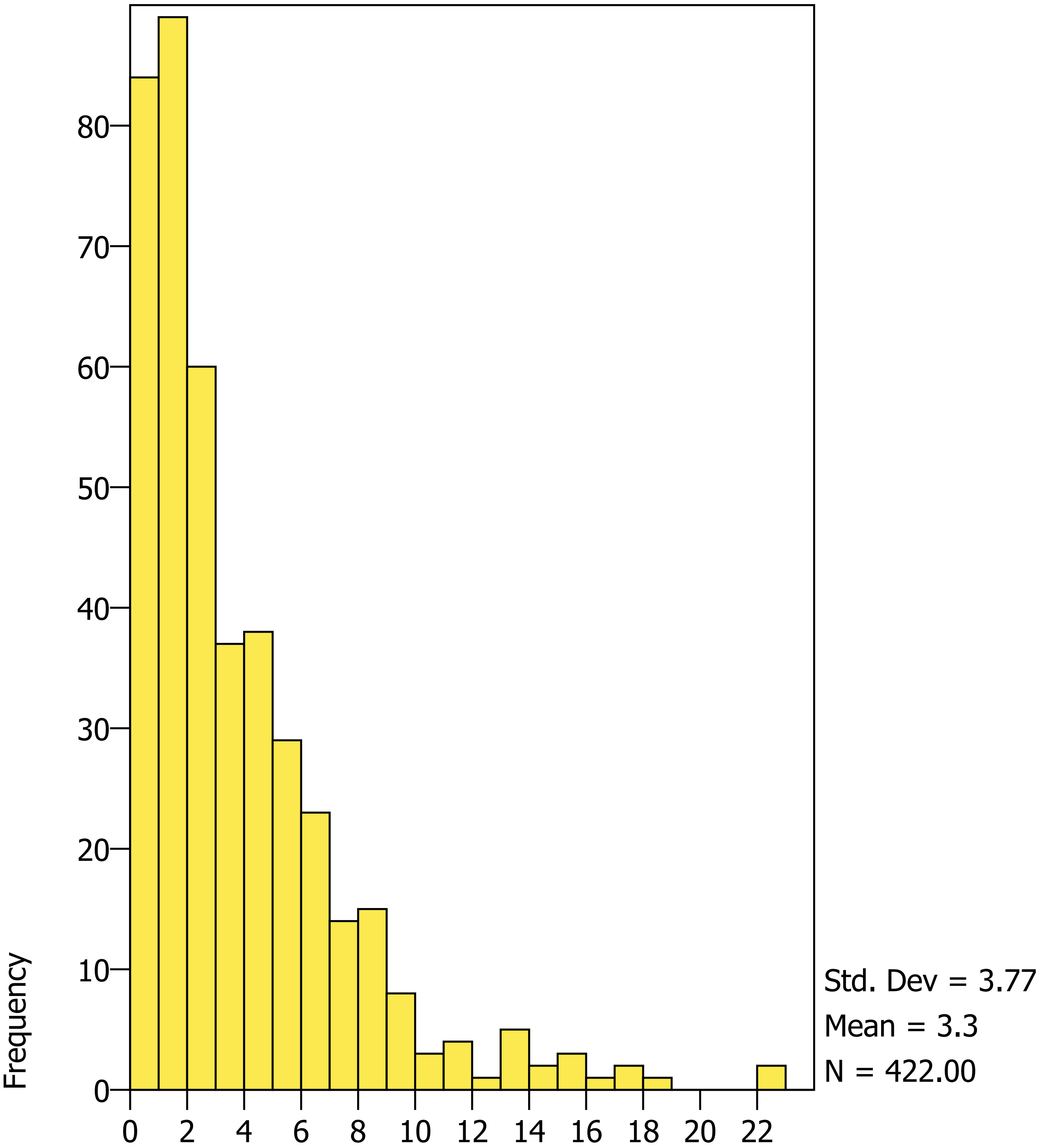

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	4.00	14	13.46	13.46	55.77
	5.00	5	4.81	4.81	60.58
	6.00	7	6.73	6.73	67.31
	7.00	6	5.77	5.77	73.08
	8.00	8	7.69	7.69	80.77
	9.00	5	4.81	4.81	85.58
	11.00	2	1.92	1.92	87.50
	12.00	3	2.88	2.88	90.38
	13.00	1	.96	.96	91.35
	15.00	1	.96	.96	92.31
	16.00	2	1.92	1.92	94.23
	18.00	1	.96	.96	95.19
	19.00	2	1.92	1.92	97.12
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	25.00	1	.96	.96	100.00
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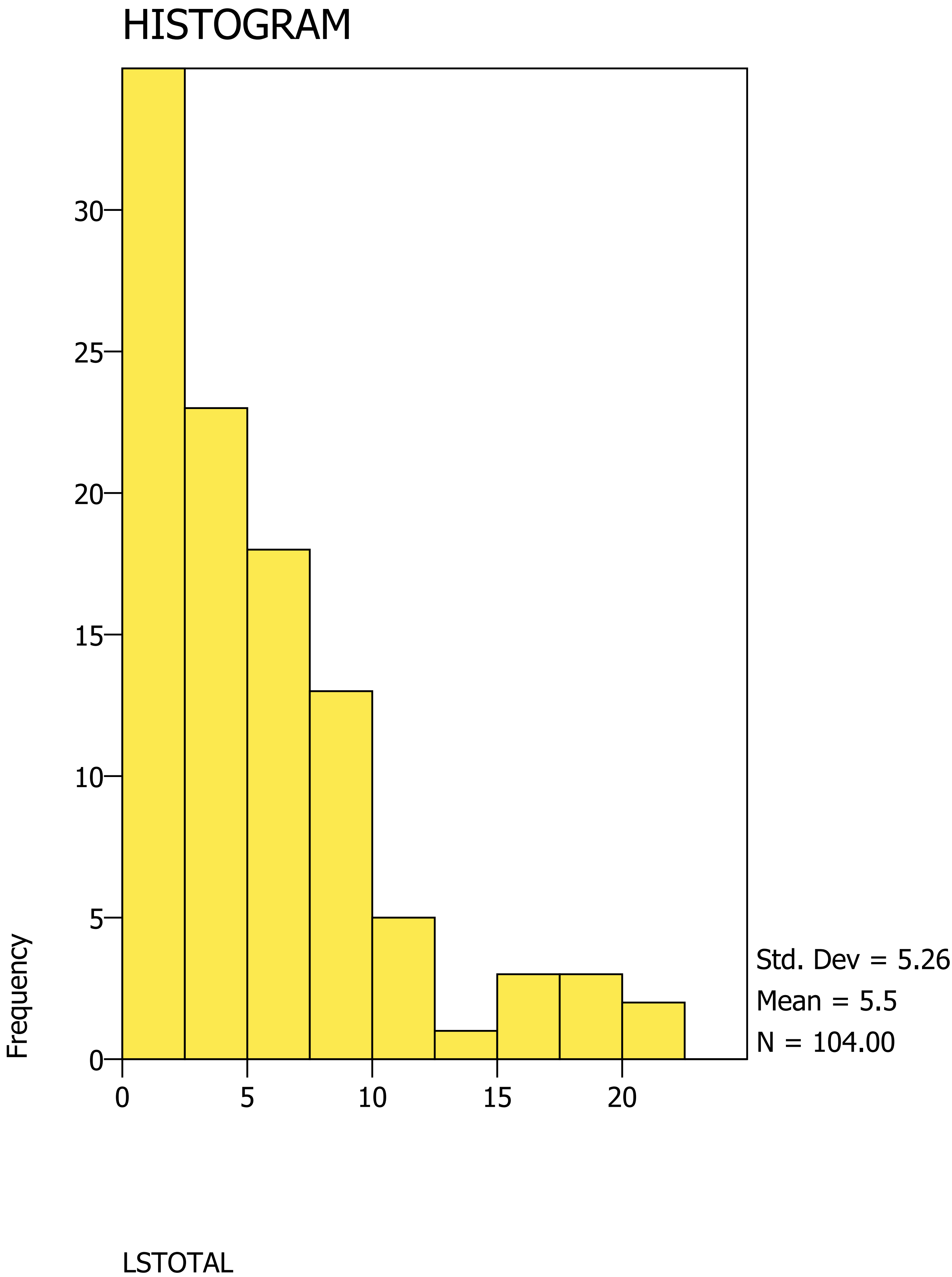
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	8.00	6	4.08	4.08	74.83
	9.00	3	2.04	2.04	76.87
	10.00	9	6.12	6.12	82.99
	11.00	3	2.04	2.04	85.03
	12.00	3	2.04	2.04	87.07
	13.00	3	2.04	2.04	89.12
	14.00	5	3.40	3.40	92.52
	15.00	2	1.36	1.36	93.88
	16.00	1	.68	.68	94.56
	17.00	1	.68	.68	95.24
	18.00	1	.68	.68	95.92
	19.00	2	1.36	1.36	97.28
	21.00	2	1.36	1.36	98.64
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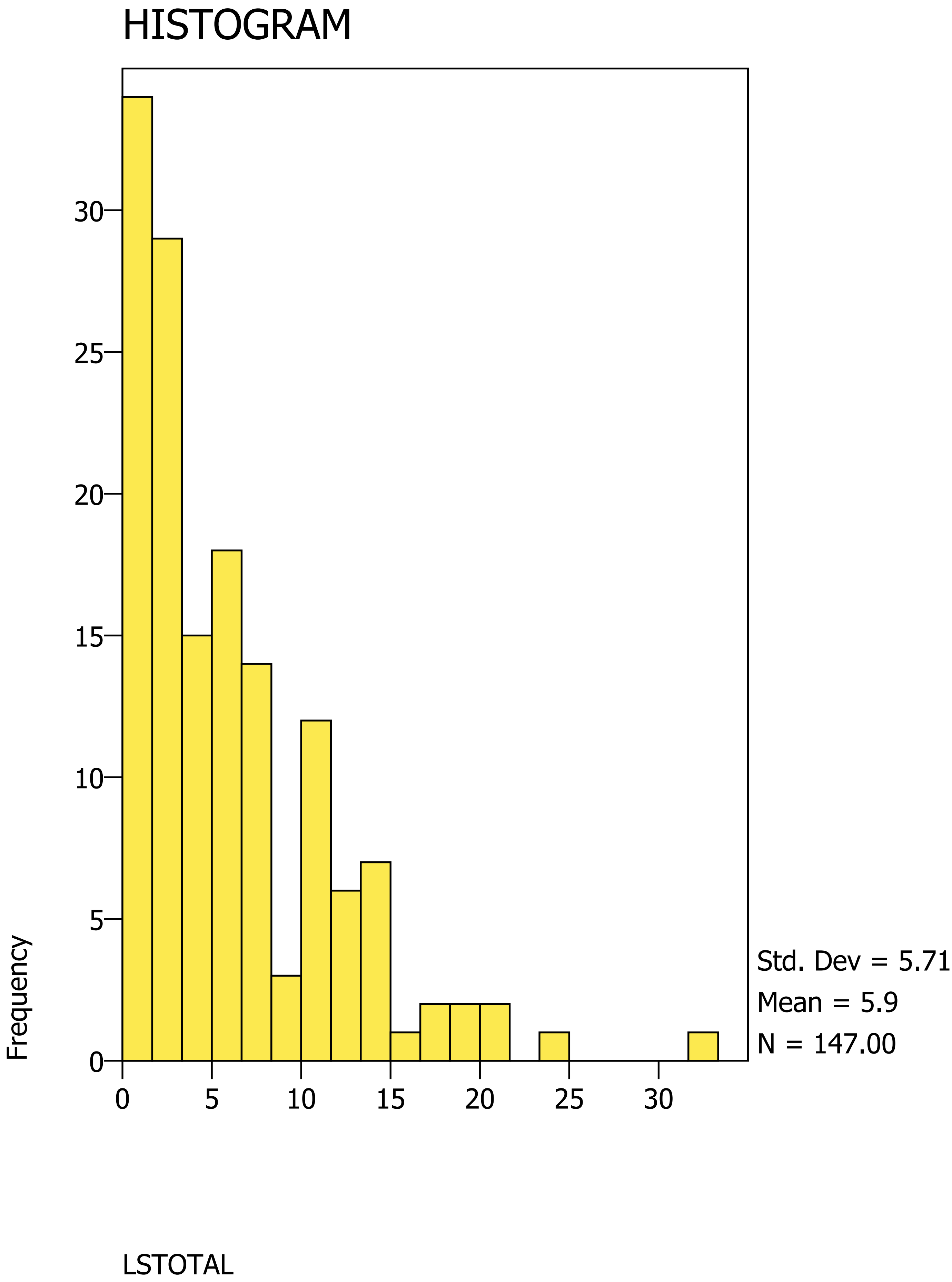
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	9.00	1	1.33	1.33	70.67
	9.33	2	2.67	2.67	73.33
	9.67	1	1.33	1.33	74.67
	10.00	2	2.67	2.67	77.33
	10.67	2	2.67	2.67	80.00
	11.00	1	1.33	1.33	81.33
	11.33	1	1.33	1.33	82.67
	11.67	1	1.33	1.33	84.00
	12.00	2	2.67	2.67	86.67
	12.67	1	1.33	1.33	88.00
	13.33	1	1.33	1.33	89.33

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	15.33	1	1.33	1.33	94.67
	16.33	1	1.33	1.33	96.00
	22.67	1	1.33	1.33	97.33
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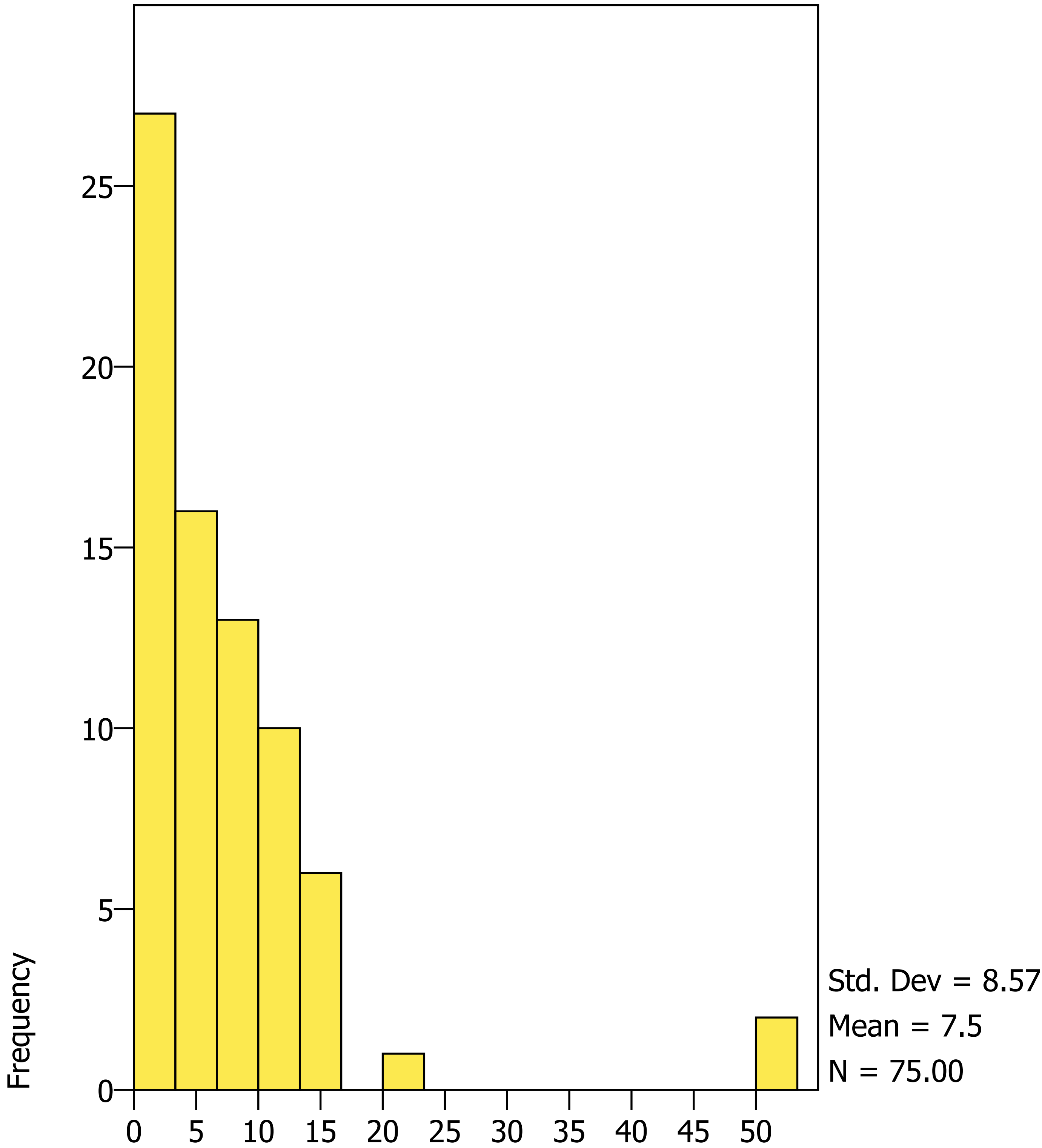

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	.67	3	2.42	2.42	10.48
	1.00	6	4.84	4.84	15.32
	1.33	5	4.03	4.03	19.35
	1.67	2	1.61	1.61	20.97
	2.00	2	1.61	1.61	22.58
	2.33	5	4.03	4.03	26.61
	2.67	5	4.03	4.03	30.65
	3.00	3	2.42	2.42	33.06
	3.33	2	1.61	1.61	34.68
	3.67	3	2.42	2.42	37.10
	4.00	6	4.84	4.84	41.94
	4.33	3	2.42	2.42	44.35
	4.67	2	1.61	1.61	45.97
	5.00	1	.81	.81	46.77
	5.67	6	4.84	4.84	51.61
	6.00	6	4.84	4.84	56.45
	6.67	2	1.61	1.61	58.06
	7.33	3	2.42	2.42	60.48
	7.67	4	3.23	3.23	63.71
	8.33	3	2.42	2.42	66.13
	8.67	1	.81	.81	66.94
	9.00	2	1.61	1.61	68.55
	9.33	2	1.61	1.61	70.16
	9.67	6	4.84	4.84	75.00
	10.00	3	2.42	2.42	77.42
	10.33	3	2.42	2.42	79.84
	10.67	2	1.61	1.61	81.45
	11.00	1	.81	.81	82.26

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
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	11.67	1	.81	.81	85.48
	12.33	3	2.42	2.42	87.90
	12.67	2	1.61	1.61	89.52
	13.67	1	.81	.81	90.32
	15.00	3	2.42	2.42	92.74
	18.00	2	1.61	1.61	94.35
	18.33	1	.81	.81	95.16
	19.67	1	.81	.81	95.97
	20.67	1	.81	.81	96.77
	22.00	1	.81	.81	97.58
	24.33	1	.81	.81	98.39
	25.67	1	.81	.81	99.19
	27.33	1	.81	.81	100.00
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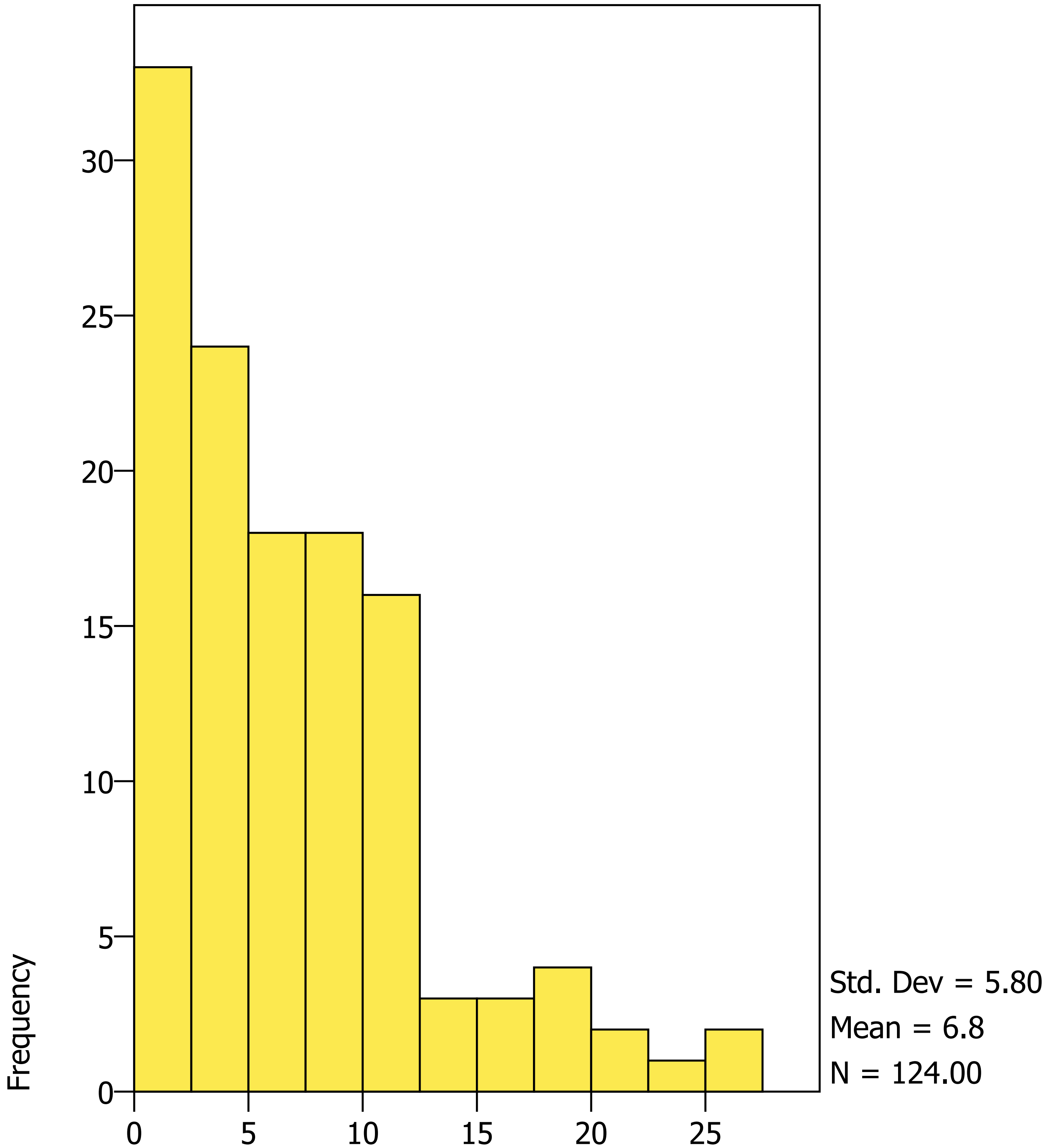

NC13

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GET FILE="C:\Documents and Settings\Judy\My Documents\RIKI\DATA\2OHS \OHS.sav".

FREQUENCIES

FREQUENCIES
    /VARIABLES= CLASSTOT
    /FORMAT=AVALUE TABLE
    /STATISTICS=NONE
    /HISTOGRAM=NONORMAL.

CLASS TOTAL OF THREE SCALES

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	8.87	1	.24	.26	.26
	9.46	1	.24	.26	.52
	10.00	2	.47	.52	1.04
	10.92	1	.24	.26	1.30
	10.94	1	.24	.26	1.56
	11.00	1	.24	.26	1.82
	11.27	1	.24	.26	2.08
	11.41	1	.24	.26	2.34
	11.59	1	.24	.26	2.60
	11.88	1	.24	.26	2.86
	11.96	1	.24	.26	3.12
	12.08	1	.24	.26	3.39
	12.11	1	.24	.26	3.65
	12.11	1	.24	.26	3.91
	12.14	1	.24	.26	4.17
	12.16	1	.24	.26	4.43
	12.21	1	.24	.26	4.69
	12.23	1	.24	.26	4.95
	12.24	1	.24	.26	5.21
	12.29	1	.24	.26	5.47
	12.33	1	.24	.26	5.73
	12.40	1	.24	.26	5.99
	12.44	1	.24	.26	6.25
	12.47	1	.24	.26	6.51
	12.47	1	.24	.26	6.77
	12.49	2	.47	.52	7.29
	12.53	1	.24	.26	7.55
	12.57	1	.24	.26	7.81
	12.62	1	.24	.26	8.07
	12.64	1	.24	.26	8.33

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	12.70	1	.24	.26	8.59
	12.73	1	.24	.26	8.85
	12.76	1	.24	.26	9.11
	12.78	1	.24	.26	9.38
	12.78	1	.24	.26	9.64
	12.80	1	.24	.26	9.90
	12.83	1	.24	.26	10.16
	12.85	1	.24	.26	10.42
	12.86	1	.24	.26	10.68
	12.88	1	.24	.26	10.94
	12.89	1	.24	.26	11.20
	12.90	1	.24	.26	11.46
	12.93	1	.24	.26	11.72
	12.95	1	.24	.26	11.98
	12.95	1	.24	.26	12.24
	12.96	1	.24	.26	12.50
	13.02	1	.24	.26	12.76
	13.03	1	.24	.26	13.02
	13.03	1	.24	.26	13.28
	13.04	1	.24	.26	13.54
	13.06	1	.24	.26	13.80
	13.08	1	.24	.26	14.06
	13.08	1	.24	.26	14.32
	13.10	1	.24	.26	14.58
	13.11	1	.24	.26	14.84
	13.13	1	.24	.26	15.10
	13.13	1	.24	.26	15.36
	13.13	1	.24	.26	15.62
	13.13	1	.24	.26	15.89
	13.14	1	.24	.26	16.15
	13.18	1	.24	.26	16.41
	13.18	1	.24	.26	16.67
	13.19	2	.47	.52	17.19
	13.19	1	.24	.26	17.45
	13.19	1	.24	.26	17.71
	13.19	1	.24	.26	17.97
	13.20	1	.24	.26	18.23
	13.22	1	.24	.26	18.49
	13.22	1	.24	.26	18.75
	13.23	1	.24	.26	19.01
	13.23	1	.24	.26	19.27
	13.23	1	.24	.26	19.53
	13.24	1	.24	.26	19.79
	13.24	1	.24	.26	20.05
	13.30	1	.24	.26	20.31
	13.31	1	.24	.26	20.57

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	13.32	1	.24	.26	20.83
	13.35	1	.24	.26	21.09
	13.35	1	.24	.26	21.35
	13.35	1	.24	.26	21.61
	13.35	1	.24	.26	21.88
	13.35	1	.24	.26	22.14
	13.36	1	.24	.26	22.40
	13.39	1	.24	.26	22.66
	13.41	1	.24	.26	22.92
	13.42	1	.24	.26	23.18
	13.43	1	.24	.26	23.44
	13.43	1	.24	.26	23.70
	13.45	1	.24	.26	23.96
	13.46	1	.24	.26	24.22
	13.47	1	.24	.26	24.48
	13.50	1	.24	.26	24.74
	13.52	1	.24	.26	25.00
	13.52	1	.24	.26	25.26
	13.52	1	.24	.26	25.52
	13.55	1	.24	.26	25.78
	13.58	1	.24	.26	26.04
	13.59	1	.24	.26	26.30
	13.60	1	.24	.26	26.56
	13.62	1	.24	.26	26.82
	13.62	1	.24	.26	27.08
	13.63	1	.24	.26	27.34
	13.64	1	.24	.26	27.60
	13.64	1	.24	.26	27.86
	13.66	1	.24	.26	28.13
	13.72	1	.24	.26	28.39
	13.73	1	.24	.26	28.65
	13.73	1	.24	.26	28.91
	13.75	1	.24	.26	29.17
	13.77	1	.24	.26	29.43
	13.79	1	.24	.26	29.69
	13.80	1	.24	.26	29.95
	13.82	1	.24	.26	30.21
	13.83	1	.24	.26	30.47
	13.83	1	.24	.26	30.73
	13.83	1	.24	.26	30.99
	13.83	1	.24	.26	31.25
	13.84	1	.24	.26	31.51
	13.85	1	.24	.26	31.77
	13.85	1	.24	.26	32.03
	13.85	1	.24	.26	32.29
	13.87	1	.24	.26	32.55

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	13.87	1	.24	.26	32.81
	13.88	1	.24	.26	33.07
	13.88	1	.24	.26	33.33
	13.89	1	.24	.26	33.59
	13.89	1	.24	.26	33.85
	13.89	1	.24	.26	34.11
	13.90	1	.24	.26	34.38
	13.90	1	.24	.26	34.64
	13.91	1	.24	.26	34.90
	13.92	1	.24	.26	35.16
	13.92	1	.24	.26	35.42
	13.92	1	.24	.26	35.68
	13.94	1	.24	.26	35.94
	13.95	1	.24	.26	36.20
	13.96	1	.24	.26	36.46
	13.96	1	.24	.26	36.72
	13.97	1	.24	.26	36.98
	13.97	1	.24	.26	37.24
	13.98	1	.24	.26	37.50
	13.98	1	.24	.26	37.76
	13.98	1	.24	.26	38.02
	14.00	1	.24	.26	38.28
	14.01	1	.24	.26	38.54
	14.02	1	.24	.26	38.80
	14.04	1	.24	.26	39.06
	14.05	1	.24	.26	39.32
	14.07	1	.24	.26	39.58
	14.07	1	.24	.26	39.84
	14.08	1	.24	.26	40.10
	14.09	1	.24	.26	40.36
	14.09	1	.24	.26	40.62
	14.09	1	.24	.26	40.89
	14.10	1	.24	.26	41.15
	14.11	1	.24	.26	41.41
	14.11	1	.24	.26	41.67
	14.12	1	.24	.26	41.93
	14.13	1	.24	.26	42.19
	14.13	1	.24	.26	42.45
	14.13	1	.24	.26	42.71
	14.14	1	.24	.26	42.97
	14.14	1	.24	.26	43.23
	14.14	1	.24	.26	43.49
	14.15	1	.24	.26	43.75
	14.16	1	.24	.26	44.01
	14.17	1	.24	.26	44.27
	14.17	1	.24	.26	44.53

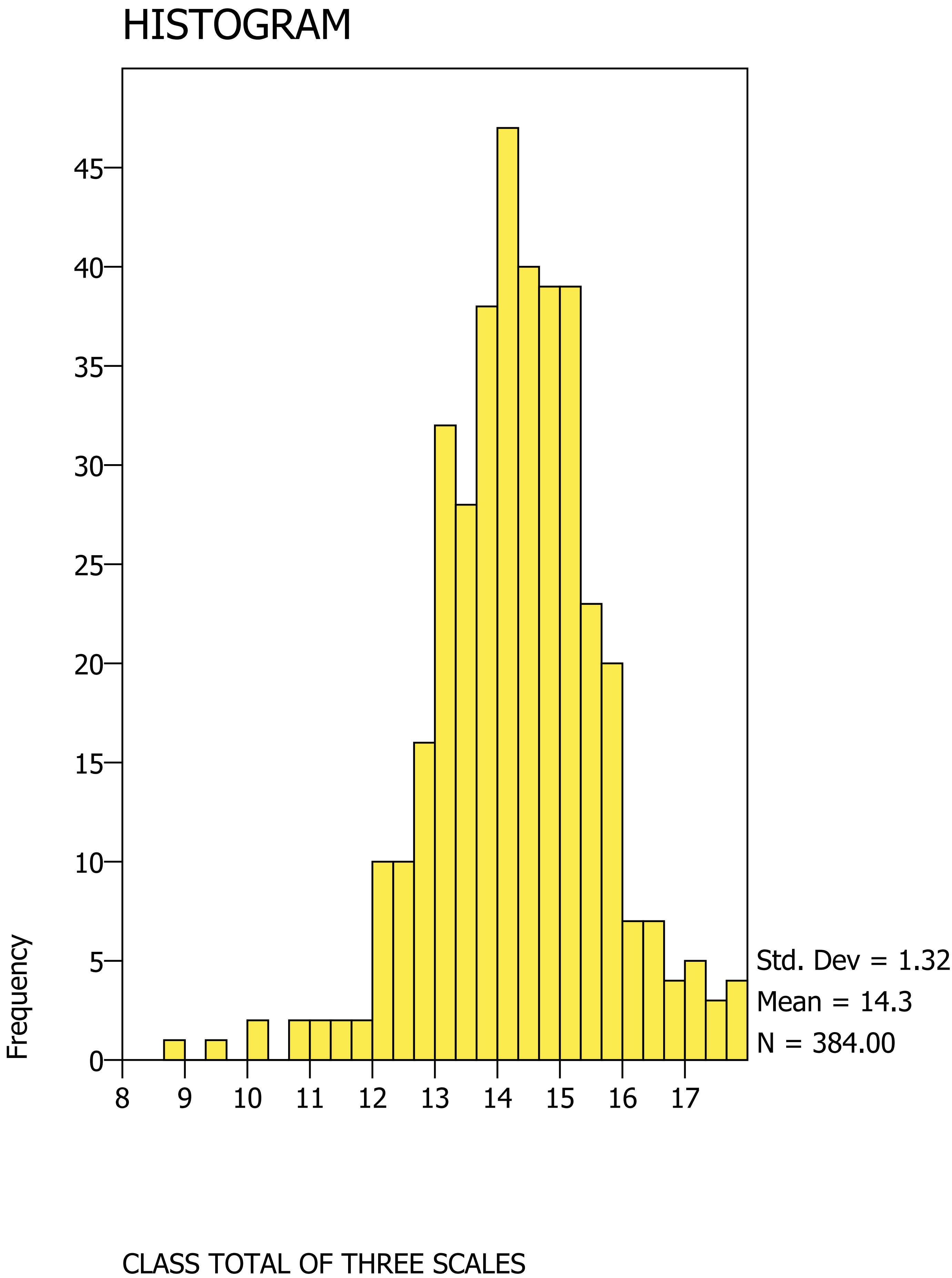
Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	14.17	1	.24	.26	44.79
	14.18	1	.24	.26	45.05
	14.19	1	.24	.26	45.31
	14.19	1	.24	.26	45.57
	14.19	1	.24	.26	45.83
	14.22	1	.24	.26	46.09
	14.22	1	.24	.26	46.35
	14.23	1	.24	.26	46.61
	14.24	1	.24	.26	46.87
	14.24	1	.24	.26	47.14
	14.25	1	.24	.26	47.40
	14.26	1	.24	.26	47.66
	14.27	1	.24	.26	47.92
	14.27	1	.24	.26	48.18
	14.27	1	.24	.26	48.44
	14.29	1	.24	.26	48.70
	14.31	1	.24	.26	48.96
	14.31	1	.24	.26	49.22
	14.31	1	.24	.26	49.48
	14.32	1	.24	.26	49.74
	14.33	1	.24	.26	50.00
	14.33	1	.24	.26	50.26
	14.34	1	.24	.26	50.52
	14.37	1	.24	.26	50.78
	14.37	1	.24	.26	51.04
	14.38	1	.24	.26	51.30
	14.41	1	.24	.26	51.56
	14.42	1	.24	.26	51.82
	14.42	1	.24	.26	52.08
	14.42	1	.24	.26	52.34
	14.43	1	.24	.26	52.60
	14.44	1	.24	.26	52.86
	14.44	1	.24	.26	53.12
	14.46	1	.24	.26	53.39
	14.46	1	.24	.26	53.65
	14.46	1	.24	.26	53.91
	14.47	1	.24	.26	54.17
	14.47	1	.24	.26	54.43
	14.48	1	.24	.26	54.69
	14.49	1	.24	.26	54.95
	14.50	1	.24	.26	55.21
	14.50	1	.24	.26	55.47
	14.51	1	.24	.26	55.73
	14.51	1	.24	.26	55.99
	14.52	1	.24	.26	56.25
	14.54	1	.24	.26	56.51

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	14.54	1	.24	.26	56.77
	14.55	1	.24	.26	57.03
	14.56	1	.24	.26	57.29
	14.57	1	.24	.26	57.55
	14.61	1	.24	.26	57.81
	14.61	1	.24	.26	58.07
	14.61	1	.24	.26	58.33
	14.62	2	.47	.52	58.85
	14.63	1	.24	.26	59.11
	14.64	1	.24	.26	59.37
	14.64	1	.24	.26	59.64
	14.64	1	.24	.26	59.90
	14.65	1	.24	.26	60.16
	14.65	1	.24	.26	60.42
	14.66	1	.24	.26	60.68
	14.69	1	.24	.26	60.94
	14.69	1	.24	.26	61.20
	14.70	1	.24	.26	61.46
	14.71	1	.24	.26	61.72
	14.71	1	.24	.26	61.98
	14.73	1	.24	.26	62.24
	14.73	1	.24	.26	62.50
	14.73	1	.24	.26	62.76
	14.74	1	.24	.26	63.02
	14.75	1	.24	.26	63.28
	14.75	1	.24	.26	63.54
	14.76	1	.24	.26	63.80
	14.76	1	.24	.26	64.06
	14.77	1	.24	.26	64.32
	14.78	1	.24	.26	64.58
	14.79	1	.24	.26	64.84
	14.79	1	.24	.26	65.10
	14.80	1	.24	.26	65.36
	14.81	1	.24	.26	65.62
	14.82	1	.24	.26	65.89
	14.82	1	.24	.26	66.15
	14.83	1	.24	.26	66.41
	14.83	1	.24	.26	66.67
	14.84	1	.24	.26	66.93
	14.86	1	.24	.26	67.19
	14.87	1	.24	.26	67.45
	14.87	1	.24	.26	67.71
	14.89	1	.24	.26	67.97
	14.89	1	.24	.26	68.23
	14.91	1	.24	.26	68.49
	14.95	1	.24	.26	68.75

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	14.96	1	.24	.26	69.01
	14.96	1	.24	.26	69.27
	14.97	1	.24	.26	69.53
	14.98	1	.24	.26	69.79
	14.99	1	.24	.26	70.05
	14.99	1	.24	.26	70.31
	14.99	1	.24	.26	70.57
	15.00	1	.24	.26	70.83
	15.02	1	.24	.26	71.09
	15.03	1	.24	.26	71.35
	15.04	1	.24	.26	71.61
	15.04	1	.24	.26	71.87
	15.04	1	.24	.26	72.14
	15.05	1	.24	.26	72.40
	15.05	1	.24	.26	72.66
	15.06	1	.24	.26	72.92
	15.08	1	.24	.26	73.18
	15.08	1	.24	.26	73.44
	15.08	1	.24	.26	73.70
	15.09	1	.24	.26	73.96
	15.09	1	.24	.26	74.22
	15.10	1	.24	.26	74.48
	15.10	1	.24	.26	74.74
	15.11	1	.24	.26	75.00
	15.11	1	.24	.26	75.26
	15.13	1	.24	.26	75.52
	15.16	1	.24	.26	75.78
	15.17	1	.24	.26	76.04
	15.17	1	.24	.26	76.30
	15.19	1	.24	.26	76.56
	15.20	1	.24	.26	76.82
	15.21	1	.24	.26	77.08
	15.21	1	.24	.26	77.34
	15.22	1	.24	.26	77.60
	15.23	1	.24	.26	77.86
	15.23	1	.24	.26	78.13
	15.24	1	.24	.26	78.39
	15.24	1	.24	.26	78.65
	15.25	1	.24	.26	78.91
	15.26	1	.24	.26	79.17
	15.26	1	.24	.26	79.43
	15.28	1	.24	.26	79.69
	15.28	2	.47	.52	80.21
	15.30	1	.24	.26	80.47
	15.31	1	.24	.26	80.73
	15.32	1	.24	.26	80.99

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	15.34	1	.24	.26	81.25
	15.35	1	.24	.26	81.51
	15.38	1	.24	.26	81.77
	15.39	1	.24	.26	82.03
	15.40	1	.24	.26	82.29
	15.44	1	.24	.26	82.55
	15.45	1	.24	.26	82.81
	15.46	1	.24	.26	83.07
	15.46	1	.24	.26	83.33
	15.46	1	.24	.26	83.59
	15.46	1	.24	.26	83.85
	15.47	1	.24	.26	84.11
	15.47	1	.24	.26	84.38
	15.49	1	.24	.26	84.64
	15.50	1	.24	.26	84.90
	15.51	1	.24	.26	85.16
	15.51	1	.24	.26	85.42
	15.55	1	.24	.26	85.68
	15.60	1	.24	.26	85.94
	15.61	1	.24	.26	86.20
	15.63	1	.24	.26	86.46
	15.64	1	.24	.26	86.72
	15.65	1	.24	.26	86.98
	15.68	1	.24	.26	87.24
	15.68	1	.24	.26	87.50
	15.72	1	.24	.26	87.76
	15.73	1	.24	.26	88.02
	15.74	1	.24	.26	88.28
	15.75	1	.24	.26	88.54
	15.76	1	.24	.26	88.80
	15.76	1	.24	.26	89.06
	15.77	1	.24	.26	89.32
	15.77	1	.24	.26	89.58
	15.78	1	.24	.26	89.84
	15.79	1	.24	.26	90.10
	15.80	1	.24	.26	90.36
	15.82	1	.24	.26	90.63
	15.84	1	.24	.26	90.89
	15.86	1	.24	.26	91.15
	15.86	1	.24	.26	91.41
	15.87	1	.24	.26	91.67
	15.94	1	.24	.26	91.93
	15.98	1	.24	.26	92.19
	16.08	1	.24	.26	92.45
	16.10	1	.24	.26	92.71
	16.13	1	.24	.26	92.97

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	16.15	1	.24	.26	93.23
	16.18	1	.24	.26	93.49
	16.20	1	.24	.26	93.75
	16.22	1	.24	.26	94.01
	16.36	1	.24	.26	94.27
	16.37	1	.24	.26	94.53
	16.39	1	.24	.26	94.79
	16.39	1	.24	.26	95.05
	16.52	1	.24	.26	95.31
	16.53	1	.24	.26	95.57
	16.66	1	.24	.26	95.83
	16.74	1	.24	.26	96.09
	16.77	1	.24	.26	96.35
	16.84	1	.24	.26	96.61
	16.85	1	.24	.26	96.88
	17.02	1	.24	.26	97.14
	17.09	1	.24	.26	97.40
	17.10	1	.24	.26	97.66
	17.18	1	.24	.26	97.92
	17.20	1	.24	.26	98.18
	17.39	1	.24	.26	98.44
	17.53	1	.24	.26	98.70
	17.56	1	.24	.26	98.96
	17.74	1	.24	.26	99.22
	17.85	1	.24	.26	99.48
	17.96	1	.24	.26	99.74
	17.99	1	.24	.26	100.00
	.	38	9.00	Missing	
	Total	422	100.0	100.0	


HISTOGRAM
Frequency
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8
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10
11
12
13
14
15
16
17
Std. Dev = 1.32
Mean = 14.3
N = 384.00
CLASS TOTAL OF THREE SCALES

GET

```
GET FILE="C:\Documents and Settings\Judy\My Documents\RIKI\DATA\PA
\PA1.sav".
```

warning: `C:\Documents and Settings\Judy\My Documents\RIKI\DATA\PA \PA1.sav': This system file does not indicate its own character encoding. Using default encoding CP1252. For best results, specify an encoding explicitly. Use SYSFILE INFO with ENCODING="DETECT" to analyze the possible encodings.

FREQUENCIES

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FREQUENCIES
	/VARIABLES= fdorec
	/FORMAT=AVALUE TABLE
	/STATISTICS=NONE
	/HISTOGRAM=NONORMAL.
```

ecers and fdcrs totals

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	1.71	1	.27	.27	.27
	1.83	1	.27	.27	.54
	1.86	1	.27	.27	.81
	2.03	1	.27	.27	1.08
	2.09	1	.27	.27	1.34
	2.11	1	.27	.27	1.61
	2.16	1	.27	.27	1.88
	2.20	1	.27	.27	2.15
	2.29	1	.27	.27	2.42
	2.31	1	.27	.27	2.69
	2.38	1	.27	.27	2.96
	2.40	1	.27	.27	3.23
	2.44	1	.27	.27	3.49
	2.48	1	.27	.27	3.76
	2.50	1	.27	.27	4.03
	2.51	1	.27	.27	4.30
	2.56	1	.27	.27	4.57
	2.60	1	.27	.27	4.84
	2.64	1	.27	.27	5.11
	2.66	1	.27	.27	5.38
	2.69	1	.27	.27	5.65
	2.71	1	.27	.27	5.91
	2.77	1	.27	.27	6.18
	2.78	1	.27	.27	6.45
	2.79	2	.54	.54	6.99

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	2.81	1	.27	.27	7.26
	2.83	3	.81	.81	8.06
	2.84	1	.27	.27	8.33
	2.88	1	.27	.27	8.60
	2.90	2	.54	.54	9.14
	2.91	2	.54	.54	9.68
	2.95	1	.27	.27	9.95
	2.97	2	.54	.54	10.48
	3.00	3	.81	.81	11.29
	3.07	1	.27	.27	11.56
	3.09	4	1.08	1.08	12.63
	3.10	3	.81	.81	13.44
	3.11	2	.54	.54	13.98
	3.12	1	.27	.27	14.25
	3.13	1	.27	.27	14.52
	3.14	1	.27	.27	14.78
	3.17	1	.27	.27	15.05
	3.19	1	.27	.27	15.32
	3.20	2	.54	.54	15.86
	3.21	1	.27	.27	16.13
	3.22	2	.54	.54	16.67
	3.23	1	.27	.27	16.94
	3.24	1	.27	.27	17.20
	3.25	3	.81	.81	18.01
	3.26	2	.54	.54	18.55
	3.27	1	.27	.27	18.82
	3.28	2	.54	.54	19.35
	3.30	2	.54	.54	19.89
	3.31	3	.81	.81	20.70
	3.33	2	.54	.54	21.24
	3.34	3	.81	.81	22.04
	3.36	2	.54	.54	22.58
	3.38	1	.27	.27	22.85
	3.39	1	.27	.27	23.12
	3.40	4	1.08	1.08	24.19
	3.41	1	.27	.27	24.46
	3.42	2	.54	.54	25.00
	3.43	3	.81	.81	25.81
	3.45	1	.27	.27	26.08
	3.46	1	.27	.27	26.34
	3.51	1	.27	.27	26.61
	3.52	2	.54	.54	27.15
	3.54	3	.81	.81	27.96
	3.55	3	.81	.81	28.76
	3.56	2	.54	.54	29.30
	3.57	1	.27	.27	29.57

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	3.58	1	.27	.27	29.84
	3.59	1	.27	.27	30.11
	3.60	7	1.88	1.88	31.99
	3.61	1	.27	.27	32.26
	3.62	1	.27	.27	32.53
	3.63	2	.54	.54	33.06
	3.64	1	.27	.27	33.33
	3.65	1	.27	.27	33.60
	3.70	2	.54	.54	34.14
	3.71	3	.81	.81	34.95
	3.72	2	.54	.54	35.48
	3.73	1	.27	.27	35.75
	3.74	1	.27	.27	36.02
	3.77	3	.81	.81	36.83
	3.78	1	.27	.27	37.10
	3.79	2	.54	.54	37.63
	3.80	2	.54	.54	38.17
	3.83	1	.27	.27	38.44
	3.85	1	.27	.27	38.71
	3.86	4	1.08	1.08	39.78
	3.87	1	.27	.27	40.05
	3.88	2	.54	.54	40.59
	3.89	3	.81	.81	41.40
	3.90	6	1.61	1.61	43.01
	3.91	2	.54	.54	43.55
	3.93	2	.54	.54	44.09
	3.95	1	.27	.27	44.35
	3.98	2	.54	.54	44.89
	4.00	3	.81	.81	45.70
	4.02	3	.81	.81	46.51
	4.03	3	.81	.81	47.31
	4.05	1	.27	.27	47.58
	4.06	2	.54	.54	48.12
	4.07	3	.81	.81	48.92
	4.09	1	.27	.27	49.19
	4.11	3	.81	.81	50.00
	4.12	1	.27	.27	50.27
	4.13	2	.54	.54	50.81
	4.14	2	.54	.54	51.34
	4.17	3	.81	.81	52.15
	4.18	2	.54	.54	52.69
	4.20	3	.81	.81	53.49
	4.21	2	.54	.54	54.03
	4.22	1	.27	.27	54.30
	4.23	1	.27	.27	54.57
	4.26	2	.54	.54	55.11

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	4.27	3	.81	.81	55.91
	4.28	2	.54	.54	56.45
	4.29	1	.27	.27	56.72
	4.30	1	.27	.27	56.99
	4.31	4	1.08	1.08	58.06
	4.34	1	.27	.27	58.33
	4.35	1	.27	.27	58.60
	4.37	1	.27	.27	58.87
	4.39	1	.27	.27	59.14
	4.40	4	1.08	1.08	60.22
	4.42	2	.54	.54	60.75
	4.43	2	.54	.54	61.29
	4.44	2	.54	.54	61.83
	4.46	2	.54	.54	62.37
	4.48	1	.27	.27	62.63
	4.50	4	1.08	1.08	63.71
	4.52	2	.54	.54	64.25
	4.53	2	.54	.54	64.78
	4.54	2	.54	.54	65.32
	4.56	2	.54	.54	65.86
	4.57	1	.27	.27	66.13
	4.59	1	.27	.27	66.40
	4.60	5	1.34	1.34	67.74
	4.61	1	.27	.27	68.01
	4.62	3	.81	.81	68.82
	4.63	3	.81	.81	69.62
	4.64	1	.27	.27	69.89
	4.65	2	.54	.54	70.43
	4.66	2	.54	.54	70.97
	4.67	2	.54	.54	71.51
	4.68	1	.27	.27	71.77
	4.69	3	.81	.81	72.58
	4.71	1	.27	.27	72.85
	4.72	1	.27	.27	73.12
	4.73	1	.27	.27	73.39
	4.74	1	.27	.27	73.66
	4.76	1	.27	.27	73.92
	4.77	2	.54	.54	74.46
	4.79	2	.54	.54	75.00
	4.80	1	.27	.27	75.27
	4.81	2	.54	.54	75.81
	4.83	3	.81	.81	76.61
	4.86	1	.27	.27	76.88
	4.88	5	1.34	1.34	78.23
	4.90	3	.81	.81	79.03
	4.91	1	.27	.27	79.30

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	4.93	1	.27	.27	79.57
	4.95	1	.27	.27	79.84
	4.98	3	.81	.81	80.65
	5.00	6	1.61	1.61	82.26
	5.02	3	.81	.81	83.06
	5.03	2	.54	.54	83.60
	5.05	1	.27	.27	83.87
	5.09	4	1.08	1.08	84.95
	5.10	2	.54	.54	85.48
	5.12	2	.54	.54	86.02
	5.13	1	.27	.27	86.29
	5.14	3	.81	.81	87.10
	5.16	1	.27	.27	87.37
	5.17	1	.27	.27	87.63
	5.20	2	.54	.54	88.17
	5.21	1	.27	.27	88.44
	5.22	1	.27	.27	88.71
	5.23	2	.54	.54	89.25
	5.26	1	.27	.27	89.52
	5.31	1	.27	.27	89.78
	5.33	1	.27	.27	90.05
	5.37	2	.54	.54	90.59
	5.38	3	.81	.81	91.40
	5.39	1	.27	.27	91.67
	5.40	1	.27	.27	91.94
	5.41	2	.54	.54	92.47
	5.43	1	.27	.27	92.74
	5.49	1	.27	.27	93.01
	5.50	2	.54	.54	93.55
	5.54	1	.27	.27	93.82
	5.55	1	.27	.27	94.09
	5.57	1	.27	.27	94.35
	5.62	1	.27	.27	94.62
	5.64	1	.27	.27	94.89
	5.66	1	.27	.27	95.16
	5.71	2	.54	.54	95.70
	5.73	2	.54	.54	96.24
	5.74	2	.54	.54	96.77
	5.75	1	.27	.27	97.04
	5.83	1	.27	.27	97.31
	5.88	2	.54	.54	97.85
	5.93	1	.27	.27	98.12
	5.95	2	.54	.54	98.66
	5.98	1	.27	.27	98.92
	6.02	1	.27	.27	99.19
	6.09	1	.27	.27	99.46

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
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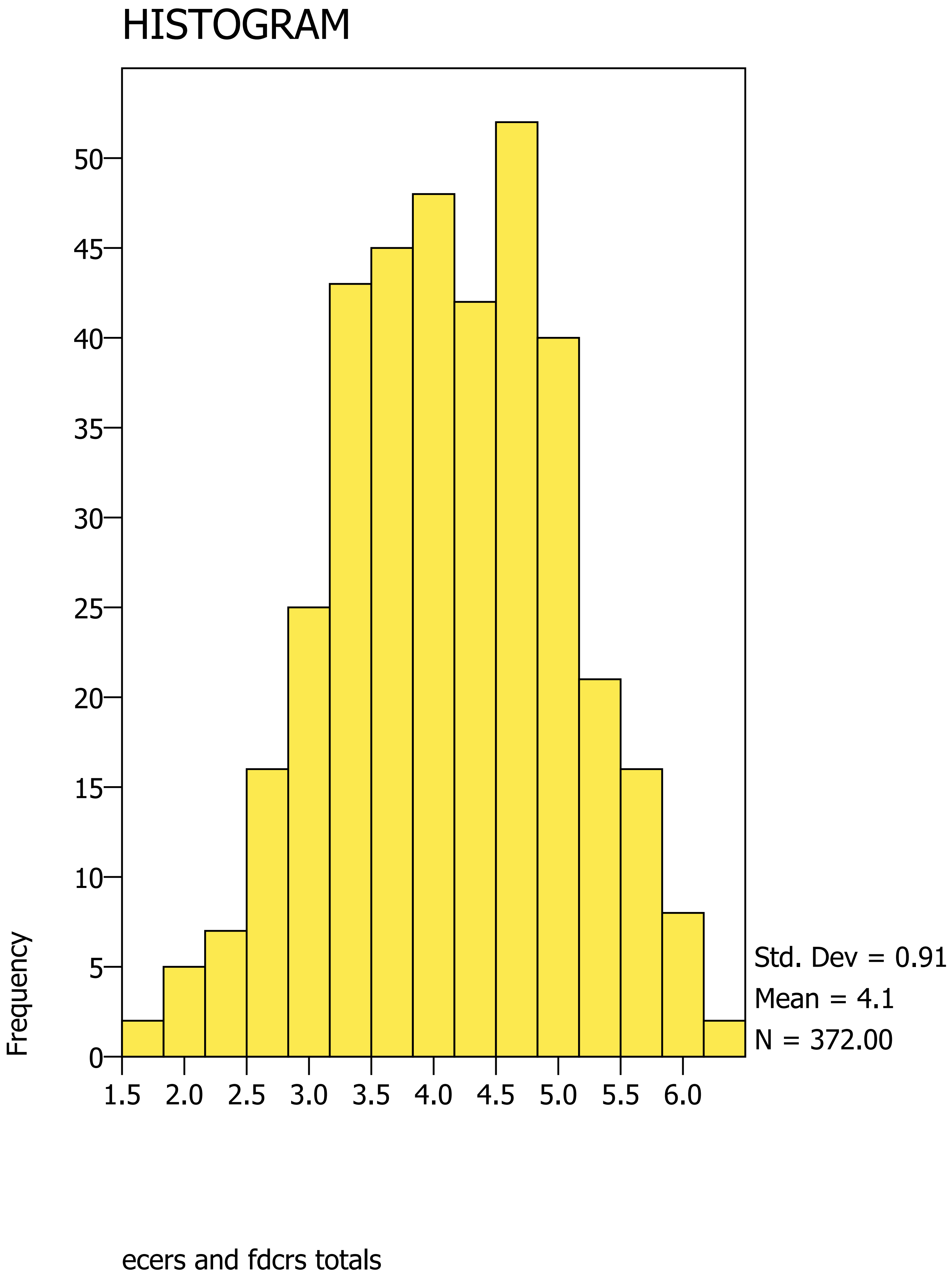
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4.5
5.0
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ecers and fdcrs totals

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FDCRS Average

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	2	1	.48	.48	.97
	2	1	.48	.48	1.45
	2	1	.48	.48	1.93
	2	1	.48	.48	2.42
	3	1	.48	.48	2.90
	3	1	.48	.48	3.38
	3	2	.96	.97	4.35
	3	1	.48	.48	4.83
	3	1	.48	.48	5.31
	3	1	.48	.48	5.80
	3	1	.48	.48	6.28
	3	1	.48	.48	6.76
	3	1	.48	.48	7.25
	3	1	.48	.48	7.73
	3	1	.48	.48	8.21
	3	1	.48	.48	8.70
	3	1	.48	.48	9.18
	3	1	.48	.48	9.66
	3	1	.48	.48	10.14
	3	1	.48	.48	10.63
	3	1	.48	.48	11.11
	3	1	.48	.48	11.59
	3	1	.48	.48	12.08
	3	2	.96	.97	13.04
	3	1	.48	.48	13.53
	3	1	.48	.48	14.01
	3	1	.48	.48	14.49
	3	1	.48	.48	14.98
	3	1	.48	.48	15.46

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	3	1	.48	.48	15.94
	3	3	1.44	1.45	17.39
	3	1	.48	.48	17.87
	3	1	.48	.48	18.36
	3	1	.48	.48	18.84
	4	3	1.44	1.45	20.29
	4	2	.96	.97	21.26
	4	1	.48	.48	21.74
	4	1	.48	.48	22.22
	4	1	.48	.48	22.71
	4	1	.48	.48	23.19
	4	1	.48	.48	23.67
	4	1	.48	.48	24.15
	4	1	.48	.48	24.64
	4	1	.48	.48	25.12
	4	1	.48	.48	25.60
	4	1	.48	.48	26.09
	4	1	.48	.48	26.57
	4	1	.48	.48	27.05
	4	1	.48	.48	27.54
	4	1	.48	.48	28.02
	4	2	.96	.97	28.99
	4	2	.96	.97	29.95
	4	2	.96	.97	30.92
	4	1	.48	.48	31.40
	4	1	.48	.48	31.88
	4	1	.48	.48	32.37
	4	1	.48	.48	32.85
	4	1	.48	.48	33.33
	4	1	.48	.48	33.82
	4	1	.48	.48	34.30
	4	1	.48	.48	34.78
	4	2	.96	.97	35.75
	4	3	1.44	1.45	37.20
	4	1	.48	.48	37.68
	4	1	.48	.48	38.16
	4	1	.48	.48	38.65
	4	1	.48	.48	39.13
	4	1	.48	.48	39.61
	4	1	.48	.48	40.10
	4	1	.48	.48	40.58
	4	1	.48	.48	41.06
	4	2	.96	.97	42.03
	4	1	.48	.48	42.51
	4	1	.48	.48	43.00
	4	1	.48	.48	43.48

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	4	1	.48	.48	43.96
	5	2	.96	.97	44.93
	5	1	.48	.48	45.41
	5	1	.48	.48	45.89
	5	1	.48	.48	46.38
	5	4	1.92	1.93	48.31
	5	1	.48	.48	48.79
	5	1	.48	.48	49.28
	5	1	.48	.48	49.76
	5	1	.48	.48	50.24
	5	1	.48	.48	50.72
	5	2	.96	.97	51.69
	5	1	.48	.48	52.17
	5	1	.48	.48	52.66
	5	1	.48	.48	53.14
	5	1	.48	.48	53.62
	5	2	.96	.97	54.59
	5	1	.48	.48	55.07
	5	2	.96	.97	56.04
	5	1	.48	.48	56.52
	5	4	1.92	1.93	58.45
	5	2	.96	.97	59.42
	5	2	.96	.97	60.39
	5	3	1.44	1.45	61.84
	5	1	.48	.48	62.32
	5	1	.48	.48	62.80
	5	3	1.44	1.45	64.25
	5	4	1.92	1.93	66.18
	5	1	.48	.48	66.67
	5	2	.96	.97	67.63
	5	1	.48	.48	68.12
	5	1	.48	.48	68.60
	5	1	.48	.48	69.08
	5	1	.48	.48	69.57
	5	1	.48	.48	70.05
	5	3	1.44	1.45	71.50
	5	2	.96	.97	72.46
	5	2	.96	.97	73.43
	5	1	.48	.48	73.91
	5	1	.48	.48	74.40
	5	2	.96	.97	75.36
	5	4	1.92	1.93	77.29
	5	1	.48	.48	77.78
	5	1	.48	.48	78.26
	5	2	.96	.97	79.23
	5	1	.48	.48	79.71

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	5	3	1.44	1.45	81.16
	5	1	.48	.48	81.64
	5	1	.48	.48	82.13
	5	1	.48	.48	82.61
	6	4	1.92	1.93	84.54
	6	1	.48	.48	85.02
	6	1	.48	.48	85.51
	6	1	.48	.48	85.99
	6	1	.48	.48	86.47
	6	1	.48	.48	86.96
	6	1	.48	.48	87.44
	6	1	.48	.48	87.92
	6	3	1.44	1.45	89.37
	6	1	.48	.48	89.86
	6	1	.48	.48	90.34
	6	1	.48	.48	90.82
	6	2	.96	.97	91.79
	6	1	.48	.48	92.27
	6	1	.48	.48	92.75
	6	1	.48	.48	93.24
	6	1	.48	.48	93.72
	6	1	.48	.48	94.20
	6	1	.48	.48	94.69
	6	1	.48	.48	95.17
	6	1	.48	.48	95.65
	6	2	.96	.97	96.62
	6	1	.48	.48	97.10
	6	1	.48	.48	97.58
	6	1	.48	.48	98.07
	6	2	.96	.97	99.03
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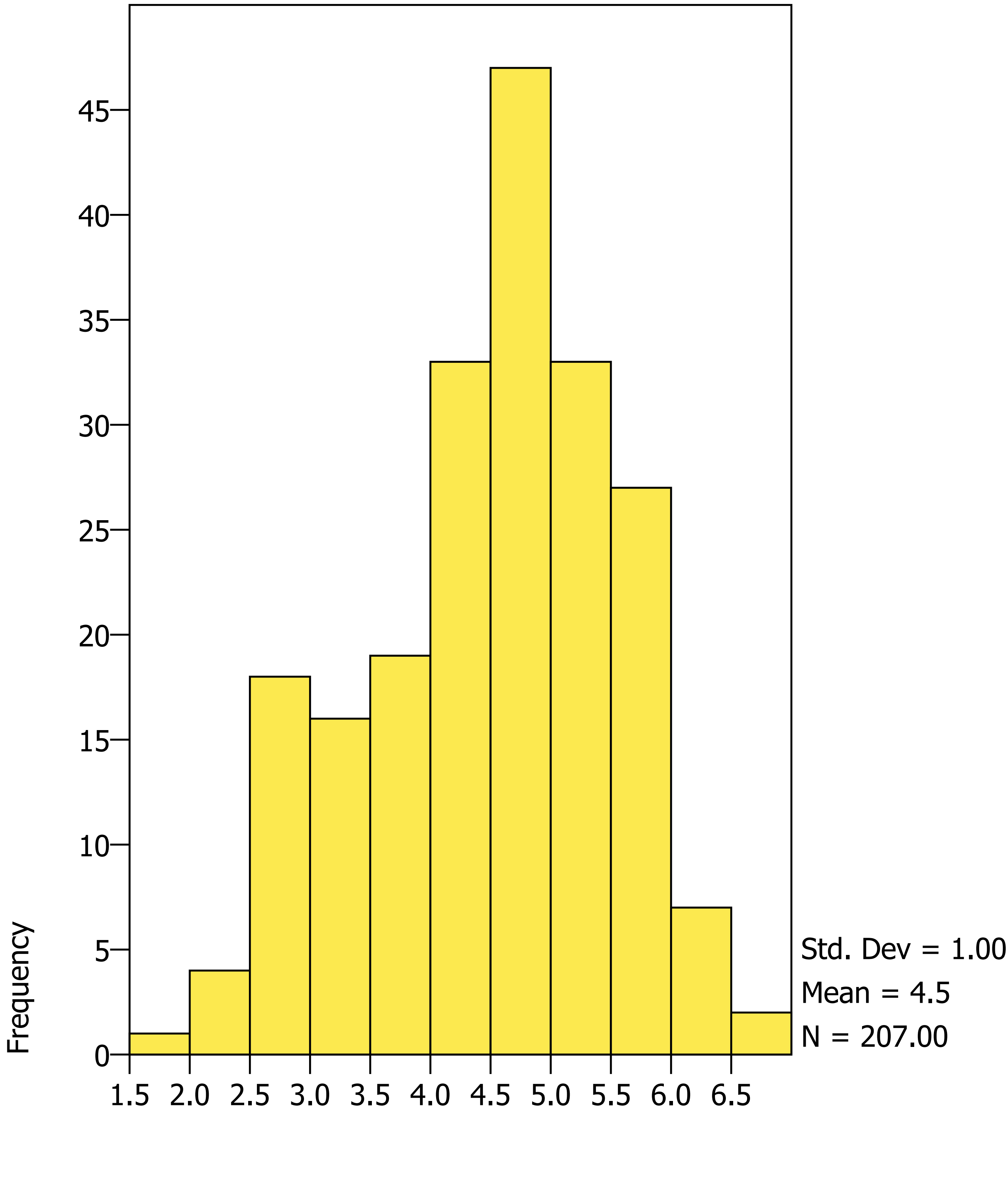

FDCRS Average

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warning: `C:\Documents and Settings\Judy\My Documents\RIKI\DATA\PA\PA2 CCC.sav': This system file does not indicate its own character encoding. Using default encoding CP1252. For best results, specify an encoding explicitly. Use SYSFILE INFO with ENCODING="DETECT" to analyze the possible encodings.

FREQUENCIES

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ECERS Average

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	2	1	.27	.28	.83
	2	1	.27	.28	1.10
	2	1	.27	.28	1.38
	2	1	.27	.28	1.66
	2	2	.54	.55	2.21
	2	1	.27	.28	2.49
	2	1	.27	.28	2.76
	2	1	.27	.28	3.04
	2	1	.27	.28	3.31
	2	1	.27	.28	3.59
	2	1	.27	.28	3.87
	2	1	.27	.28	4.14
	3	1	.27	.28	4.42
	3	1	.27	.28	4.70
	3	1	.27	.28	4.97
	3	2	.54	.55	5.52
	3	1	.27	.28	5.80
	3	1	.27	.28	6.08
	3	1	.27	.28	6.35
	3	1	.27	.28	6.63
	3	1	.27	.28	6.91
	3	1	.27	.28	7.18
	3	1	.27	.28	7.46

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	3	1	.27	.28	7.73
	3	1	.27	.28	8.01
	3	1	.27	.28	8.29
	3	1	.27	.28	8.56
	3	1	.27	.28	8.84
	3	3	.81	.83	9.67
	3	1	.27	.28	9.94
	3	1	.27	.28	10.22
	3	1	.27	.28	10.50
	3	1	.27	.28	10.77
	3	1	.27	.28	11.05
	3	1	.27	.28	11.33
	3	1	.27	.28	11.60
	3	1	.27	.28	11.88
	3	1	.27	.28	12.15
	3	1	.27	.28	12.43
	3	1	.27	.28	12.71
	3	1	.27	.28	12.98
	3	2	.54	.55	13.54
	3	1	.27	.28	13.81
	3	1	.27	.28	14.09
	3	1	.27	.28	14.36
	3	1	.27	.28	14.64
	3	1	.27	.28	14.92
	3	1	.27	.28	15.19
	3	1	.27	.28	15.47
	3	2	.54	.55	16.02
	3	1	.27	.28	16.30
	4	1	.27	.28	16.57
	4	2	.54	.55	17.13
	4	1	.27	.28	17.40
	4	1	.27	.28	17.68
	4	1	.27	.28	17.96
	4	1	.27	.28	18.23
	4	3	.81	.83	19.06
	4	1	.27	.28	19.34
	4	1	.27	.28	19.61
	4	1	.27	.28	19.89
	4	1	.27	.28	20.17
	4	1	.27	.28	20.44
	4	1	.27	.28	20.72
	4	1	.27	.28	20.99
	4	2	.54	.55	21.55
	4	1	.27	.28	21.82
	4	2	.54	.55	22.38
	4	1	.27	.28	22.65

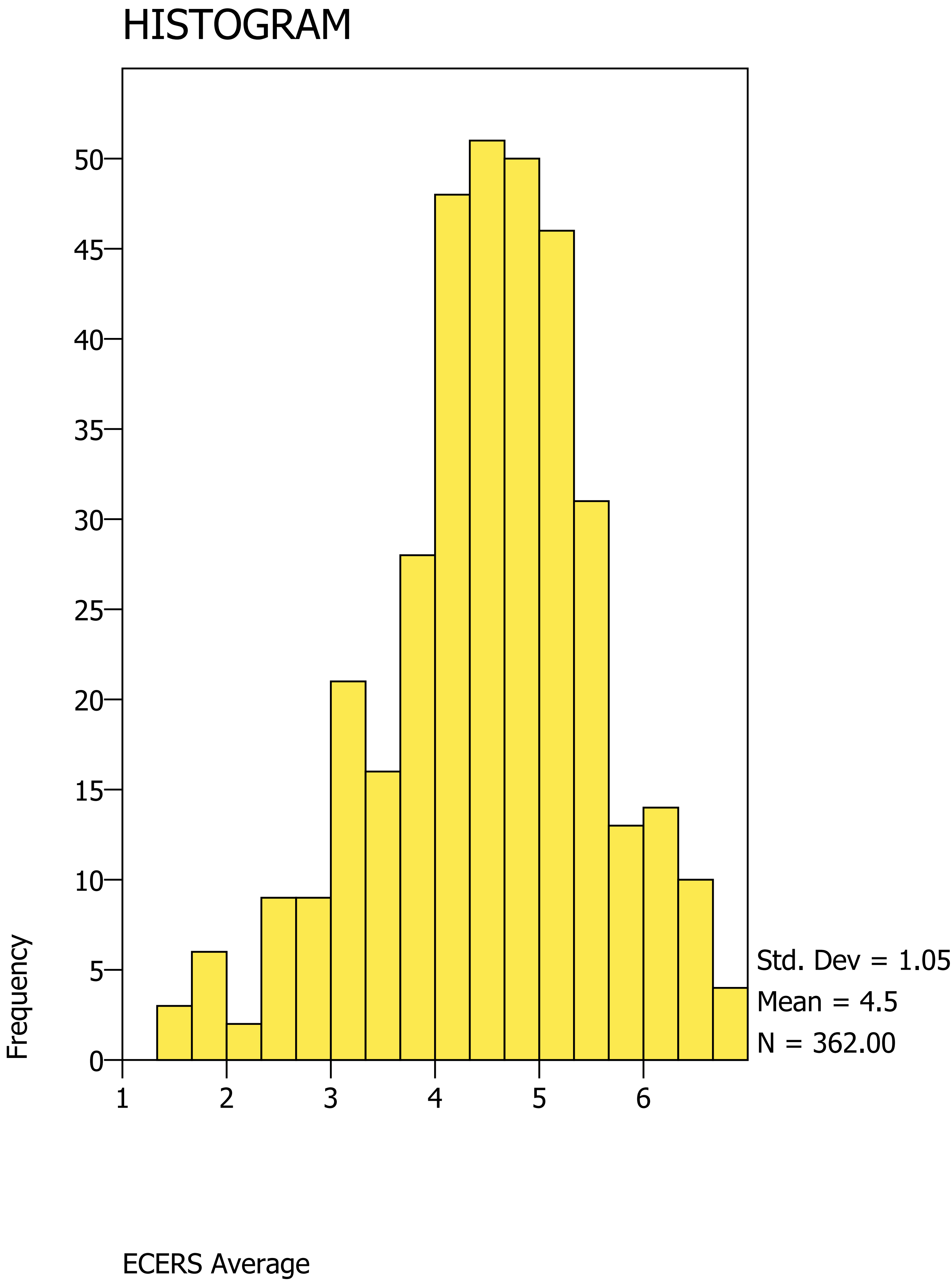
Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	4	1	.27	.28	22.93
	4	1	.27	.28	23.20
	4	1	.27	.28	23.48
	4	1	.27	.28	23.76
	4	1	.27	.28	24.03
	4	2	.54	.55	24.59
	4	1	.27	.28	24.86
	4	1	.27	.28	25.14
	4	1	.27	.28	25.41
	4	2	.54	.55	25.97
	4	3	.81	.83	26.80
	4	1	.27	.28	27.07
	4	1	.27	.28	27.35
	4	1	.27	.28	27.62
	4	2	.54	.55	28.18
	4	2	.54	.55	28.73
	4	3	.81	.83	29.56
	4	4	1.08	1.10	30.66
	4	1	.27	.28	30.94
	4	1	.27	.28	31.22
	4	2	.54	.55	31.77
	4	1	.27	.28	32.04
	4	1	.27	.28	32.32
	4	1	.27	.28	32.60
	4	1	.27	.28	32.87
	4	3	.81	.83	33.70
	4	1	.27	.28	33.98
	4	2	.54	.55	34.53
	4	3	.81	.83	35.36
	4	1	.27	.28	35.64
	4	5	1.36	1.38	37.02
	4	1	.27	.28	37.29
	4	3	.81	.83	38.12
	4	1	.27	.28	38.40
	4	2	.54	.55	38.95
	4	1	.27	.28	39.23
	4	4	1.08	1.10	40.33
	4	1	.27	.28	40.61
	4	1	.27	.28	40.88
	4	1	.27	.28	41.16
	4	2	.54	.55	41.71
	4	1	.27	.28	41.99
	4	2	.54	.55	42.54
	4	1	.27	.28	42.82
	4	1	.27	.28	43.09
	4	2	.54	.55	43.65

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	4	3	.81	.83	44.48
	4	1	.27	.28	44.75
	4	2	.54	.55	45.30
	4	1	.27	.28	45.58
	4	1	.27	.28	45.86
	4	2	.54	.55	46.41
	5	1	.27	.28	46.69
	5	1	.27	.28	46.96
	5	1	.27	.28	47.24
	5	1	.27	.28	47.51
	5	1	.27	.28	47.79
	5	2	.54	.55	48.34
	5	2	.54	.55	48.90
	5	1	.27	.28	49.17
	5	3	.81	.83	50.00
	5	2	.54	.55	50.55
	5	1	.27	.28	50.83
	5	2	.54	.55	51.38
	5	1	.27	.28	51.66
	5	1	.27	.28	51.93
	5	1	.27	.28	52.21
	5	4	1.08	1.10	53.31
	5	1	.27	.28	53.59
	5	1	.27	.28	53.87
	5	1	.27	.28	54.14
	5	1	.27	.28	54.42
	5	3	.81	.83	55.25
	5	1	.27	.28	55.52
	5	2	.54	.55	56.08
	5	1	.27	.28	56.35
	5	2	.54	.55	56.91
	5	1	.27	.28	57.18
	5	1	.27	.28	57.46
	5	1	.27	.28	57.73
	5	2	.54	.55	58.29
	5	1	.27	.28	58.56
	5	1	.27	.28	58.84
	5	1	.27	.28	59.12
	5	1	.27	.28	59.39
	5	1	.27	.28	59.67
	5	3	.81	.83	60.50
	5	1	.27	.28	60.77
	5	1	.27	.28	61.05
	5	2	.54	.55	61.60
	5	1	.27	.28	61.88
	5	3	.81	.83	62.71

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	5	1	.27	.28	62.98
	5	1	.27	.28	63.26
	5	5	1.36	1.38	64.64
	5	1	.27	.28	64.92
	5	1	.27	.28	65.19
	5	1	.27	.28	65.47
	5	1	.27	.28	65.75
	5	1	.27	.28	66.02
	5	2	.54	.55	66.57
	5	1	.27	.28	66.85
	5	1	.27	.28	67.13
	5	2	.54	.55	67.68
	5	1	.27	.28	67.96
	5	3	.81	.83	68.78
	5	1	.27	.28	69.06
	5	1	.27	.28	69.34
	5	1	.27	.28	69.61
	5	1	.27	.28	69.89
	5	1	.27	.28	70.17
	5	1	.27	.28	70.44
	5	2	.54	.55	70.99
	5	1	.27	.28	71.27
	5	1	.27	.28	71.55
	5	1	.27	.28	71.82
	5	1	.27	.28	72.10
	5	2	.54	.55	72.65
	5	1	.27	.28	72.93
	5	1	.27	.28	73.20
	5	1	.27	.28	73.48
	5	2	.54	.55	74.03
	5	2	.54	.55	74.59
	5	1	.27	.28	74.86
	5	1	.27	.28	75.14
	5	2	.54	.55	75.69
	5	1	.27	.28	75.97
	5	2	.54	.55	76.52
	5	2	.54	.55	77.07
	5	2	.54	.55	77.62
	5	1	.27	.28	77.90
	5	1	.27	.28	78.18
	5	2	.54	.55	78.73
	5	1	.27	.28	79.01
	5	1	.27	.28	79.28
	5	1	.27	.28	79.56
	5	1	.27	.28	79.83
	5	1	.27	.28	80.11

Value Label	*Value*	*Frequency*	*Percent*	*Valid Percent*	*Cum Percent*
	5	1	.27	.28	80.39
	5	1	.27	.28	80.66
	5	1	.27	.28	80.94
	5	1	.27	.28	81.22
	5	2	.54	.55	81.77
	5	1	.27	.28	82.04
	5	1	.27	.28	82.32
	5	2	.54	.55	82.87
	5	1	.27	.28	83.15
	5	2	.54	.55	83.70
	5	1	.27	.28	83.98
	5	1	.27	.28	84.25
	6	2	.54	.55	84.81
	6	1	.27	.28	85.08
	6	1	.27	.28	85.36
	6	3	.81	.83	86.19
	6	1	.27	.28	86.46
	6	1	.27	.28	86.74
	6	1	.27	.28	87.02
	6	1	.27	.28	87.29
	6	1	.27	.28	87.57
	6	1	.27	.28	87.85
	6	2	.54	.55	88.40
	6	1	.27	.28	88.67
	6	1	.27	.28	88.95
	6	1	.27	.28	89.23
	6	1	.27	.28	89.50
	6	1	.27	.28	89.78
	6	1	.27	.28	90.06
	6	3	.81	.83	90.88
	6	1	.27	.28	91.16
	6	1	.27	.28	91.44
	6	1	.27	.28	91.71
	6	1	.27	.28	91.99
	6	3	.81	.83	92.82
	6	1	.27	.28	93.09
	6	1	.27	.28	93.37
	6	1	.27	.28	93.65
	6	1	.27	.28	93.92
	6	1	.27	.28	94.20
	6	1	.27	.28	94.48
	6	2	.54	.55	95.03
	6	1	.27	.28	95.30
	6	1	.27	.28	95.58
	6	1	.27	.28	95.86
	6	1	.27	.28	96.13

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	6	1	.27	.28	96.41
	6	1	.27	.28	96.69
	6	1	.27	.28	96.96
	7	1	.27	.28	97.24
	7	1	.27	.28	97.51
	7	1	.27	.28	97.79
	7	1	.27	.28	98.07
	7	1	.27	.28	98.34
	7	1	.27	.28	98.62
	7	1	.27	.28	98.90
	7	1	.27	.28	99.17
	7	1	.27	.28	99.45
	7	1	.27	.28	99.72
	7	1	.27	.28	100.00
	.	7	1.90	Missing	
	Total	369	100.0	100.0	


HISTOGRAM
Frequency
50
45
40
35
30
25
20
15
10
5
0
1
2
3
4
5
6
Std. Dev = 1.05
Mean = 4.5
N = 362.00
ECERS Average

Regulatory Compliance (RC) and Program Quality (PQ) Data Distributions

Richard Fiene, Ph.D.

July 2019

This report will provide the data distributions for a series of regulatory compliance (RC) and program quality (PQ) studies which show dramatically different frequencies and centralized statistics. The regulatory compliance data distributions have some very important limitations that will be noted as well as some potential adjustments that can be made to the data sets to make statistical analyses more meaningful. These data distributions are from the USA and Canada.

For purposes of reading the following Table 1, a Legend is provided:
Data Set = the study that the data are drawn from.
Sites = the number of sites in the particular study.
mean = the average of the scores.
sd = standard deviation.
p0 = the average score at the 0 percentile.
p25 = the average score at the 25th percentile.
p50 = the average score at the 50th percentile or the median.
p75 = the average score at the 75th percentile.
p100 = the average score at the 100th percentile.

Table 1

Data Set	Sites	mean	sd	p0	p25	p50	p75	p100	PQ or RC
ECERS total score	209	4.24	0.94	1.86	3.52	4.27	4.98	6.29	PQ
FDCRS total score	163	3.97	0.86	1.71	3.36	4.03	4.62	5.54	PQ
ECERS and FDCRS totals	372	4.12	0.91	1.71	3.43	4.12	4.79	6.29	PQ
ECERS prek	48	4.15	0.74	2.56	3.6	4.15	4.65	5.56	PQ
ECERS preschool	102	3.42	0.86	1.86	2.82	3.26	4.02	5.97	PQ
ITERS	91	2.72	1.14	1.27	1.87	2.34	3.19	5.97	PQ
FDCRS	146	2.49	0.8	1.21	1.87	2.42	2.93	4.58	PQ
CCC RC	104	5.51	5.26	0	2	4	8	25	RC
FCC RC	147	5.85	5.71	0	2	4	8.5	33	RC
CCC RC	482	7.44	6.78	0	2	6	11	38	RC
FDC RC	500	3.52	4.05	0	0	2	5	34	RC
CI Total Violations	422	3.33	3.77	0	1	2	5	24	RC – PQ
CLASS ES	384	5.89	0.36	4.38	5.69	5.91	6.12	6.91	PQ
CLASS CO	384	5.45	0.49	3.07	5.18	5.48	5.77	6.56	PQ
CLASS IS	384	2.98	0.7	1.12	2.5	2.95	3.37	5.74	PQ
CLASS TOTAL OF THREE SCALES	384	14.33	1.32	8.87	13.52	14.33	15.11	17.99	PQ
ECERS Average	362	4.52	1.05	1.49	3.95	4.58	5.25	7	PQ
FDCRS Average	207	4.5	1	1.86	3.83	4.66	5.31	6.71	PQ
CCC RC	585	5.3	5.33	0	2	4	8	51	RC

QRIS	585	2.78	1.24	0	2	3	4	4	PQ
FDC RC	2486	2.27	3.42	0	0	1	3	34	RC
FDC PQ	2486	1.35	1.26	0	0	1	2	4	PQ
CCC RC	199	7.77	8.62	0	3	6	10	61	RC
CCC RC	199	6.69	10.32	0	1	4	8	98	RC
CCC RC	199	6.77	7.91	0	1.5	4	8.5	57	RC
QRIS	199	1.06	1.32	0	0	1	2	4	PQ
CCC RC	199	7.08	6.96	0	2.33	5.67	9.84	52	RC
QRIS	381	2.55	0.93	0	2	3	3	4	PQ
CCC RC	1399	1.13	2.1	0	0	0	1	20	RC
CCC RC	153	5.28	5.97	0	1	3	6	32	RC
FDC RC	82	3.52	4.36	0	0	2	4	21	RC

It is obvious when one observes the PQ as versus the RC data distributions that the RC data distributions are much more skewed, medians and means are significantly different, and kurtosis values are much higher which means that the data contain several outliers. These data distributions are provided for researchers who may be assessing regulatory compliance (RC) data for the first time. There are certain limitations of these data which are not present in more parametric data distributions which are more characteristic of program quality (PQ) data.

To deal with the level of skewness of RC data, weighted risk assessments have been suggested in order to introduce additional variance into the data distributions. Also, dichotomization of data has been used successfully with very skewed data distributions as well. One of the problems with very skewed data distributions is that it is very difficult to distinguish between high performing providers and mediocre preforming providers. Skewed data distributions provide no limitations in distinguishing low preforming providers from their more successful providers.

Regulatory Compliance and Quality: How are They Different?

Richard Fiene, Ph.D.

June 2021

This technical research note will delineate the differences between regulatory compliance and quality. It will provide the essential principles and elements that clearly demonstrate the differences and their potential impact on program monitoring.

When we think about regulatory compliance, we are discussing licensing systems. When we think about quality, we are discussing Quality Rating and Improvement Systems (QRIS), accreditation, professional development, or one of the myriad quality assessment tools, such as the CLASS or ERS's. All these systems have been designed to help improve the health and safety of programs (licensing) to building more environmental quality (ERS), positive interactions amongst teachers and children (CLASS), enhancing quality standards (QRIS, accreditation), or enhancing teacher skills (professional development).

There are eight basic principles or elements to be presented (they are presented in a binary fashion demonstrating differences):

1) Do no harm versus Do good.
2) Closed system versus Open system.
3) Standards/Rules versus Indicators.
4) Nominal versus Ordinal measurement.
5) Full versus Partial compliance.
6) Ceiling effect versus No Ceiling effect.
7) Gatekeeper versus Enabler.
8) Risk versus Performance.

First: Let's start with the first principal element, Do No Harm versus Do Good. In licensing, the philosophy is to do no harm, its emphasis is on prevention, to reduce risk to children in a particular setting. There is a good deal of emphasis on health and safety and not so much on developmentally appropriate programming.

In the quality systems, such as QRIS, accreditation, professional development, ERS, CLASS, the philosophy is to do good, its emphasis is looking at all the positive aspects of a setting. There is a good deal of emphasis on improving the programming that the children are exposed to or increasing the skill set of teachers, or improving the overall environment or interaction that children are exposed to.

Second: Closed system versus Open system. Licensing is basically a closed system. It has an upper limit with full compliance (100%) with all standards/rules/regulations. The goal is to have all programs fully comply with all rules. However, the value of this assumption has been challenged over the years with the introduction of the Regulatory Compliance Theory of Diminishing Returns.

With quality systems, they have a tendency to be more open and far reaching where attaining a perfect score is very difficult to come by. The majority of programs are more normally distributed where with licensing rules the majority of programs are skewed positively in either substantial or full compliance. It is far more difficult to distinguish between the really best programs and the mediocre programs within licensing but more successful in quality systems.

Third: Standards/Rules/Regulations versus Indicators/Best Practices. Licensing systems are based around specific standards/rules/regulations that either are in compliance or out of compliance. It is either a program is in compliance or out of compliance with the specific rule.

With quality systems, there is more emphasis on indicators or best practices that are measured a bit more broadly and deal more with process than structure which is the case with licensing. It is the difference between hard and soft data as many legal counsels term it. There is greater flexibility in quality systems.

Fourth: Nominal versus Ordinal measurement. Licensing systems are nominally based measurement systems. Either you are in compliance or out of compliance. Nothing in-between. It is either a yes or no response for each rule. No maybe or partial compliance.

With quality systems, they are generally measured on an ordinal level or a Likert scale. The may run from 1 to 3, or 1 to 5, or 1 to 7. There is more chances for variability in the data than in licensing which has 1 or 0 response. This increases the robustness of the data distribution with ordinal measurement.

Fifth: Full or None versus Gradients or Gray. Building off of the fourth element, licensing scoring is either full or not. As suggested in the above elements, there is no in-between category, no gradient or gray area.

This is definitely not the case with quality systems in which there are gradients and substantial gray areas. Each best practice can be measured on a Likert scale with subtle gradients in improving the overall practice.

Sixth: Ceiling effect versus No Ceiling. With licensing there is definitely a ceiling effect because of the emphasis on full 100% compliance with all rules. That is the goal of a licensing program, to have full compliance.

With quality systems, it more open ended in which the sky is not a limit. Programs have many ways to attain excellence.

Seventh: Gatekeeper versus Enabler: Licensing has always been called a gatekeeper system. It is the entry way to providing care, to providing services. It is a mandatory system in which all programs need to be licensed to operate.

In Quality systems, these are voluntary systems. A program chooses to participate, there is no mandate to participate. It is more enabling for programs building upon successes. There are enhancements in many cases.

Eight: Risk versus Performance: Licensing systems are based upon mitigating or reducing risks to children when in out of home care.

Quality systems are based upon performance and excellence where this is rewarded in their particular scoring by the addition of a new Star level or a Digital Badge or an Accreditation Certificate.

There has been a great deal of discussion in the early care and education field about the relationship between licensing, accreditation, QRIS, professional development, and technical assistance. It is important as we continue this discussion to pay attention to the key elements and principles in how licensing and these quality systems are the same and different in their emphases and goals.

Enhanced Dichotomization Model for Generating Licensing Key Indicators Technical Research Note

Richard Fiene, Ph.D.

The Pennsylvania State University, Research Institute for Key Indicators, & National Association for Regulatory Administration

December 2019

The licensing key indicator methodology has been evolving over the past decade in making it more sensitive to the selection process of the specific rules to be included as key indicators. Some of the enhancements can occur because of state licensing data systems being able to provide population data rather than having to select sample data. Because of the nominal nature of licensing data and the severe skewness of the data distributions, non-parametric statistical approaches need to be employed in the analysis of the data.

A key component in the analysis of the licensing data distributions is to dichotomization of the data which is generally not warranted but is acceptable with very skewed data distributions. The dichotomization that has been most successful is a H25/M50/L25 distribution in which H25 represents the High Group of regulatory compliance, M50 which represents the Mediocre or Middle Group of regulatory compliance, L25 which represents the Lowest Group of regulatory compliance. In the past, the methodology allowed for full and substantial compliance within the High Group. This decision is no longer recommended. Rather, in order to decrease the number of False Negatives, it is now recommended that only Full (100%) regulatory compliance is used in defining the High Group. This eliminates the possibility of False Negatives.

By making this above change and in using the full distribution of licensing data, it enhances the results for generating the licensing key indicator rules. For additional information on this modeling please see:

Fiene, Richard (2018), “ECPQIM National Data Base”, Mendeley Data, V1.
http://dx.doi.org/10.17632/kzk6xssx4d.1

This data base provides the detailed ECPQIM data distributions for the above changes. The enhancements increase the phi coefficients and reliability in either moving or not moving from abbreviated inspections to full comprehensive inspections. This data base also contains clear demonstrations of the efficacy of the ECPQIM – Early Childhood Program Quality Improvement and Indicator Model as a vehicle for improving early care and education programs.

The Relationship of Licensing, Head Start, Pre-K, QRIS, Accreditation, and Professional Development and their Potential Impact on Child Outcomes

Richard Fiene, Ph.D.

October 11, 2013

ABSTRACT

This short paper will provide some thoughts about the various public policy initiatives/systems to improve early care and education, such as licensing, Head Start, Pre-K, QRIS, accreditation, and professional development and their potential impact on child outcomes. Early care and education is at a major crossroads as a profession in attempting to determine which quality initiatives have the greatest impact on children. Results are starting to come in from early studies which may provide some guidance as policy makers begin making decisions about where to focus their limited funding resources.

Improving early care and education programs has a long public policy history as we attempt to find the most cost effective and efficient means for attaining this lofty goal. There have been many ups and downs over the years where funding was adequate and when it was not, but our desire to accomplish this goal has always been front and center. Now, as a profession, we are at somewhat of a cross-roads in determining which of the many quality initiatives appear to have the greatest impact on children's development. When I refer to children's development, I am looking at the whole child from the perspective of a child's developmental status as well as the child's health and safety.

Presently we have many quality initiatives to look at which is a very good thing since at times in the past we did not always have so many choices. Probably the one constant throughout the history of early care and education in the past century has been licensing or regulations/rule formulation. Some many argue that licensing is not a quality initiative but I would suggest that licensing has many of the structural aspects of quality that have been identified in the research literature. The other quality initiatives I will discuss have really started and been implemented in the very later part of the 20^{th} century so we are talking about a relatively new science when we think about having its intended impact on children. Also, I am talking about large public policy initiatives rather than highly structured, single focused research studies involving small samples of children.

Let's start with licensing since this system has been present for the longest period of time. The purpose of licensing is to act as the gatekeeper to the early care and education field in which only those providers who meet specific standards, generally called rules or regulations are permitted to operate and care for children. The rules are dominated by health and safety concerns with less emphasis on curriculum planning and staff-child interactions. The rules measure more structural aspects of quality than the process aspects of quality; dealing with what attorney's call the "hard data" rather than the "soft data".

Since licensing rules allow entry into the early care and education field to provide services usually the rules are not overally stringent with the majority of providers being in high compliance if not full compliance with all the rules. This would be expected since these are basic health and safety standards. And in fact when one looks at compliance data, it is extremely skewed with the majority of providers having very high compliance scores with relatively few violations of the rules. However, this does introduce a certain difficulty in using these data for decision making purposes at an aggregate level because so many providers score at a high level it becomes increasingly difficult to distinguish between the really excellent providers and the somewhat mediocre providers. Another way of looking at this skewing of the data is to term it as a plateau effect in which there is very little variance at the upper ends of the compliance spectrum. This is a major issue with skewed data and basic standards which is an important consideration with licensing but will also be an important consideration when one looks at the other quality initiatives to be addressed shortly.

Because of this plateau effect with licensing data, it may explain much of the lack of relationships found between compliance with rules and any types of outcomes related to children's outcomes and provider's overall quality. However, with licensing data and making comparisons to children's outcomes we should be looking at general health data such as immunization status and safety data such as the number of injuries at programs with varying levels of compliance with health and safety rules.

A significant development over the past two decades has been the development of national health and safety standards with the publication of Caring for Our Children (CFOC3) and Stepping Stones (SS3). Although these standards are not required but are only recommended practice that provides guidance to states as they revise their rules, these two documents have been embraced by the licensing/regulatory administration field. Although unlikely, if not impossible, to comply with all the CFOC3 standards, it would be interesting to compare states on this set of standards which may add a good deal of variance to the basic health and safety data that has been missing with licensing rules.

The next system to look at is the national Head Start program. Out of the major programs that are national in scope, Head Start has a long history of providing services to low income children and their families. Head Start Performance Standards are definitely more stringent than licensing rules but not as stringent as accreditation standards. Based upon Head Start's more stringent standards and the additional supports that are part of its program, Head Start generally scores higher on program quality tools (e.g., CLASS or ERS) than licensed child care in states.

With Head Start programs, we at times find skewing or plateauing of data when we compare compliance with the Head Start Performance Standards (HSPS) and program quality tools such as the CLASS. However, this is dependent upon the various subscales within the CLASS in which the plateauing of data does not occur all of the time. I think that has a lot to do with the HSPS being fairly stringent standards as compared to state licensing rules in general.

A program that has gotten a good deal of support at the state level are Pre-K programs. These programs come with stricter standards than licensed child care with an emphasis on the professional development of staff. There is more concern about the process aspects of quality which focus more on teacher-child interactions. This emphasis on teacher-child interaction has paid off in which these programs generally are high performers when you compare Pre-K funded classrooms to licensed child care classrooms. In fact, Pre-K funding appears to have a positive impact on licensed child care in raising overall quality scores on the ECERS-R for all classrooms in programs that receive Pre-K funding even if some of the classrooms are not the direct beneficiaries of the funding. This is a very significant finding because we knew that Pre-K funding increased the quality of care in classrooms receiving those funds, but now, it appears that there is a spillover effect to all classrooms co-located with Pre-K funded classrooms. I must admit that I was initially skeptical when Pre-K funding was first proposed because I thought it would take funding and the focus away from improving licensed child care at the state level; but it appears that the advocates for Pre-K were right in their assertion that Pre-K would increase the quality of all early care and education which includes licensed child care.

A more recent entry into the state funding scene are QRIS (Quality Rating and Improvement Systems) which build upon licensing systems, are voluntary, and have substantial financial incentives for participating in this quality improvement system. It is too early to really determine if QRIS is having the intended impact because the program is so new (50% of states have a QRIS), and the penetration rate is usually below 50% in any given state (remember the system is voluntary). However, in the few studies done, the results are mixed. It does appear that programs which move up the various star levels do increase the quality of care they provide; but in a most recent study looking at child outcomes, no relationship was found between increasing levels of compliance with QRIS standards and how well children did in those programs with the exception of CLASS scores in which teacher-child interactions were measured and emphasized – here there were significant relationships between higher scores on the CLASS and child outcomes.

Accreditation systems come in many varieties but there are only three that I know of in which empirical studies have been done to validate their systems: NAEYC, NECPA for centers and NAFDC for homes. Also reliability testing has been done in each of these systems. Accreditation is a rigorous self-study that really improves programs through the self-study process. This should come as no surprise because we have known for some time that program monitoring all by itself leads to program improvements. Now when you couple that with technical assistance you see even more improvement. Accreditation is usually the other pillar of a QRIS system with licensing being the first pillar. The QRIS standards fill the gap from licensing to accreditation. Accreditation is a voluntary system just as in most cases with QRIS. However, in accreditation we are reaching less than 10% of the programs with the majority of these attaining NAEYC accreditation. NECPA and NAFDC have much smaller market shares.

The last system to be addressed is the professional development systems that have been established in all states. This is one quality improvement initiative that has 100% penetration in all states. It is usually tied to QRIS through technical assistance and mentoring (coaching). When it focuses on mentoring rather than workshops, it has demonstrated its effectiveness in changing teachers behaviors in how they interact with children in their care in a very positive fashion. This is very important because the research literature is clear about the importance of the teacher-child interaction when it comes to child outcomes. Professional development runs the gamut from pre-service (University based programs) to in-service (training, technical assistance, mentoring, coaching) programming for teachers and directors.

So where does this leave us when policy makers begin to try to determine which quality improvement initiatives should be invested in to start with, which to increase in funding, and maybe even which ones should be defunded. I think there are some trends we need to begin to look at, such as the following:

1) Having stringent and rigorous standards is very important. The more that we do not, the more opportunities for mediocre programs to score artificially higher on whatever scale that is used. This is evident with licensing data where the data are significantly skewed with a major plateau effect at the upper end of compliance rules/regulations.

2) Emphasis on teacher-child interaction needs to be paramount in our quality improvement initiatives. Working with teachers through mentoring/coaching appears to be most effective in changing teachers' behaviors in interacting more positively with children.

3) Making sure we are measuring the right outcomes. Match health and safety standards with health and safety outcomes for children. Match developmental outcomes for children with standards that emphasize positive teacher-child interactions.

4) Building upon #1 above, find what the key indicators are with all the data that we collect. We are spending too much time in looking at too many things which in many cases are simply just not the right things to look at. As states' data systems become more sophisticated, and they are, this will be easier to do. Let's begin to utilize the data we have already collected.

Regulatory Compliance Scoring System and Scale

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December 2019

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 go from blue to red which indicate increasing risk of non-compliance and a lower level of overall regulatory compliance which is not a good think 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.

So Which Is Better: Differential Monitoring & Abbreviated Inspections or Comprehensive Inspections?
Technical Research Note #98

Richard Fiene, Ph.D.

March 2020

During 2019 and 2020, several validation studies have been or are being completed in the states of Washington, Indiana, and in the Province of Saskatchewan. These validation studies are determining if the key indicator and risk assessment methodologies are valid approaches to conducting abbreviated inspections in comparison to more comprehensive inspections in which all rules are assessed. These abbreviated inspections are a form of differential or targeted monitoring. This technical research note focuses on the empirical evidence to determine the efficacy of these approaches, are they better than doing comprehensive reviews when it comes to health and safety outcomes.

When the key indicator and risk assessment methods were originally proposed in the 1980's, an outcome validation study was completed in Pennsylvania during 1985 – 1987 by Kontos and Fiene to determine what impact those methods had on children's development. In that original study, it was determined that the Child Development Program Evaluation Indicator Checklist (CDPEIC) was more effective and efficient in predicting child development outcomes than the more comprehensive Child Development Program Evaluation. In fact, the CDPEIC and the accompanying Caregiver Observation Scale (COFAS) were as effective and more efficient than the ECERS – Early Childhood Environmental Rating Scale in that study.

Fast forward to 2019 – 2020, in the province of Saskatchewan, Canada, and a similar study was undertaken but in this case the outcomes were more based upon health and safety rather than child development developmental outcomes. In this case, again the key indicator and risk assessment tool was both a more effective and efficient model over the more comprehensive inspection approach giving credence to utilizing differential monitoring with abbreviated inspections.

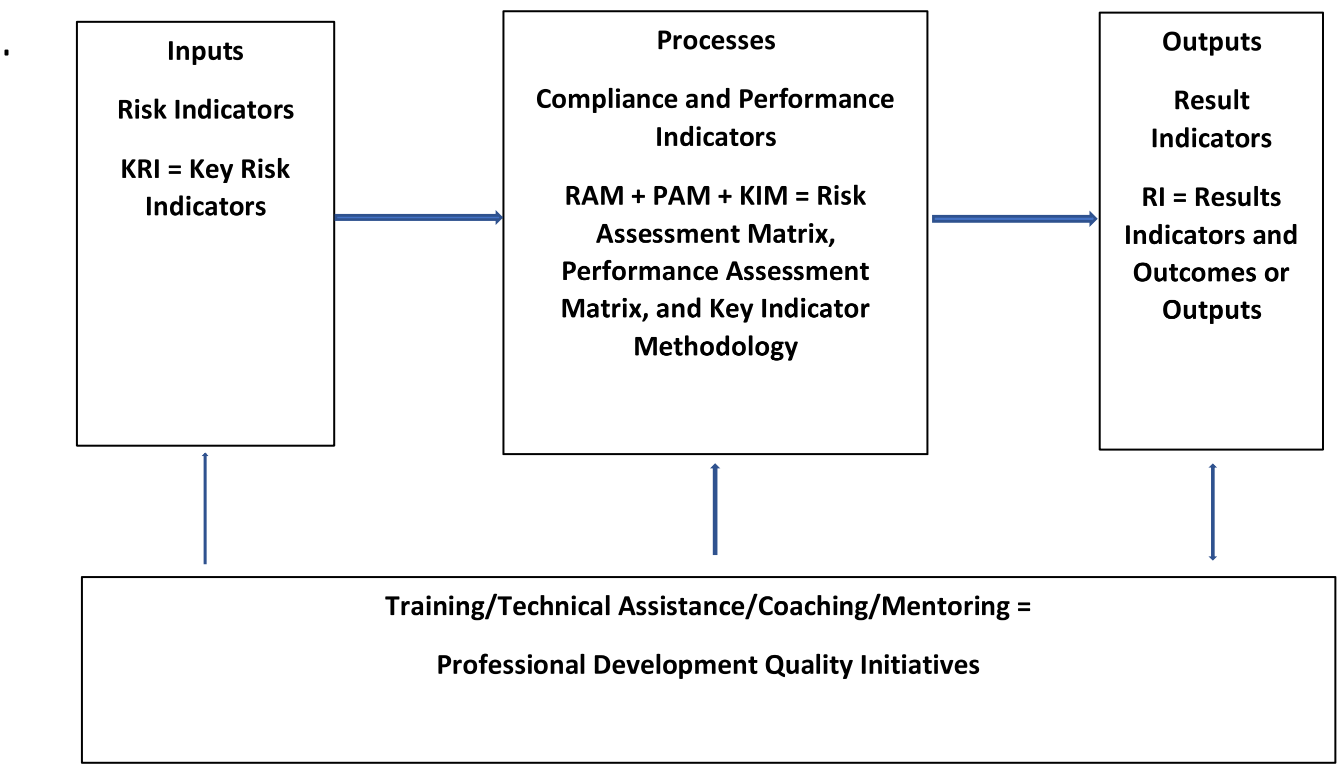
In both of the above validation studies involving either child development assessment outcomes or health & safety outcomes, a 16 to 28% increase in effectiveness was observed in the outcome data. In the abbreviated or targeted inspections, 33% of the total rules or less are used to make the determination of regulatory compliance. It is like having the best of both worlds when it comes to effectiveness (16 – 28% increase in outcomes) and in efficiency (66% fewer rules being used). These studies help to validate the use of differential monitoring as a viable alternative to the more comprehensive one-size-fits-all monitoring reviews.

ECPQIM5: Early Childhood Program Quality Improvement/Indicator Model Version 5 Technical Research Note

Richard Fiene, Ph.D.

April 2022

The purpose of this brief technical research note is to introduce the latest version of the Early Childhood Program Quality Improvement/Indicator Model (Version 5). This latest version takes into account the previous versions of the ECPQIMs and incorporates the latest monitoring research into the model.



The above figure depicts the relationships of risk indicators to compliance and performance indicators to outcome/result indicators. It also demonstrates the importance of quality initiatives such as professional development systems engaged in training, technical assistance, coaching, and mentoring of teachers. ECPQIM5 has taken all the best components from previous versions and has combined it in this present Version Five.

Another way of thinking about the relationships is to think in terms of a typical information system that involves inputs, processes, and outputs. ECPQIM2 was organized in this fashion while the other versions of ECPQIM were organized more according to the dictates of a logic model.

The best example of this version of the model is the Head Start Grantee Performance Management System (GPMS) that is under development and revision as we speak. There has been a great deal of interest in developing similar models in various state and Canadian Provinces. Head Start appears to have the lead in developing this state-of-the-art program monitoring system.

The other thing to notice with ECPQIM5 is the balance of compliance and performance indicators. This can occur with a deliberate effort to build in best practices or promising practices or through the use of other quality initiatives from Quality Rating and Improvement Systems, Accreditation Systems, or Professional Development Systems. And it is with the constant tie ins to professional development that really increases the strength of this latest version of ECPQIM5.

Also, the addition of Risk Indicators is an important design consideration which should have been introduced much earlier. It has been present in licensing and compliance but it is a critical element that will help to either make or break a program monitoring system. It helps to get programs off on a good start and not behind the eight ball.

As with any program monitoring system it is attempting to find the critical paths of those agencies that are successful and those that are struggling. It is through the use of validation studies to determine what the appropriate paths are statistically so that the proper balance of key indicators can be put in place to produce the greatest outputs/outcomes/results.

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