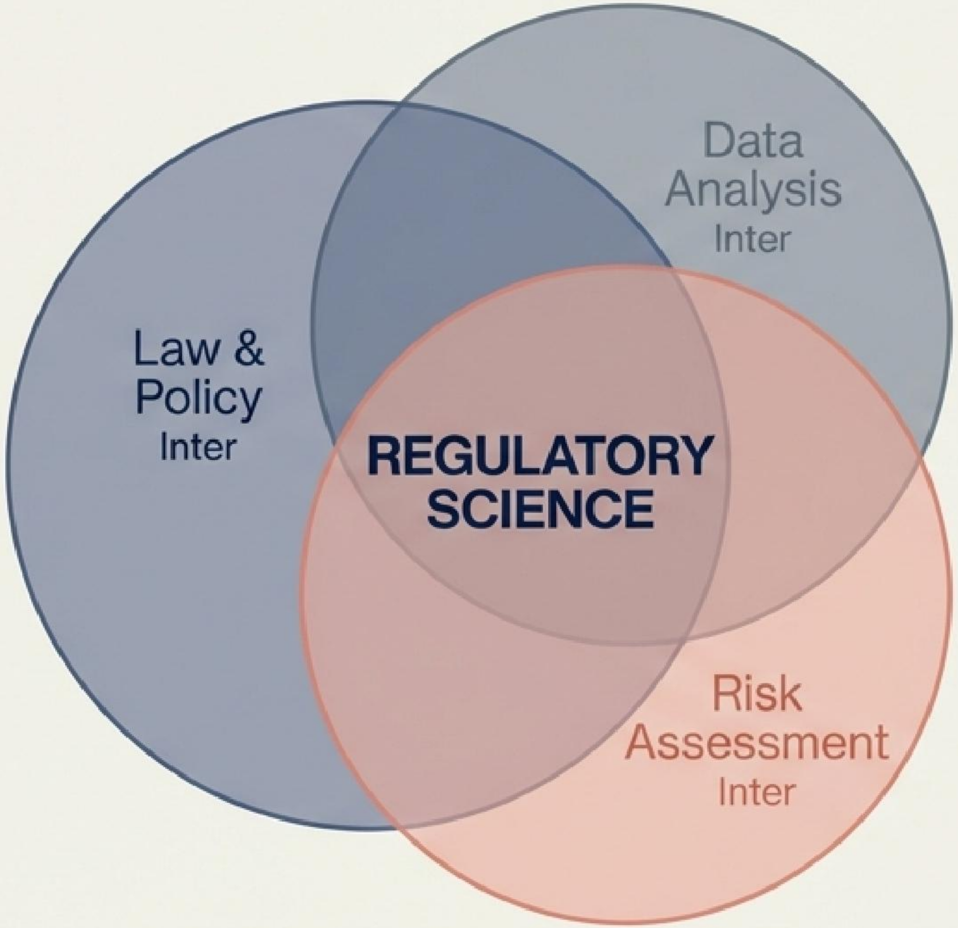
Regulatory Science in Human Services

Modernizing Licensing, Monitoring, and Compliance through Data-Driven Systems

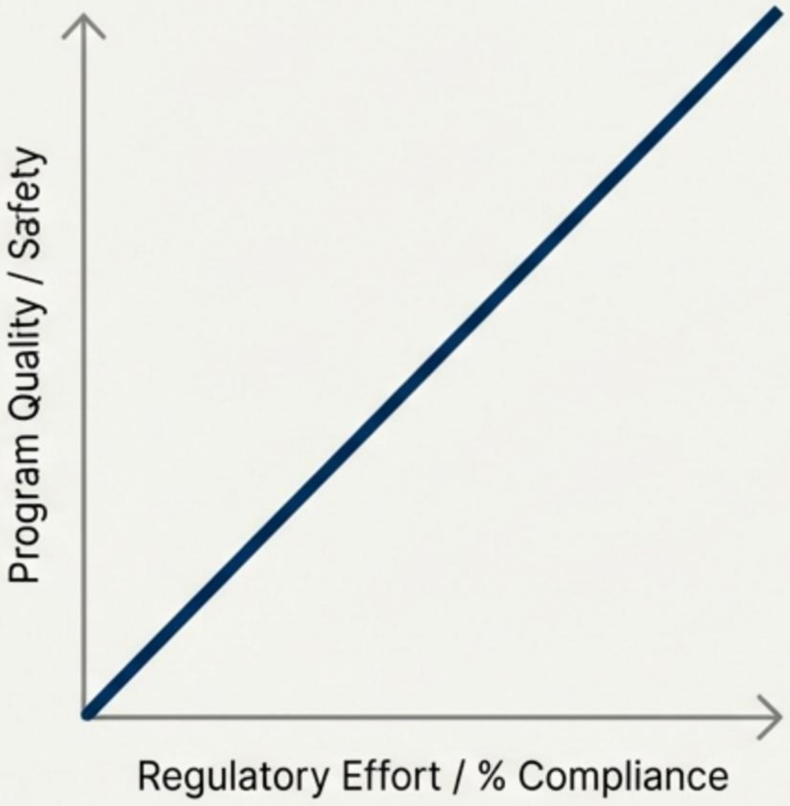
Based on the research of Richard Fiene PhD,
Penn State University (Sept 2023)

The Paradigm Shift: Defining Regulatory Science



Regulatory science moves administration from "gut feeling" to "evidence-based."
It bridges abstract legal requirements with concrete measurement, aiding in the development of policies that are scientifically validated.

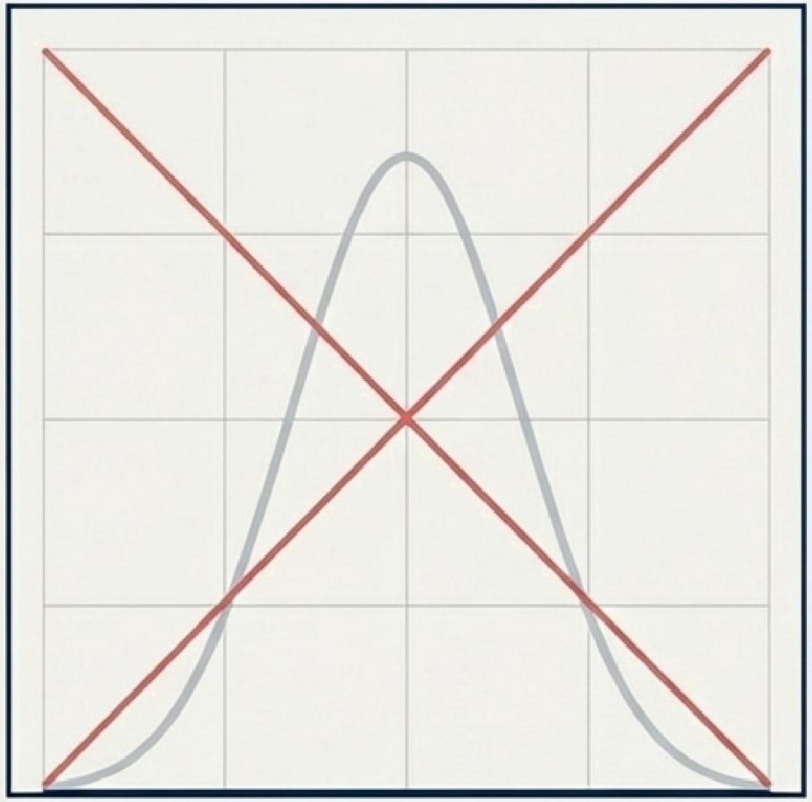
The Linear Assumption



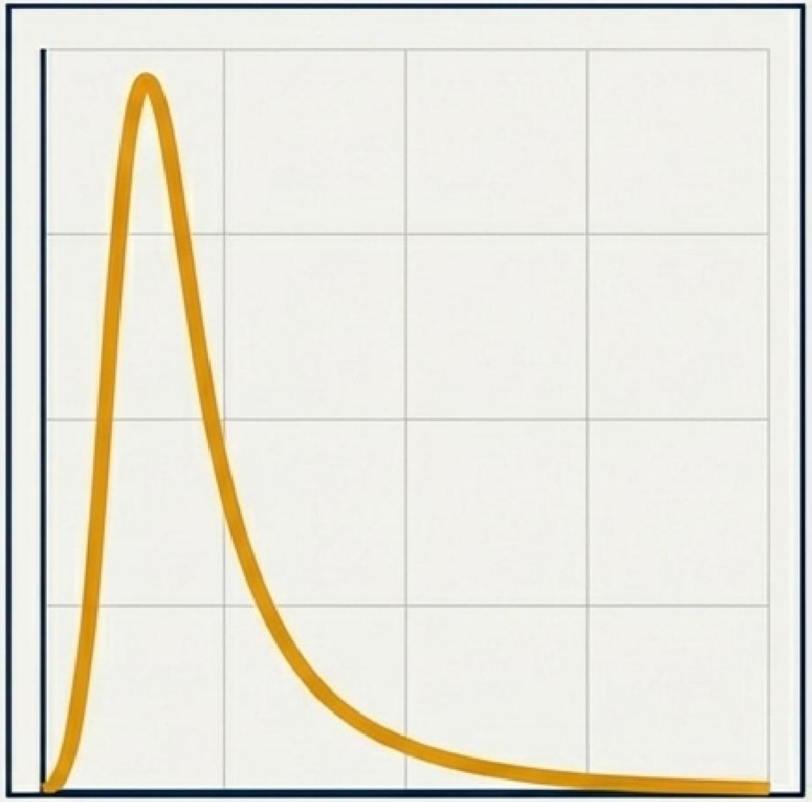
The traditional regulatory model assumed more was always better.

- Historically, regulatory systems operated on a linear assumption: increased monitoring and a push for 100% compliance would invariably lead to better outcomes.
- This led to a uniform, “one-size-fits-all” monitoring approach where all entities were subject to the same level and frequency of inspection, regardless of their compliance history or risk profile.
- This model was often based on anecdotal evidence rather than empirical data, leading to an inefficient allocation of limited regulatory resources.

The Statistical Reality of Licensing Data



The Assumption: Traditional Social Science Methods

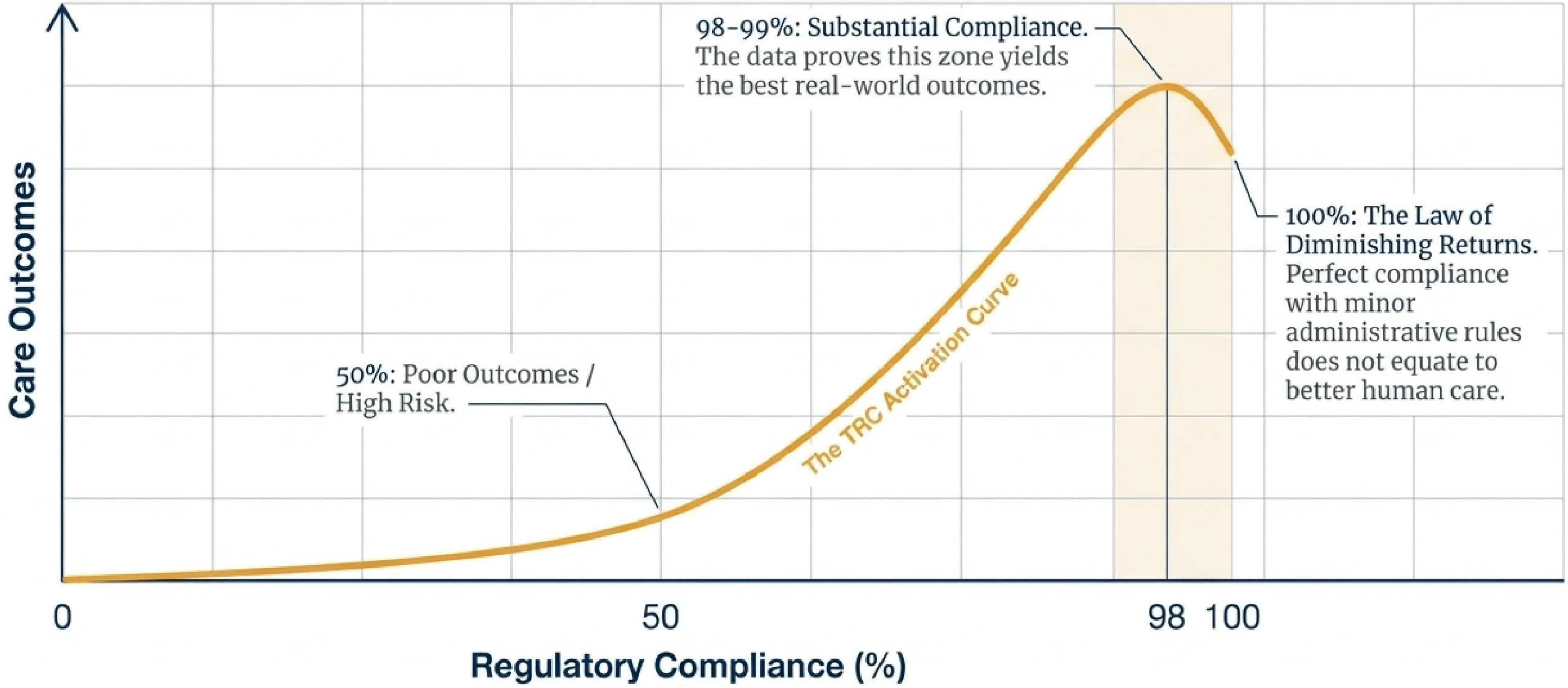


The Reality: Fiene's Regulatory Science Framework

Traditional statistics assume a normal distribution. Fiene's foundational breakthrough proved that human care lic data is inherently skewed and nonparametric.

Regulators were using the wrong mathematical tools to measure safety—until Fiene built a custom statistical framework designed exclusively for the realities of regulatory compliance.

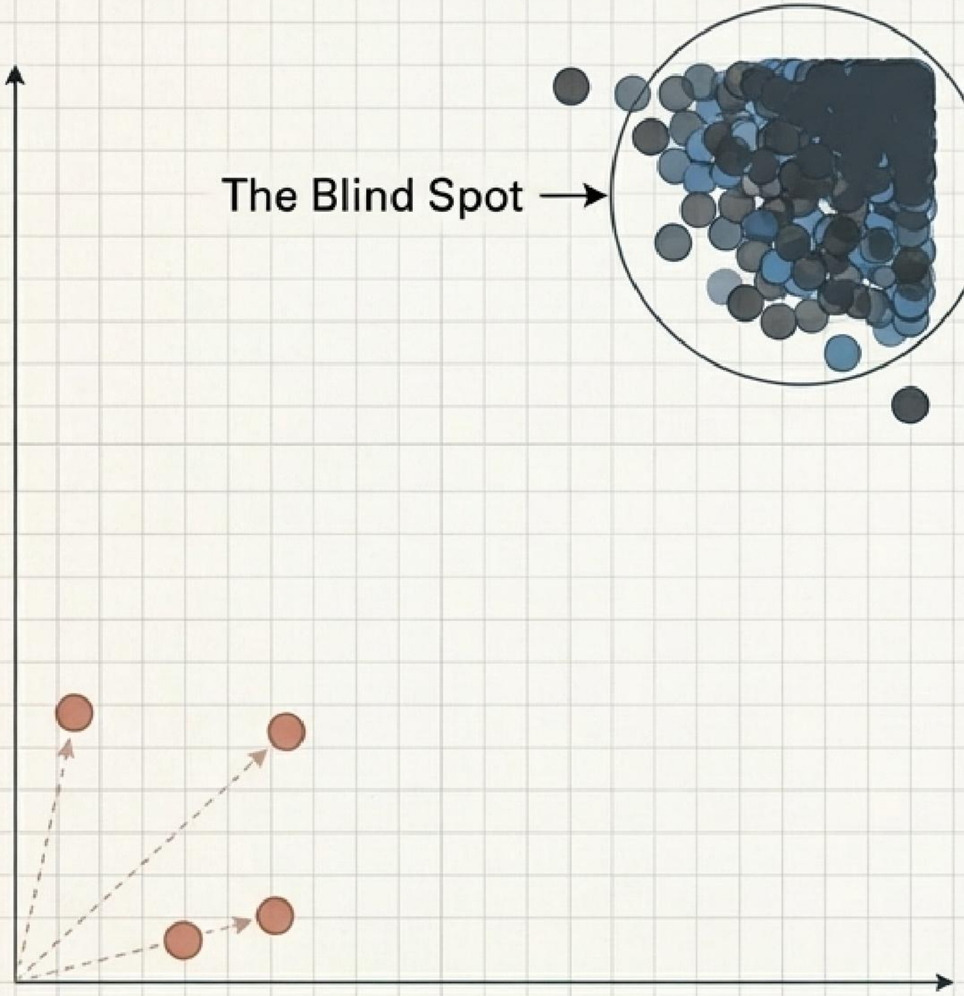
Theory of Regulatory Compliance (TRC)



Visualizing the Plateau Effect

This data, replicated across eight states and three Canadian provinces, called into question the long-held policy of requiring full compliance for licensure. It showed that the pursuit of perfection was not just inefficient, but counterproductive.

The Separation Problem



The Bell Curve Myth

If you find a normal bell curve in licensing data, do not trust that facility. Because basic safety rules demand high compliance, honest data is perpetually clustered at 100%.

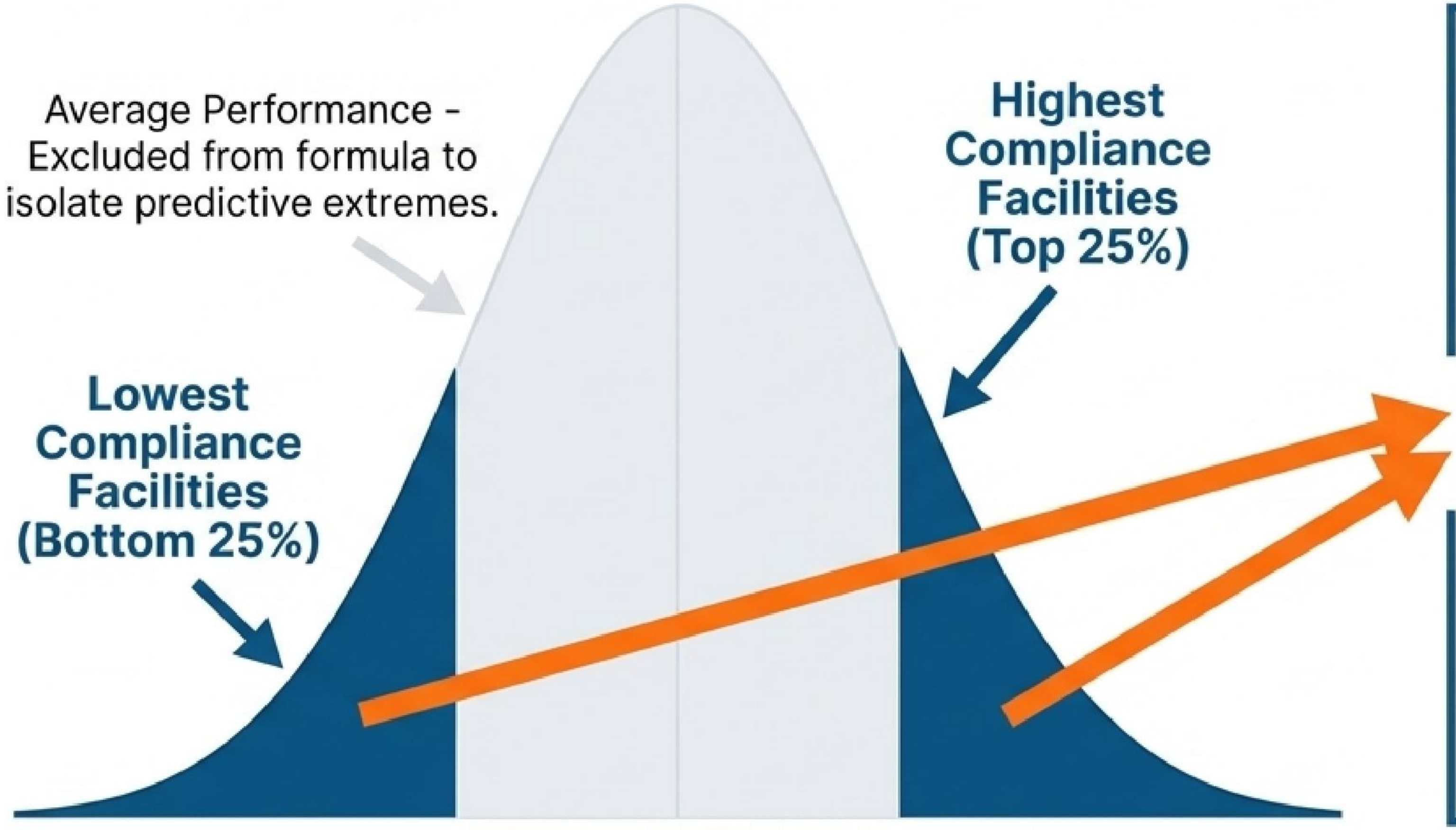
The Easy Task

Statistically separating low-compliant performers from the rest of the pack is simple.

The Hard Task

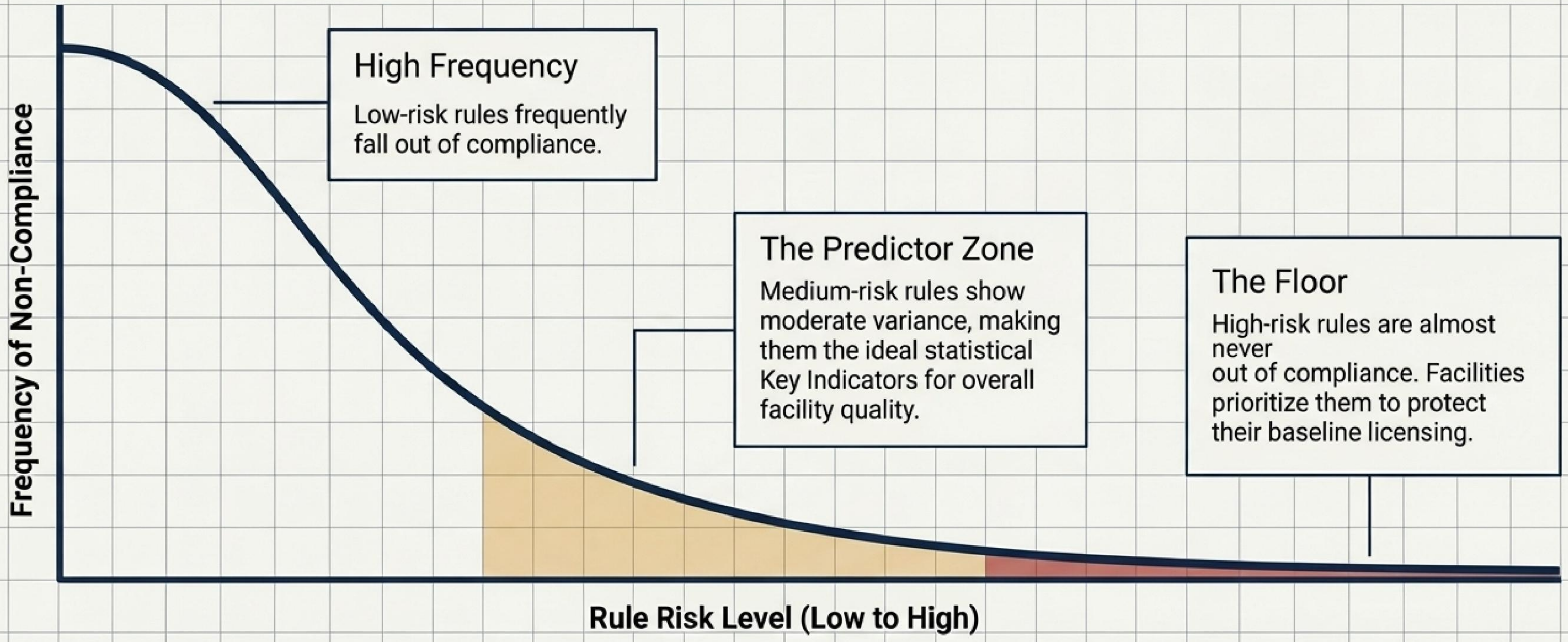
Because of the ceiling effect and massive data bunching at the top, mathematically distinguishing a mediocre performer from a truly elite performer requires highly calibrated, risk-weighted measurement.

Defining the Extremes: Quartile Isolation



Only data from these two extreme quartiles are fed into the Predictor Matrix to calculate the final coefficient.

The Regulatory Compliance Gravity Curve



"High risk rules being out of compliance is generally not the case; but with low-risk rules this is where a higher rate of non-compliance will be found." (Fiene, 2024)

NotebookLM

A Better Way: The 'Relative/Differential' Paradigm

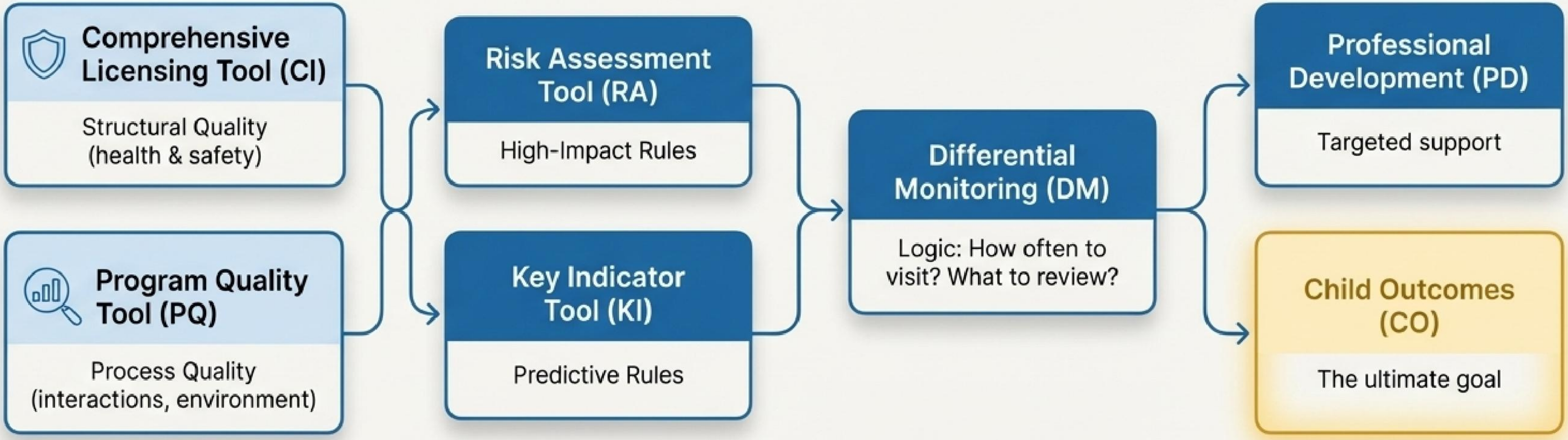
If not all rules are equal, we can use data to focus our resources on the rules that matter most, leading to a system that is both more efficient and more effective.

Absolute Paradigm (The Old Way)	Relative/Differential Paradigm (The New Way)
All rules are created equal.	All rules are **not** created equal.
100% compliance is the only goal.	**Substantial compliance** on what matters is the goal.
The relationship between compliance (PC) and **quality** (PQ) is linear.	The PC + PQ relationship is **not** linear (due to the plateau effect).
All rules are reviewed all the time.	**Selected, high-impact rules** are reviewed strategically.

This isn't about lowering standards.
It's about raising intelligence.

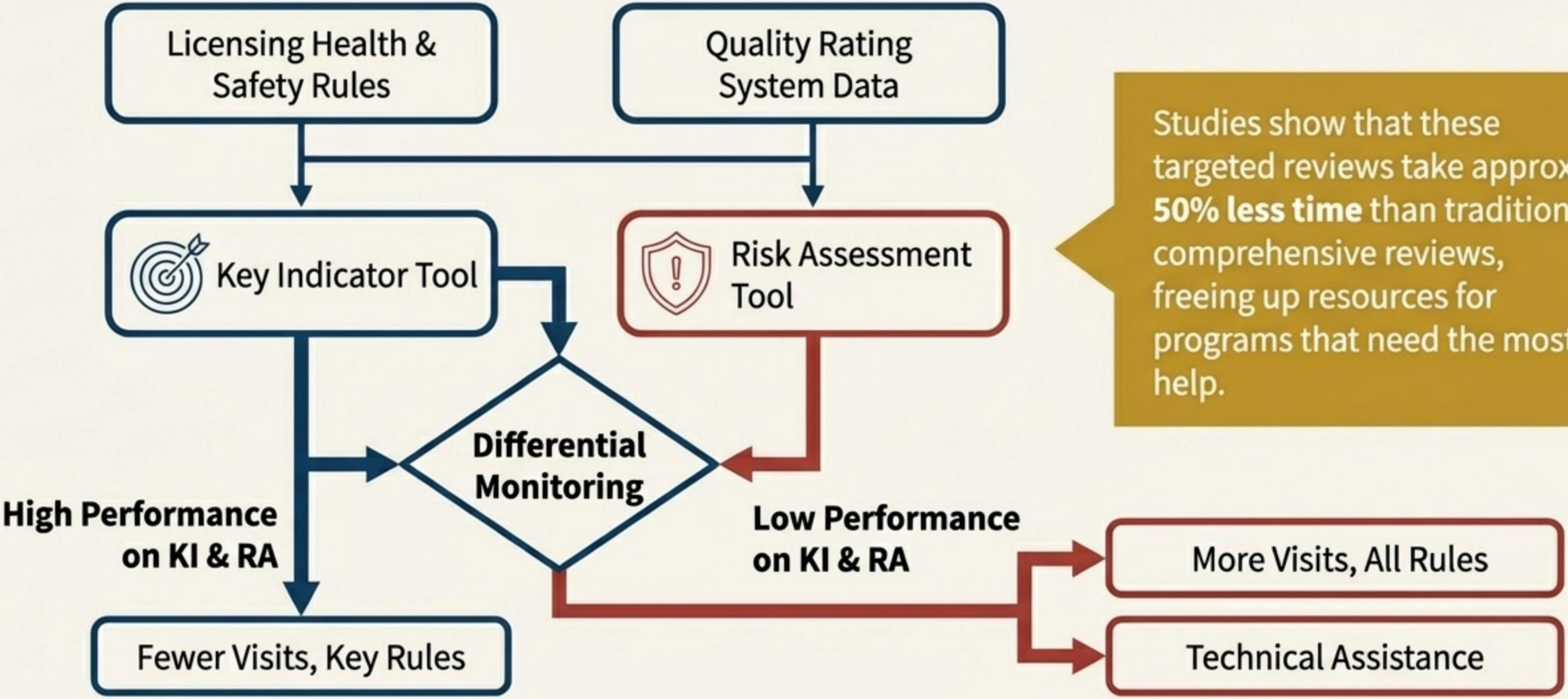
The System: Differential Monitoring Logic Model & Algorithm (DMLMA)

DMLMA is a 4th-generation quality indicator model that integrates multiple data points into a unified, intelligent monitoring system.



CI: Comprehensive Instrument; PQ: Program Quality; RA: Risk Assessment; KI: Key Indicators; DM: Differential Monitoring; PD: Professional Development; CO: Child Outcomes

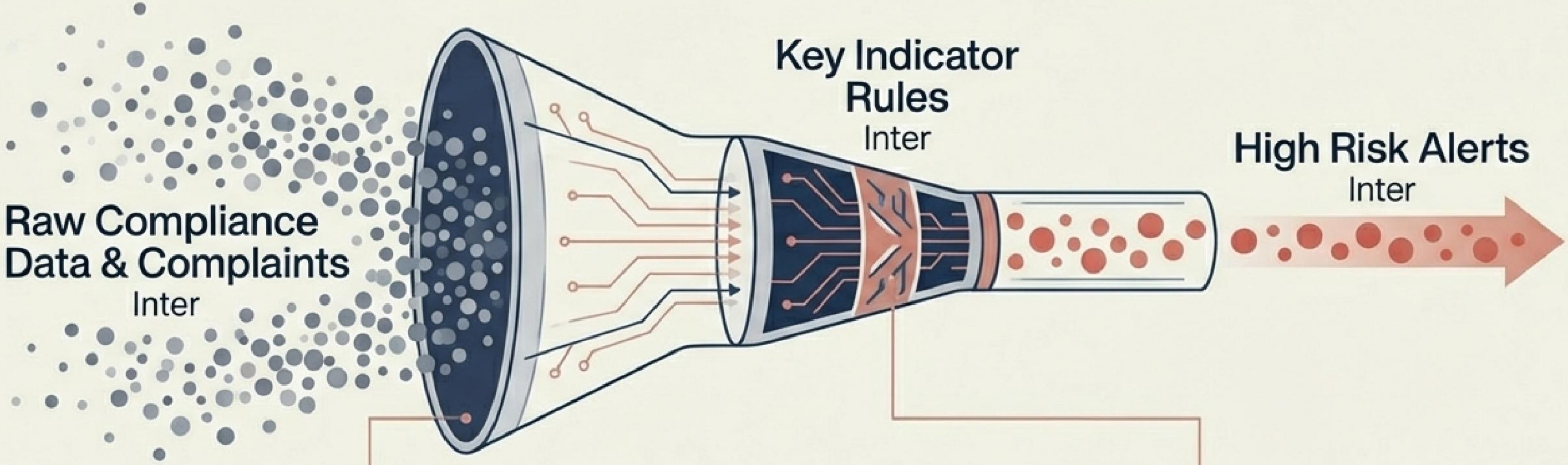
The Differential Monitoring System in Action



Studies show that these targeted reviews take approx. **50% less time** than traditional comprehensive reviews, freeing up resources for programs that need the most help.

Comprehensive reviews are still required every 3-4 years to validate the predictive power of the Key Indicators and Risk Assessment rules.

Algorithm-Driven Oversight



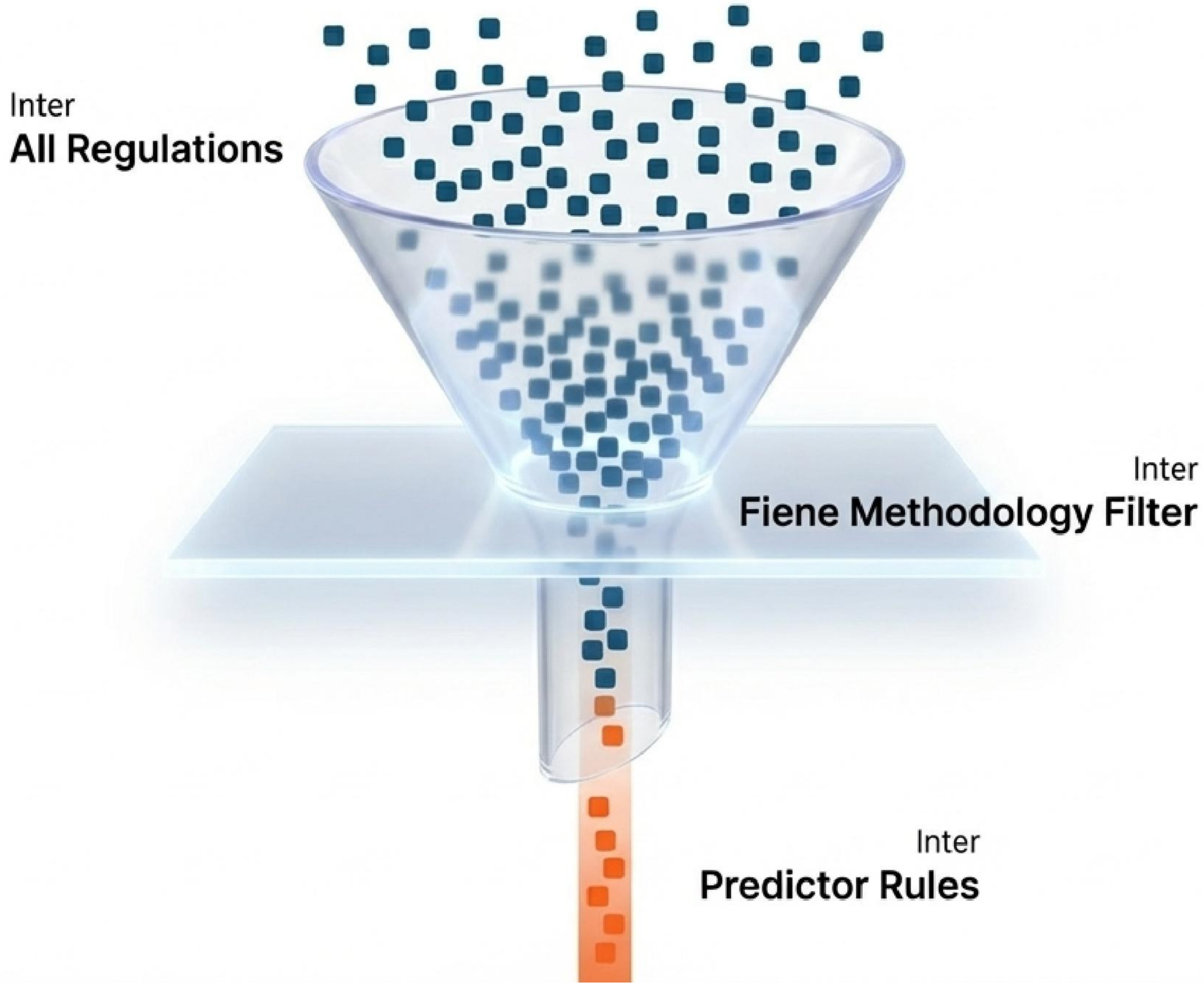
Differential Monitoring

Using algorithms to analyze compliance history and focus on high-risk providers.

Key Indicator Rules

Identifying the specific subset of regulations that statistically predict overall compliance.

The Solution: Differential Monitoring via Fiene Indicators



Inter
What is a Key Indicator?
Source Sans Pro
Statistically, they are predictor rules of overall compliance with all rules for a particular service type.

Inter
The Operational Value
Source Sans Pro
This differential monitoring approach predicts overall facility safety by tracking only the most statistically significant indicators, drastically optimizing inspection efficiency.

Component 1: Key Indicators

Definition:
Key Indicators are a small subset of rules that are statistical predictors of overall compliance.

How They Work:

- They are identified through statistical analysis of historical data.
- If a facility follows these specific rules, it strongly suggests they will follow most other rules as well.
- This allows for highly efficient and predictive inspections without needing to review all 200-400 regulations every single time.

Think of them as the **'canary in the coal mine'** for regulatory health.

Component 2: Risk Assessment

Definition:

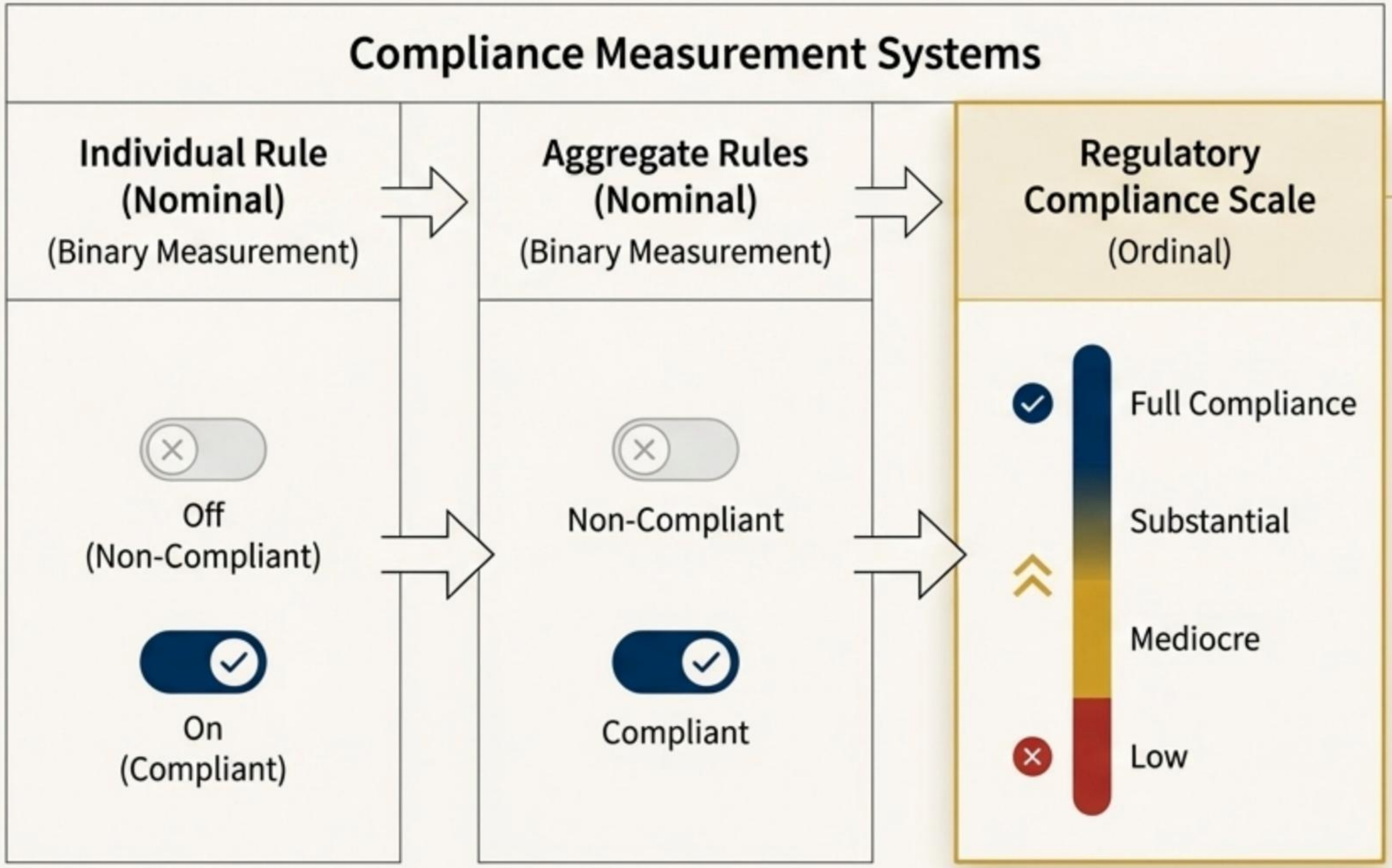
Risk Assessment focuses on rules and regulations which, when breached, place children at the greatest risk of sickness, injury, or death.

How It Works:

- Stakeholders (providers, parents, licensing staff) collaboratively "weight" each rule's risk on a scale (typically 1-10).
- Rules with high-risk weights (e.g., related to supervision, hazardous materials) become part of every single differential monitoring review.

> **While Key Indicators predict broad compliance, Risk Assessment ensures that the most critical health and safety rules are never overlooked.**

The Solution: Evolving from a Binary Switch to a Graded Scale



Inspired by the 1-7 Likert scales already used in quality measurement, a new Regulatory Compliance Scale is being developed. This transforms licensing data from a simple violation tally into a more useful and intuitive scale. It allows us to see the difference between "excellent," "good," and "mediocre" compliance, aligning the data with real-world quality.

The Psychology of Compliance

Prospect Theory: The root cause of regulatory variance

Aversion Bias

The overriding human drive to avoid catastrophic outcomes at all costs. In licensing, this manifests as avoiding being cited for high-risk rules that jeopardize a license renewal.

Certainty Bias

The human drive to establish strict control over minor details. In licensing, this manifests as a strict regulatory stance on low-risk rules where nit-picking creates a false sense of certainty.

Diagnostic Matrix: Bias and Systemic Impact

	The False Positive	The False Negative
Assessor Bias	**Certainty** (Seeking control)	**Aversion** (Avoiding conflict)
Assessor Behavior	Stringent / Nit-picking	**Lenient** / Hesitant
Target Rules	Low-Risk Regulations	High-Risk Regulations
Harmed Stakeholder	Providers and Facilities	Clients and Insurance Carriers
Real-World Consequence	Unfair Liability Insurance Costs	Unsafe Conditions and Physical Injuries

Mapping System Alignment

Vertical Axis: Actual Overall Reality
The Ground Truth: Is the facility actually in a High compliant state or Low compliant state?

True Positive
Assessor observes the rule is IN compliance.
Reality: The facility is HIGHLY compliant.

True Negative
Assessor observes the rule is OUT of compliance.
Reality: The facility is in a LOW compliant state.

Horizontal Axis: Individual Observation
The Assessor's View: Did the assessor mark the individual rule In or Out of compliance?

Context Note: When the system operates in these quadrants, licensing decisions are accurate. The goal of the algorithm is to maximize these outcomes.

Defining the Friction Zones

Vertical Axis: Actual Overall Reality.
The Ground Truth: Is the facility actually in a High compliant state or Low compliant state?

False Positive

Observation: OUT.
Reality: HIGH Compliance.

(The Stringent Assessor nit-picking compliant facilities).

False Negative

Observation: IN.
Reality: LOW Compliance.

(The Lenient Assessor missing violations in dangerous facilities. The most disturbing outcome.)

Horizontal Axis: Individual Observation.
The Assessor's View: Did the assessor mark the individual rule In or Out of compliance?

But How Do We Know It's Working? The Validation Process

To ensure the abbreviated (KI/RA) system is reliable, we must validate it by comparing its results against the full, comprehensive review.

	Passes Abbreviated (KI) Review	Fails Abbreviated (KI) Review
Passes Full Comprehensive Review	Agreement (Correct): The system works as intended.	False Positive (FP): Inefficient, but safe. We review a good program more deeply.
Fails Full Comprehensive Review	False Negative (FN): A critical error. The system misses a problem. **This must be minimized.**	Agreement (Correct): The system correctly identifies a problem.

Key Validation Goal

The validation process aims for a high Agreement Ratio (ideally over 90%) and an extremely low False Negative Ratio (ideally under 5%). This proves the abbreviated tool is an effective proxy for the full review.

The IRF Algorithm Deconstructed

The Master Equation

$$IRF = (FC = .50+) + (F- = 0) + (F+ = wgt1 \times 3)$$

Dial 1: The Predictability Dial
(FC = .50+)

Maximizes specific rule predictability using the Fiene Coefficient.

Dial 2: The Safety Dial
(F- = 0)

Eliminates catastrophic human safety errors.

Dial 3: The Fairness Dial
(F+ = wgt1 x 3)

Decreases unfair provider penalization to a manageable number.

Thank you.

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