



Exploring Predictive Analytic Threat Assessment Models Built Upon the SOFIT Insider Threat Ontology

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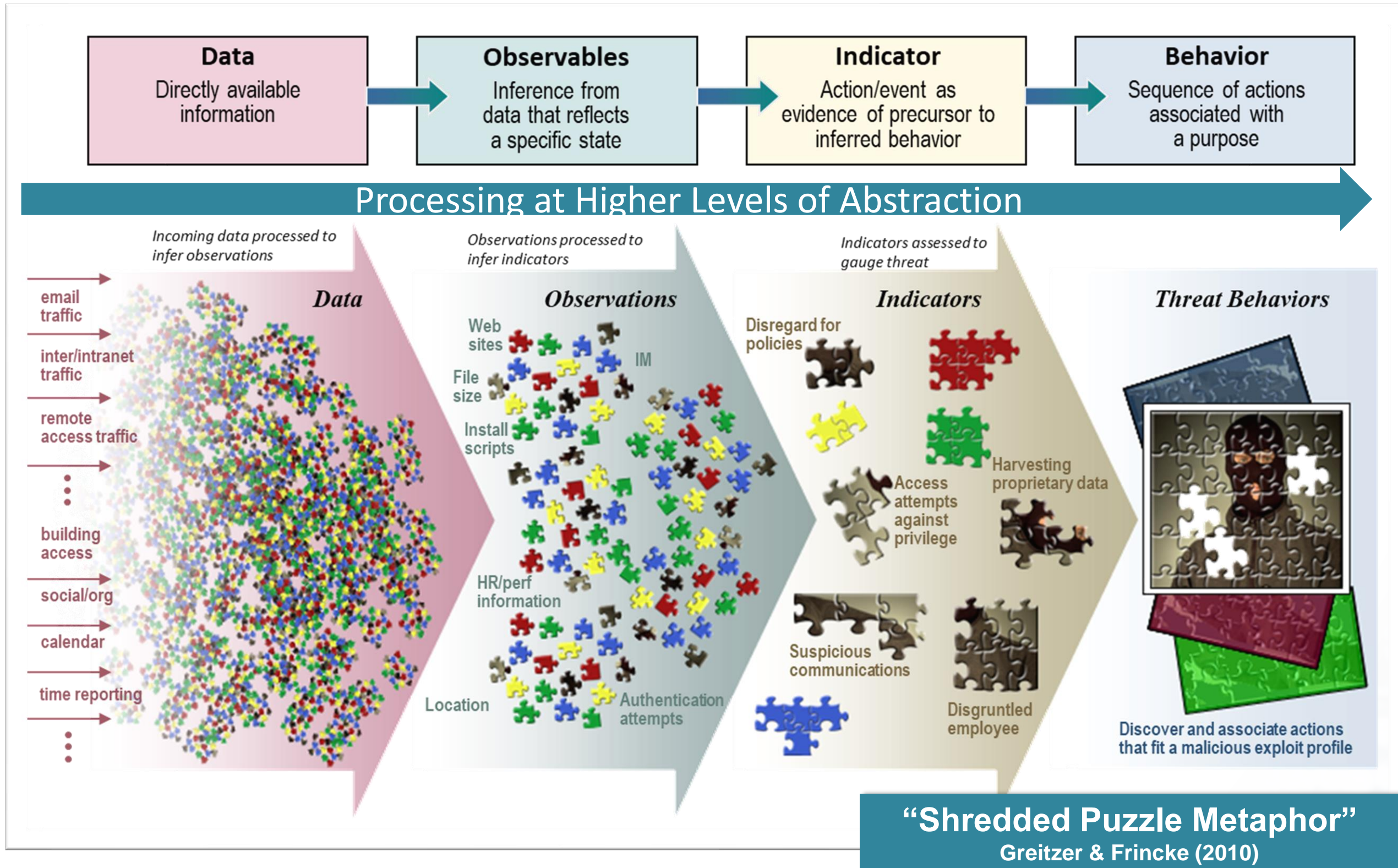
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TOPICS

- Conceptual Model and Insider Threat Indicator Knowledge Base
- Potential Risk Indicators (PRIs)
- Using Expert Judgments to estimate PRI “weights”
- Limitations in traditional predictive models
- Applying a hierarchical/pattern-based model
- Conclusions and Path Forward

CONCEPTUAL PREDICTIVE CLASSIFICATION MODEL



- Data processed to identify “observables”
- Observables analyzed to recognize Potential Risk Indicators (PRIs)
- PRIs analyzed to recognize behavioral patterns relating to insider risks

Development of PRI ontology: Sociotechnical and Organizational Factors for Insider Threat (SOFIT)

POTENTIAL RISK INDICATORS (PRI)s

disciplinary actions

accessing classified information without need-to-know
violating security practices

poor time management

lack of attention
high workload/cognitive load

persistent lateness

illness

lack of knowledge, awareness, training

exhibiting incidents of physical violence

ties to foreign defense contractor

manipulation or destruction of sensitive information

possessing illegal weapons

engaged in criminal activity

frequent personal travel

lying to investigators

extremist views

emotional problems

disgruntlement

unexplained affluence

associating with extremist group

failure to comply with regulations for reporting foreign contacts or foreign travel

narcissism

misuse of U.S. Government information systems

passed over for promotion

dismissal

declining work performance
access via other users' credentials

demotion

failure to return company property

frequent, unreported contact with foreign persons

past

financial concerns – excessive debts

depression

anxiety

sleep

disturbances

mental health counseling

expressing ill will toward U.S. Government

untruthfulness

possessing illegal drugs

attempts to access files without authorization

OF COURSE...

Behavioral PRIs

Technical PRIs

Intrusion Detection

Data Loss Prevention

Access Control

Security Information and Event Management

CYBER DATA COLLECTION

- Registry entries
- IDS events
- Firewall logs
- DNS logs/Internet sites accessed
- Host event logs
- Host print logs
- Network print logs
- Search engine query log data
- Physical security (prox-card data)
- Database server logs
- Web server Logs
- File permissions
- Access to account
- Digital signatures
- Local stored or cached file
- Applications installed
- Patch status
- Keystroke record

to-know

lack of attention
high workload/cognitive load

lack of knowledge, awareness, training

manipulation or
destruction of sensitive
information

emotional problems

possessing
illegal
weapons

use of U.S. Government
information systems

work access via other users' credentials

**past
truthfulness**

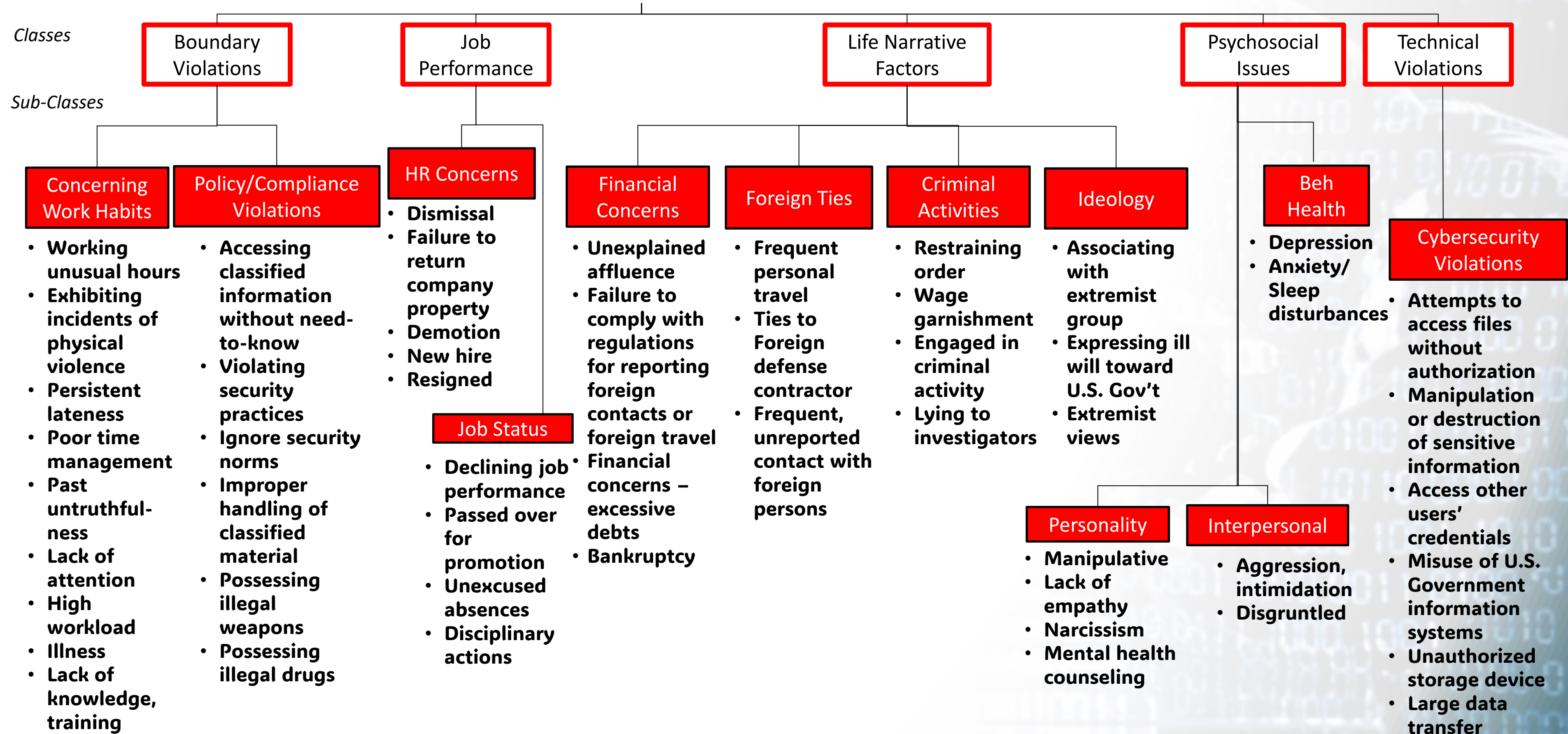
possessing illegal
drugs

demotion

financial concerns -
excessive debts

attempts to access files
without authorizati

SOFIT PRI KNOWLEDGE BASE

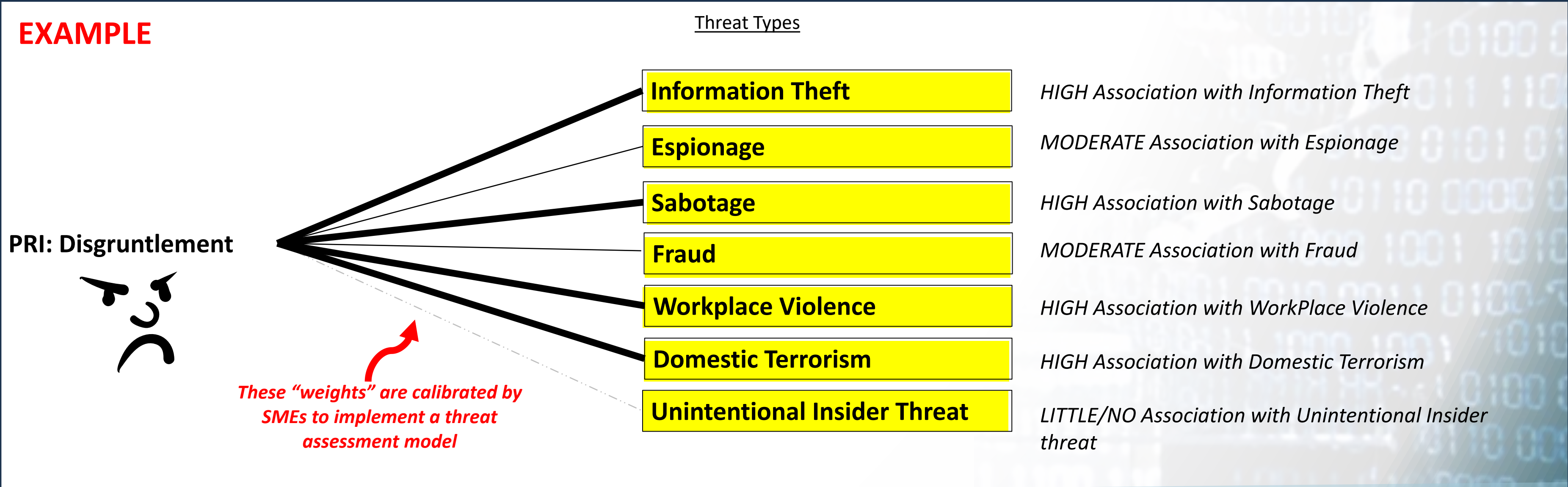


[This is a subset representing approximately 10% of the entire SOFIT PRI Framework]

PRI “CALIBRATION”

Estimating Strength of Association between a PRI and a Threat Behavior

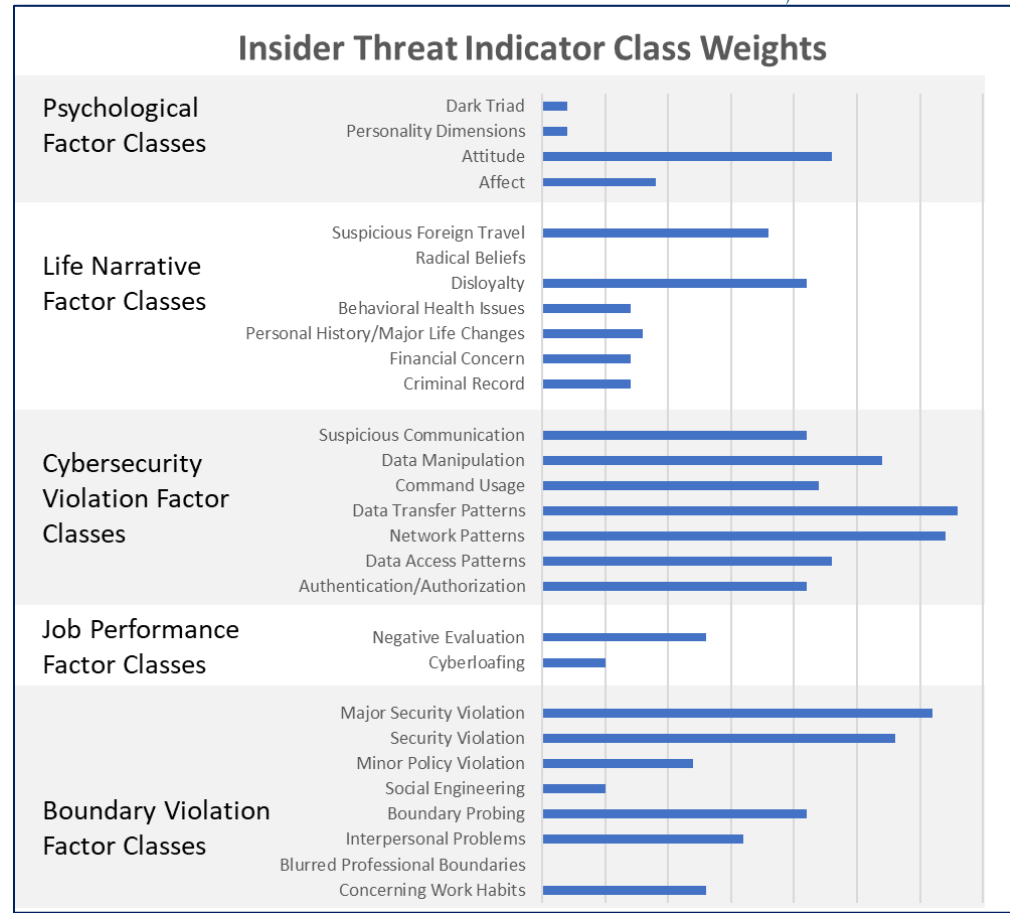
- Each PRI is mapped to relevant Threat Types
- Strength of association may be thought of as a “weight” or “probability”
Higher weight means that the observation of a PRI significantly increases the likelihood that the Behavior is present



WHAT WE'VE LEARNED FROM PRI CALIBRATION STUDIES

1. PRIs vary in their strength/ association with insider threat behaviors

2. It's difficult to get reliable PRI "weight" estimates!



- Threat/Behavior Types**
- Exfiltration/theft
 - Sabotage
 - Workplace Violence
 - Fraud
 - Unintentional Insider Threat
 - Espionage
 - Suicidal Ideation

Greitzer et al. (2018)

When we ask our analysts/experts to provide judgments about PRI weights or severity or likelihood, what are they really thinking?

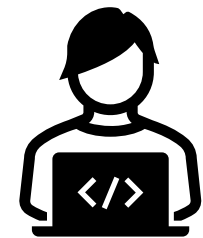
We don't know!

*We use terms like **PRI risk, probability, weight, severity** interchangeably. But in our calibration exercises, our SMEs may be thinking about these weights in different ways.*

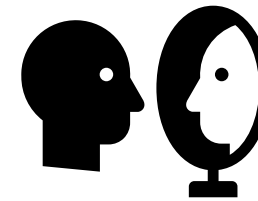
*For our probabilistic models, we need to devise an expert knowledge elicitation method that encourages experts to have the same **mindset**—i.e., focus on probability/likelihood interpretation. I'm currently using a calibration method that acquires **Likelihood Ratio** estimates.*

3. PRIs vary in the span of time during which they influence judgments of insider threat

Greitzer et al. (2022)



Transient impact: Failed login attempt after a password was changed.



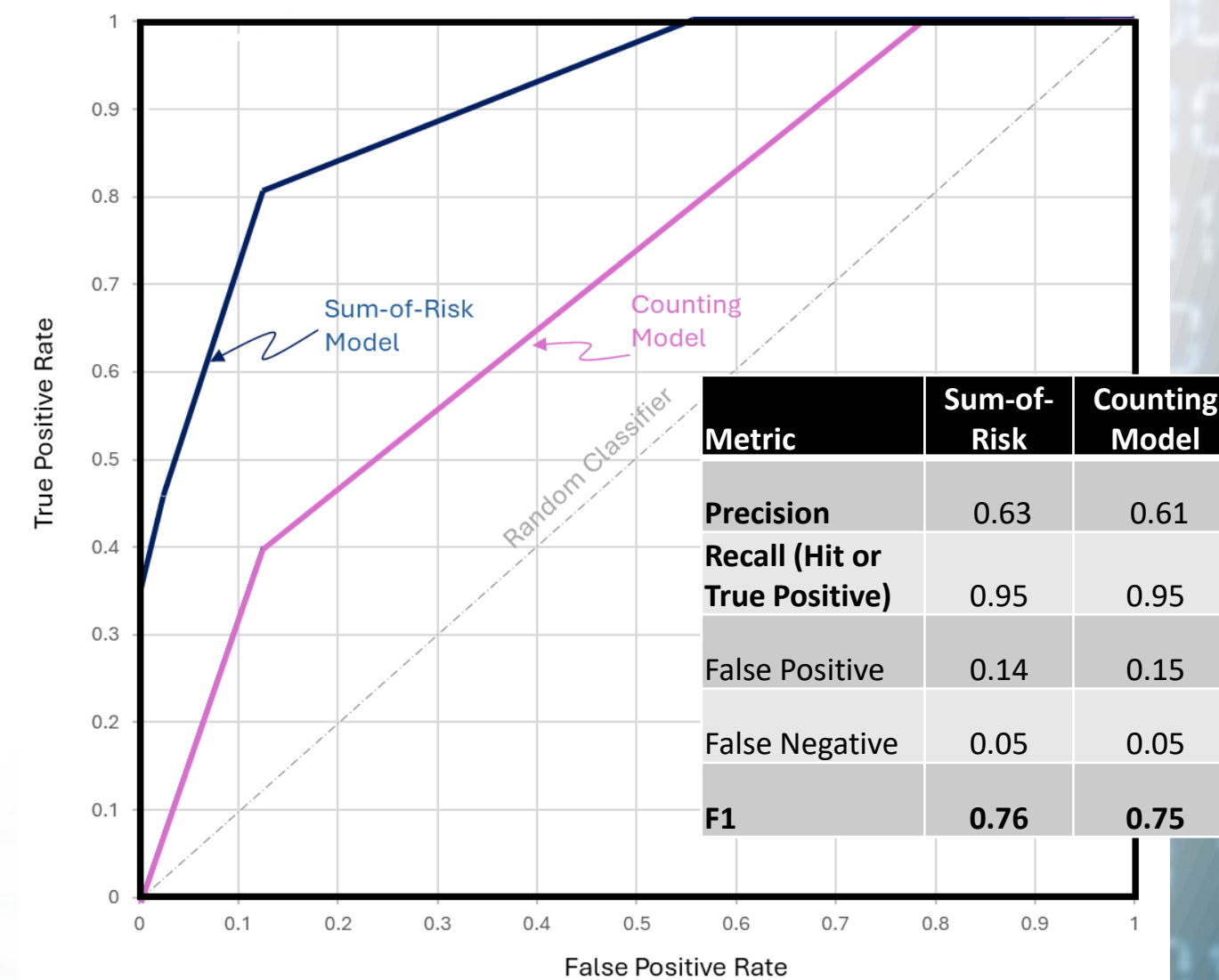
Stable impact: Narcissism – many psychological factors, and especially personality traits, are very stable over many years

COMPUTING INSIDER RISKS BASED ON EXPERT JUDGMENTS OF PRI “WEIGHTS”

- My research investigated computational models predicting expert judgments of insider threat risk based on expert judgments of PRI “level of concern”
 - Counting Model
 - Sum-of-Risk Model
 - Probabilistic models (e.g. Bayesian networks)
- Performance metrics:
 - Receiver Operating Characteristic (ROC)
 - Precision, Recall, False Positives, False Negatives, F1 score
- Results indicate that these models exhibit modest predictive value, accounting for 50-60% of variance in predicting expert judgments



Based on Greitzer et al. (2018) data...
ROC Curves



• Possible limitations:

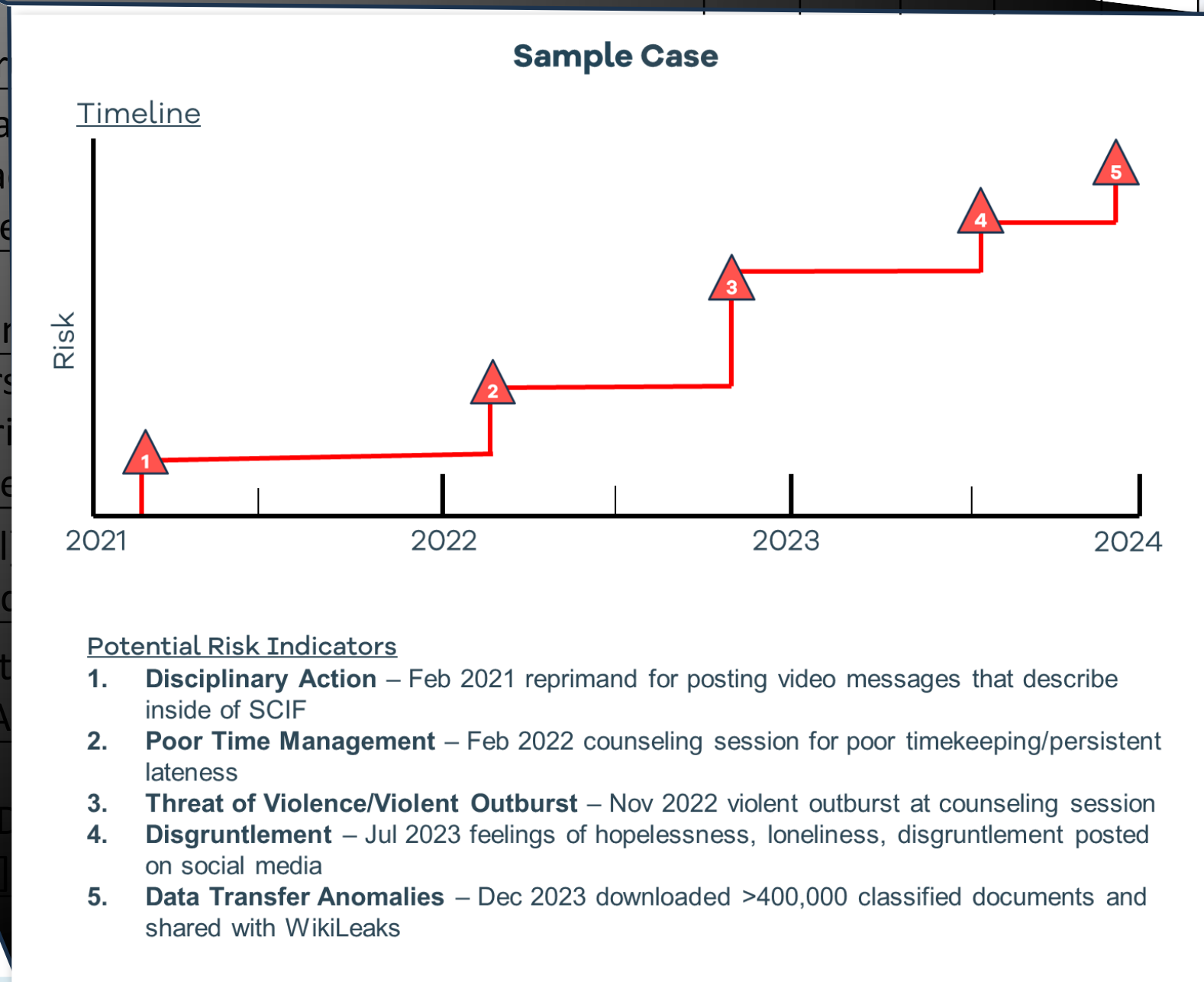
- This early work obtained SME judgments of PRI “weights” for a generic “Insider Threat” instead of specific threat behaviors—we know PRIs contribute differentially to threat behaviors
- Expert judgments may be conflating multiple aspects of PRIs, including probability and severity

- **Precision:** Out of all the cases predicted to be threats, what percentage was a TRUE threat?
- **Recall:** Out of all the TRUE threats, what percentage was predicted to be threats?
- **F1 = harmonic mean of precision and recall**

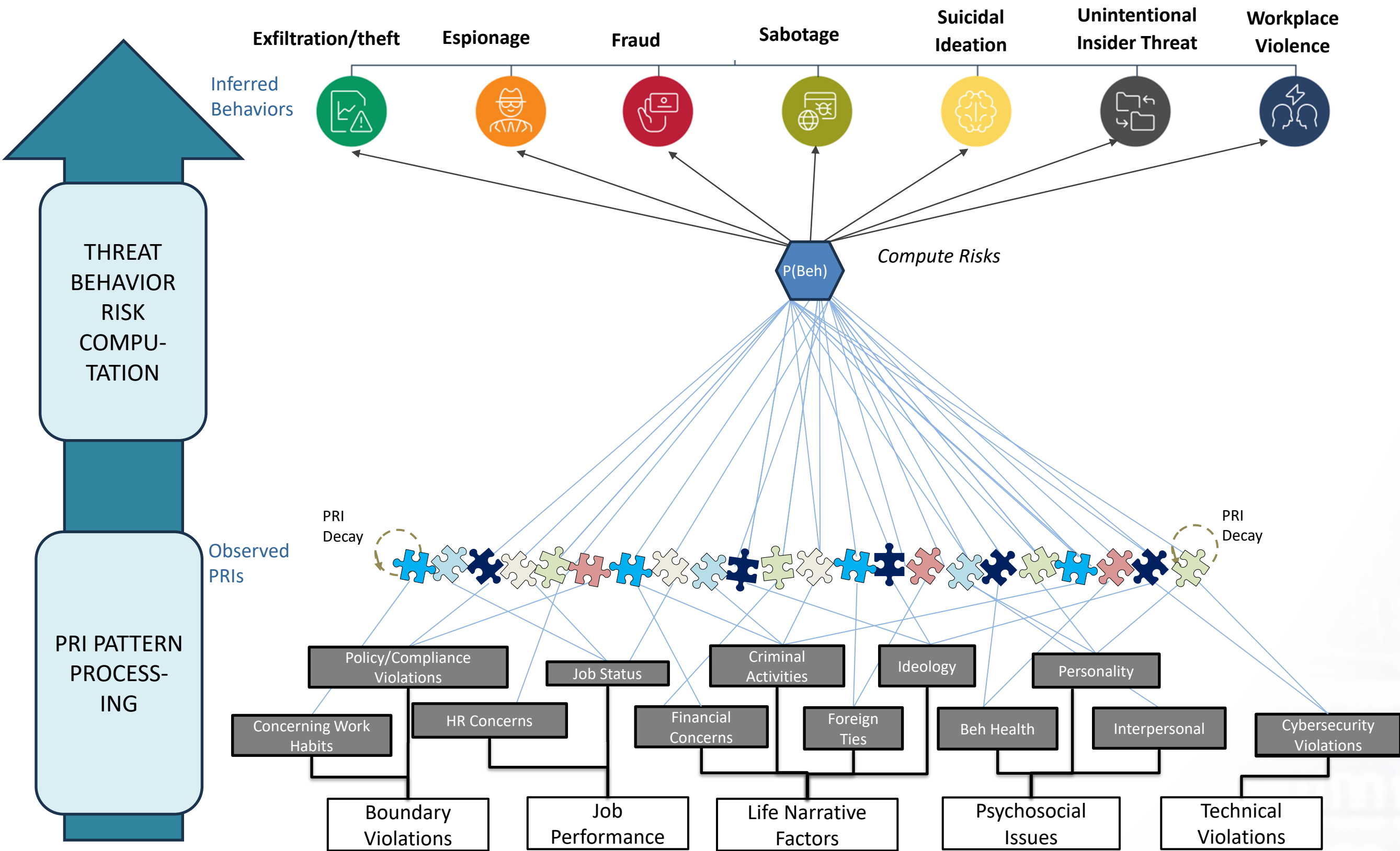
RECENT TESTS OF MODELS USING SYNTHETIC DATA

- Informal study with a new set of synthetic data
 - 100 cases created
 - 1-5 PRIs chosen from SOFIT ontology
- Expert classified cases as “threat” vs “no-threat”
- Used new “Likelihood Ratio” method to estimate PRI weights (probabilities) for individual threat behaviors
- Applied and tested different threat models:
 - Counting Model
 - Sum-of-Risk Model
 - COGYNT Model

Case #	Description [List of observed PRIs]	PRI-1	PRI-2	PRI-3	PRI-4	PRI-5
90	[Poor Time Management][Disciplinary Action][Threat of Violence][Disgruntlement][Data Transfer Anomalies]	1.1.2	2.1.4	4.2.3	4.3.1	5.4.6
1	[Poor Time Management][][][][]	1.1.2				
2	[Threat of Violence][Disgr					
91	[Living Beyond One's Mea Travel][Unreported Conta Communication With Fore					
3	[Excessive Communication					
92	[Negative Evaluation][Pers Suspension)][Abuse Of Pri Documents][Disgruntleme					
93	[Suspicious Foreign Travel Edit Audit Logs][Encrypte					
4	[Personnel Action (Demot Features)][Delete or Edit A					
94	[Unauthorized Weapon][Beliefs][Substance Abuse]					



COGYNT HIERARCHICAL COMPLEX EVENT PROCESSING MODEL



Display final RISK scores

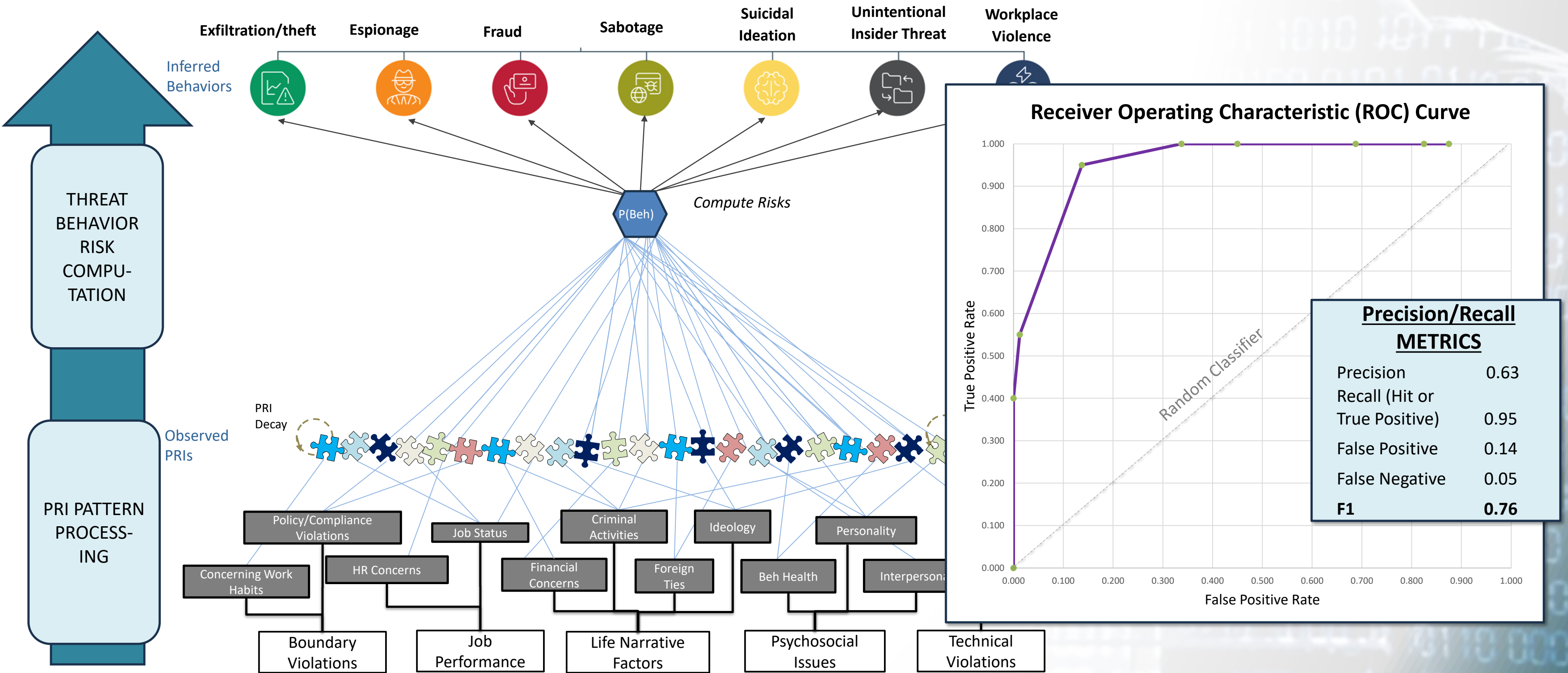
Compute risks by aggregating probabilities of observed PRIs

PRIs are “calibrated” for “weights” or probabilities associated with Behaviors

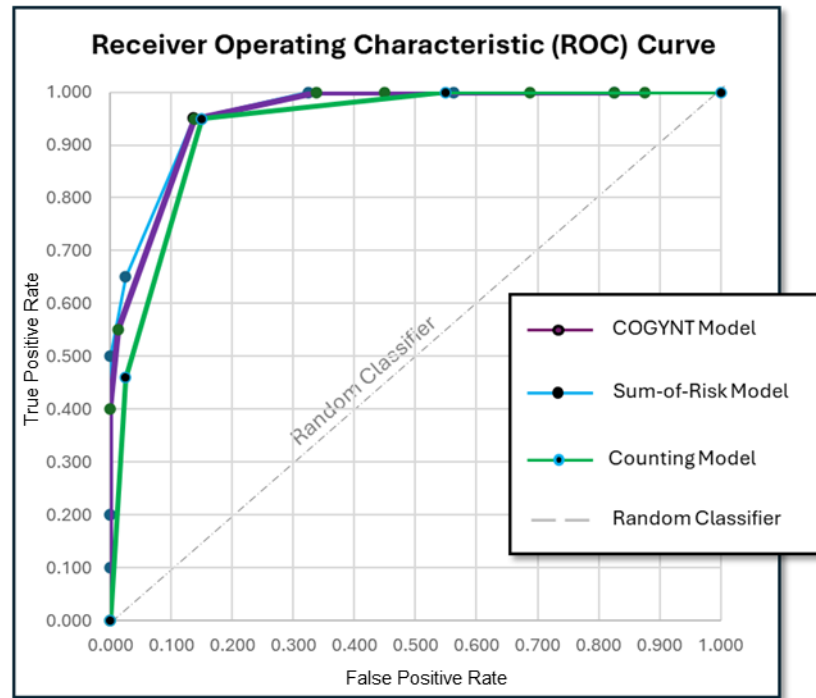
Pattern Processing of “observables” to Recognize PRIs

Incorporates SOFIT ONTOLOGY

COGYNT HIERARCHICAL COMPLEX EVENT PROCESSING MODEL



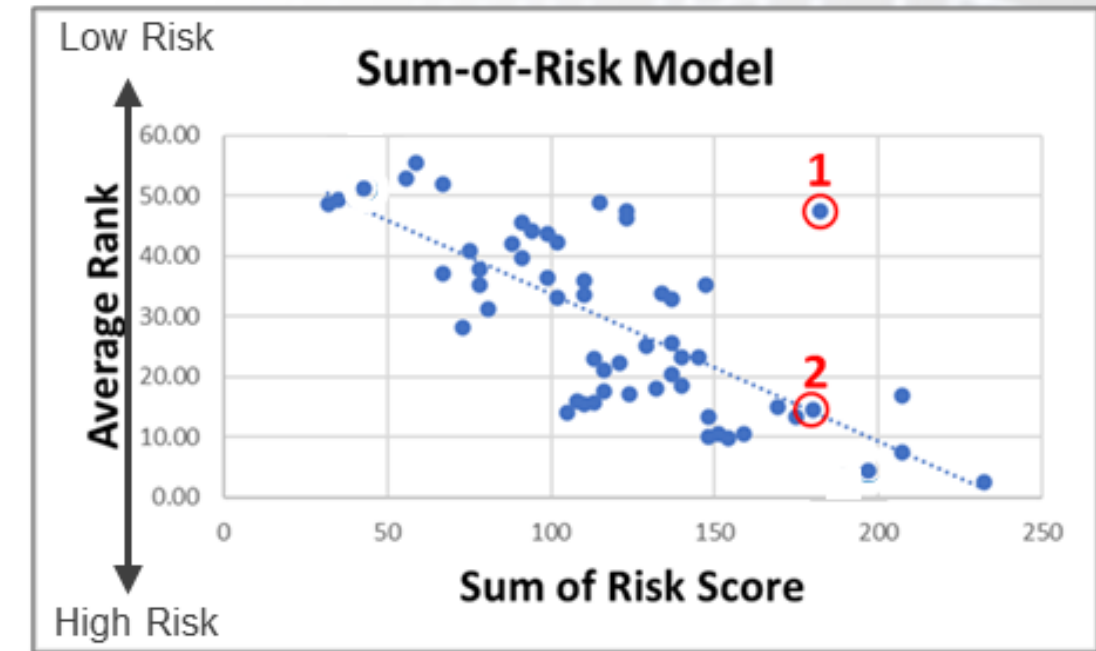
EACH OF THESE MODELS EXHIBIT PERFORMANCE LIMITATIONS



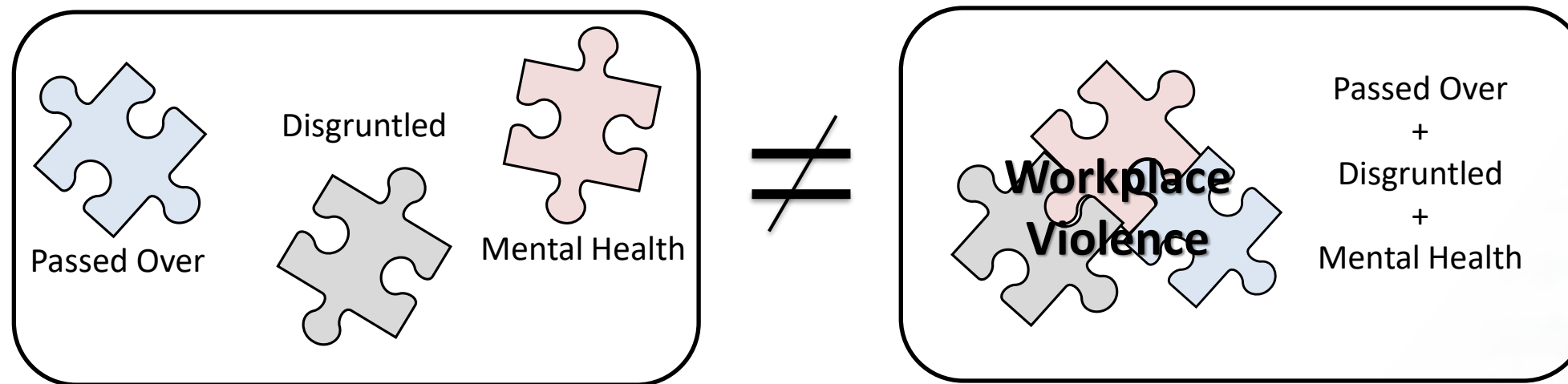
Precision ~ 0.6
Recall ~ 0.95
F1 ~ 0.75

Possible Reason: PRIs interact! They do not always contribute independently to risk

- Most computational risk modeling approaches assume that PRIs contribute independently to risk
- Research suggests that certain combinations of PRIs (**PATTERNS**) yield expert judgments of threat that are not consistent with this “independence” assumption.



Greitzer & Purl (2022)



“The whole is not equal to the sum of its parts.”

We need to account for PRI Patterns...

PATTERN PROCESSING APPROACH

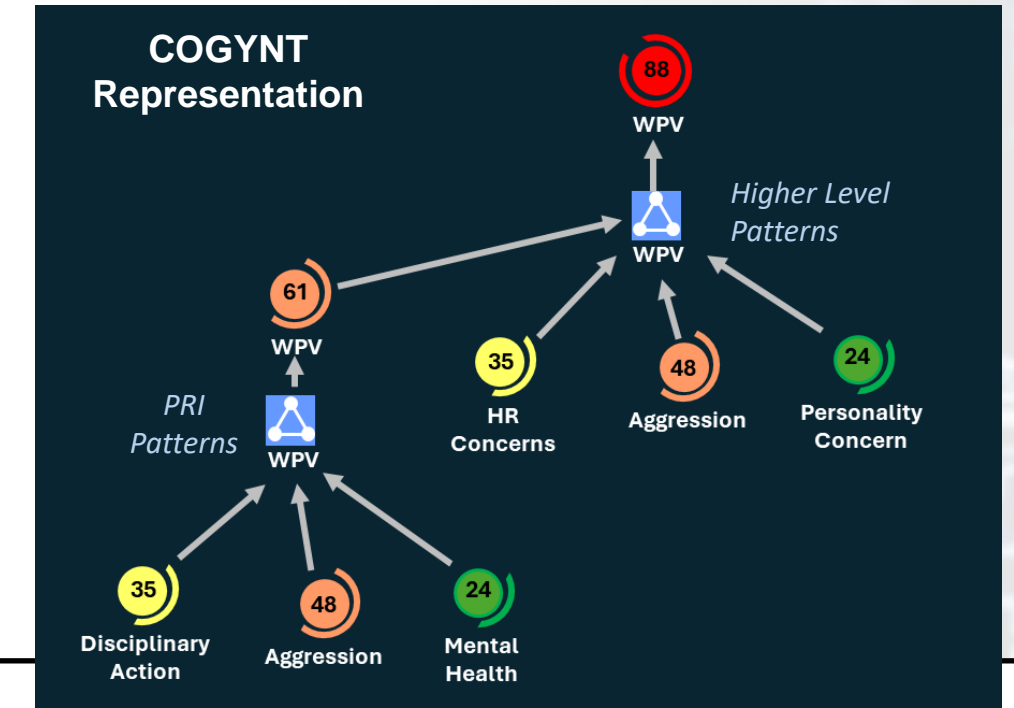
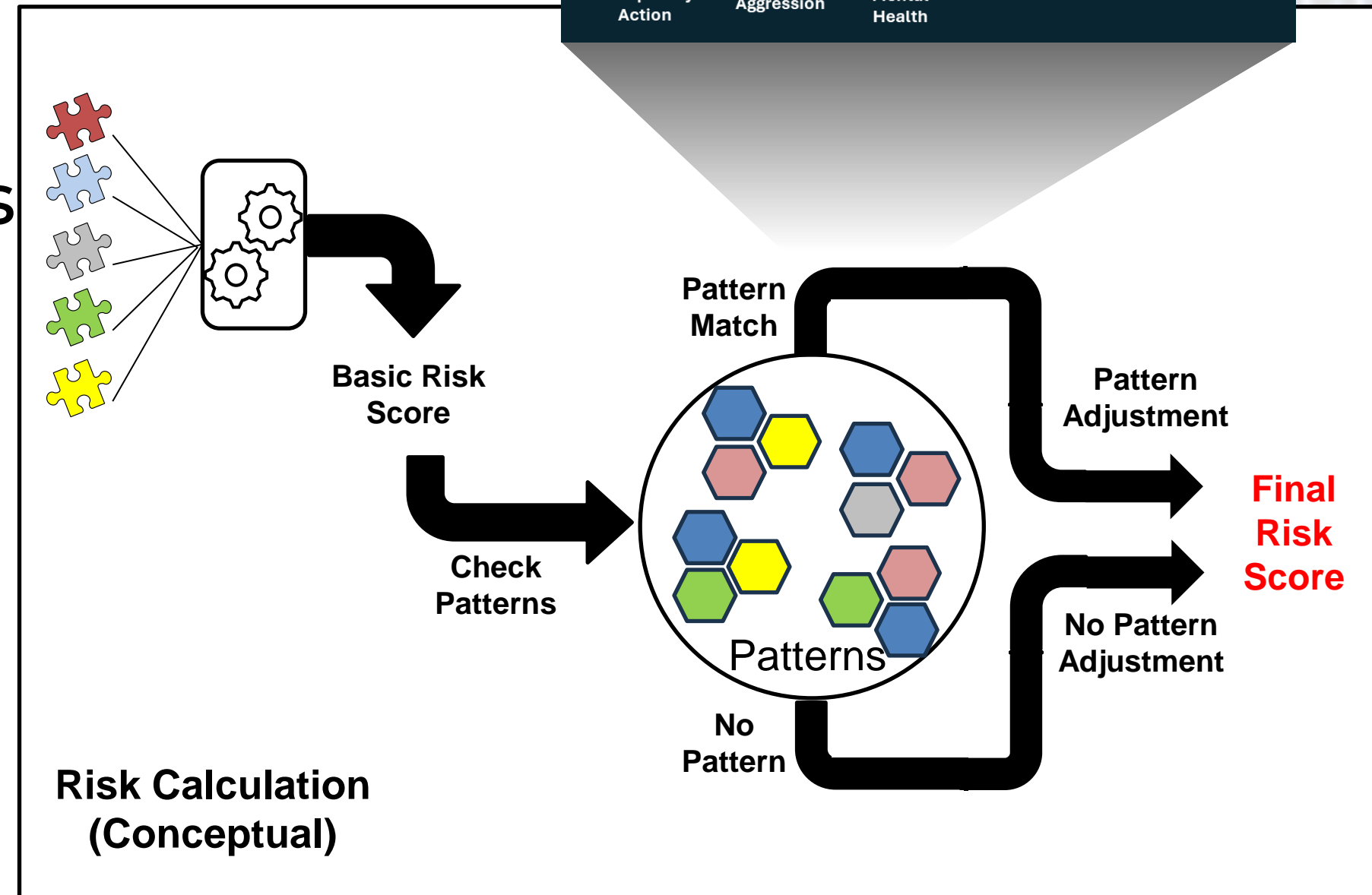
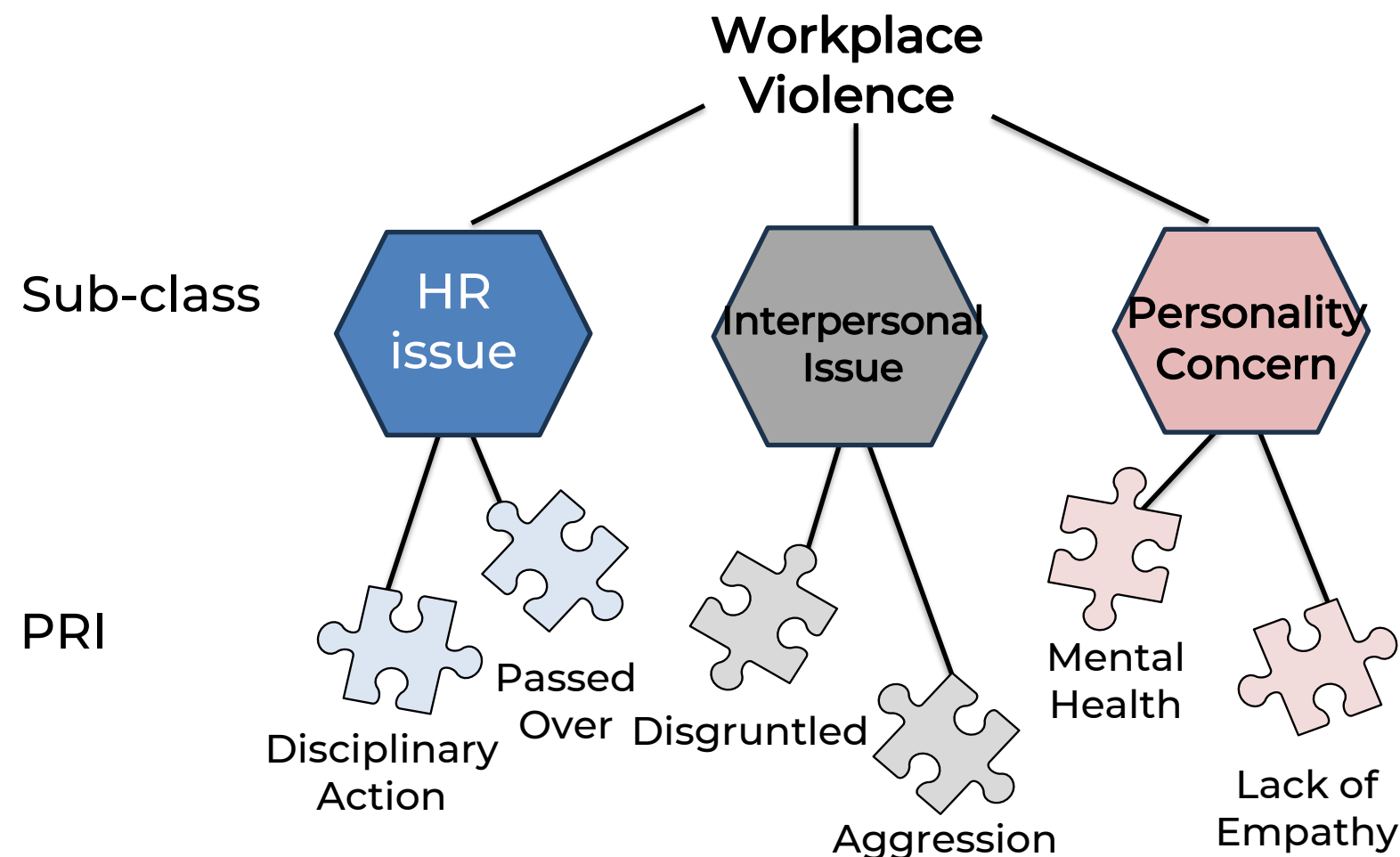
- **Bottom-Up** Examine all possible patterns...

Power Set Limitation: 2^N patterns!

With a set of 100 PRIs, the number of patterns is $2^{100} = 1,267,650,600,228,229,401,496,703,205,376$

Even if we limit patterns to at most 5 PRIs, the number of combinations (patterns) is 79,375,495!

- **Top-Down** Define patterns for behaviors based on PRI sub-classes



PATTERN PROCESSING APPROACH

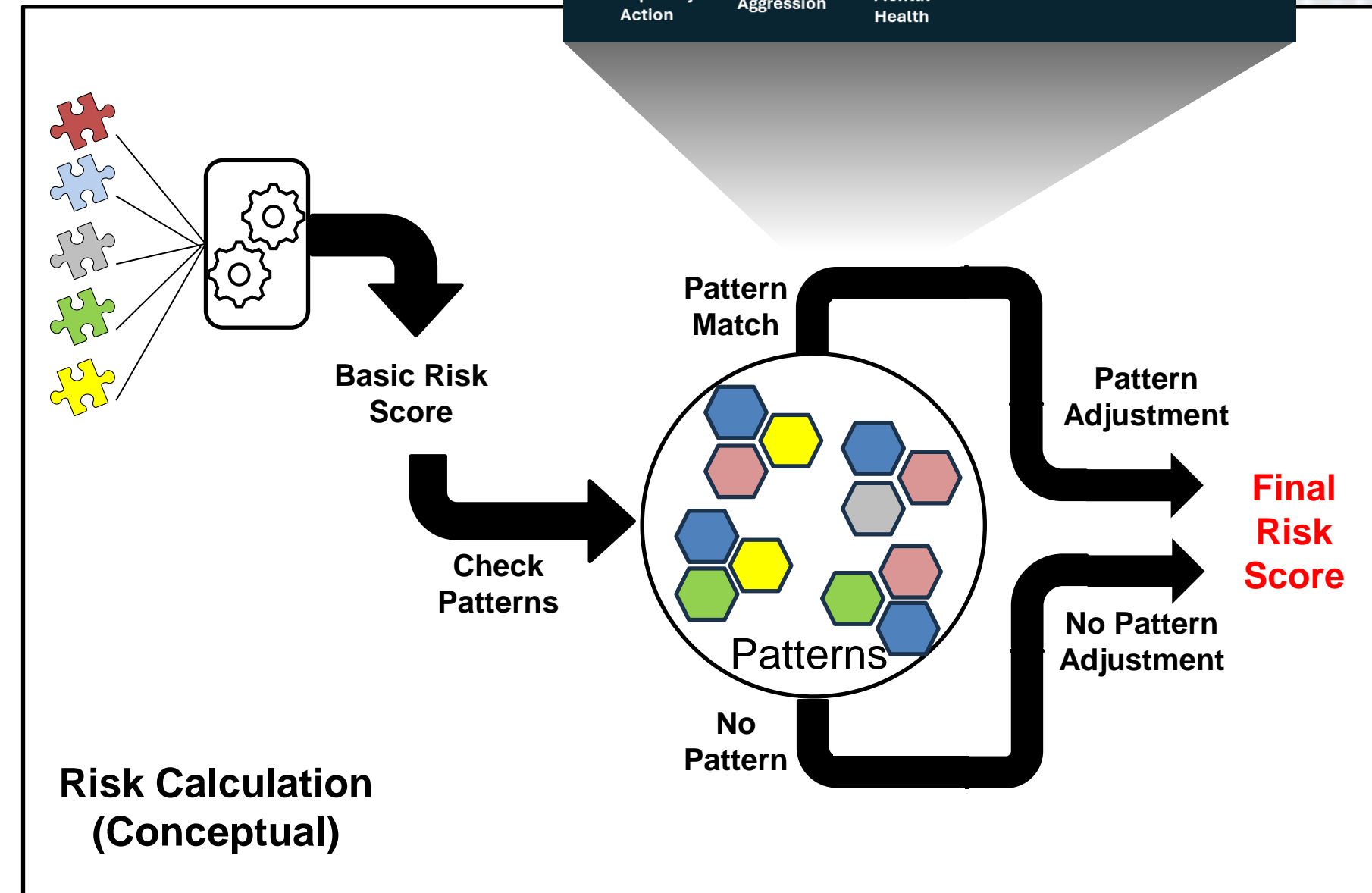
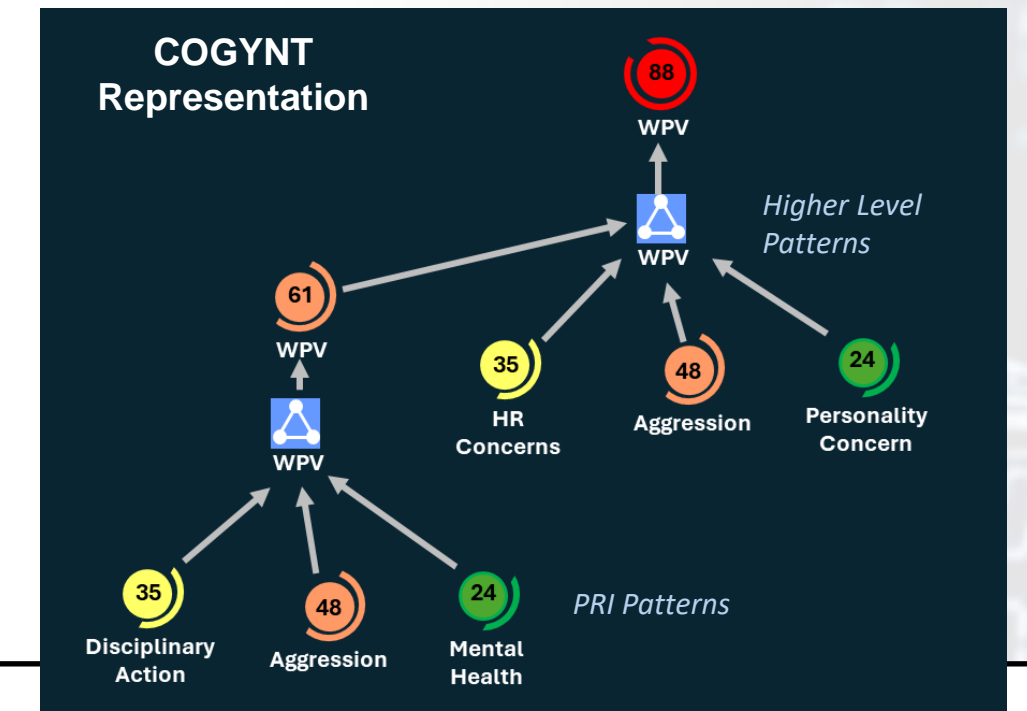
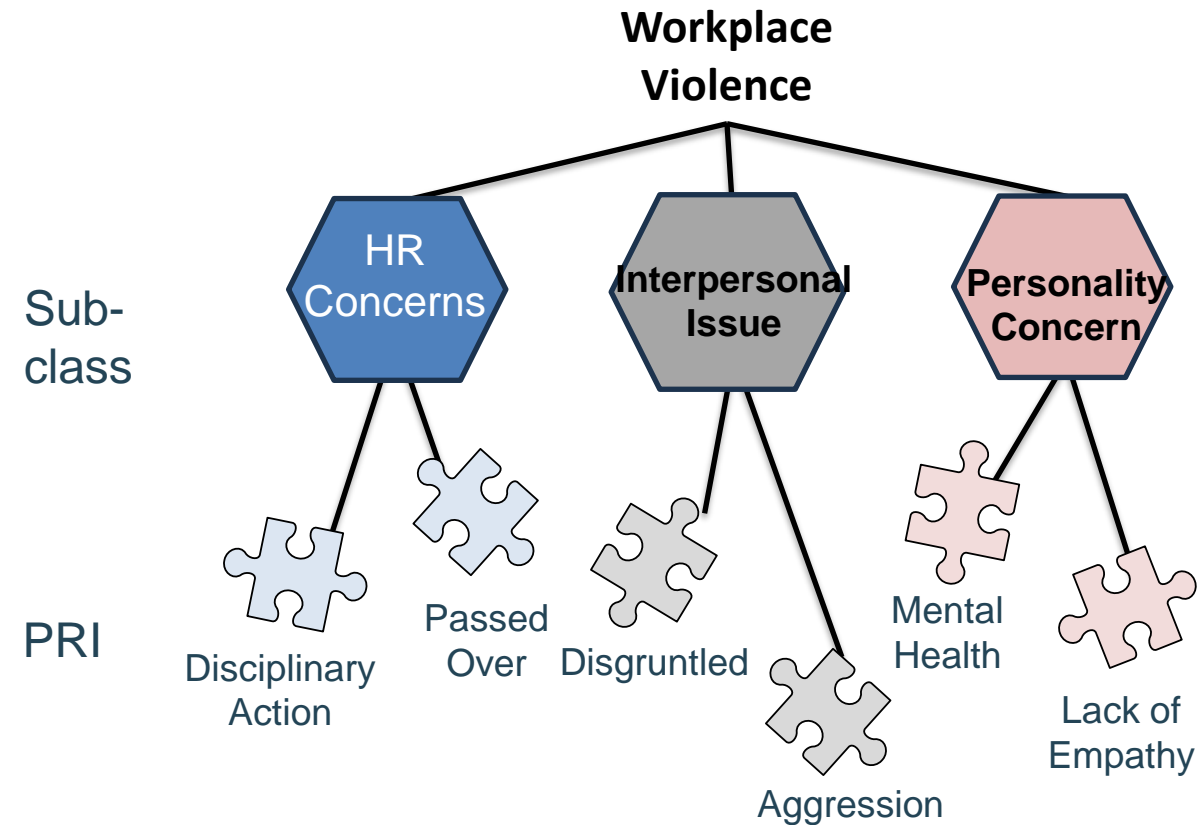
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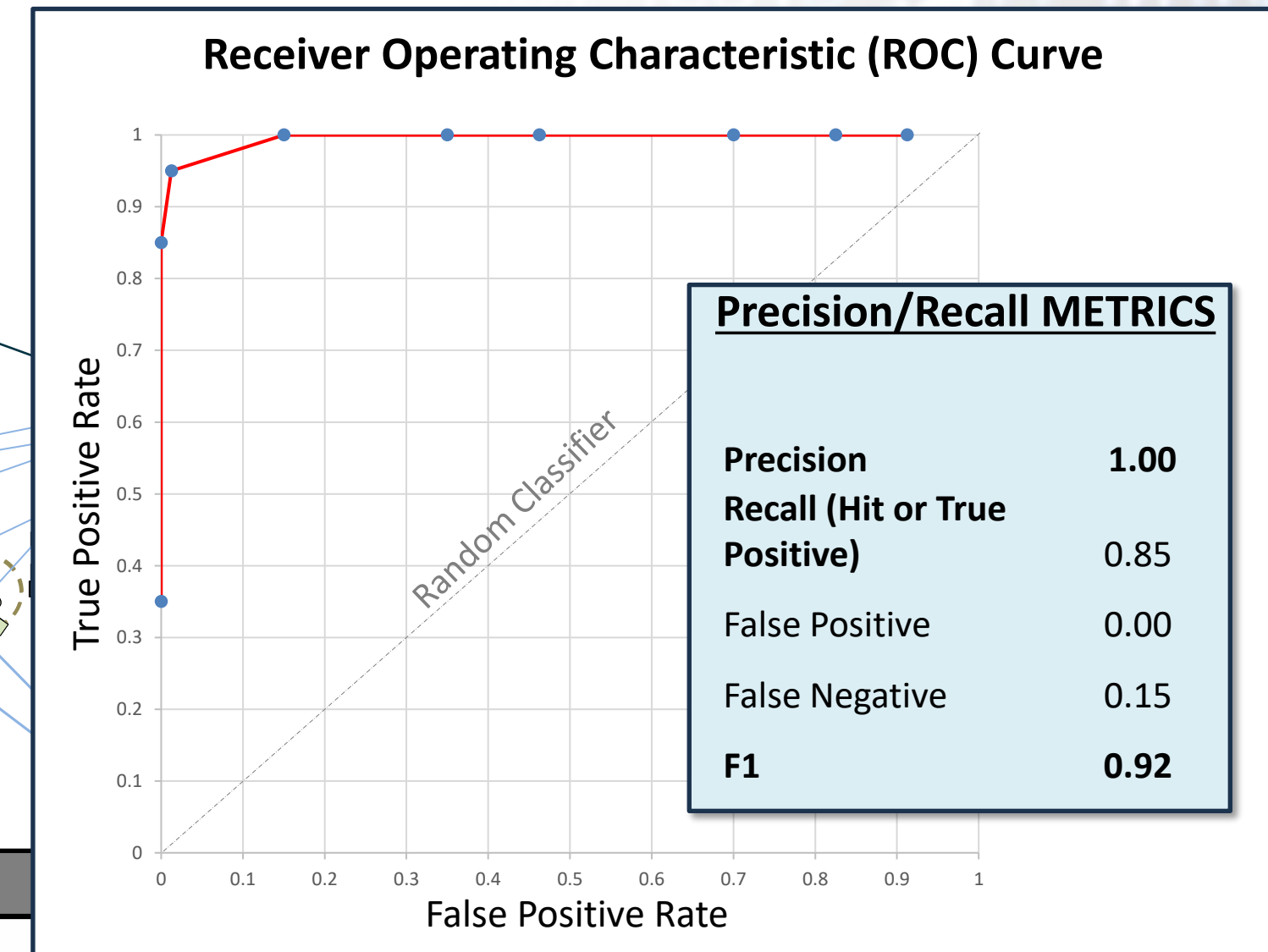
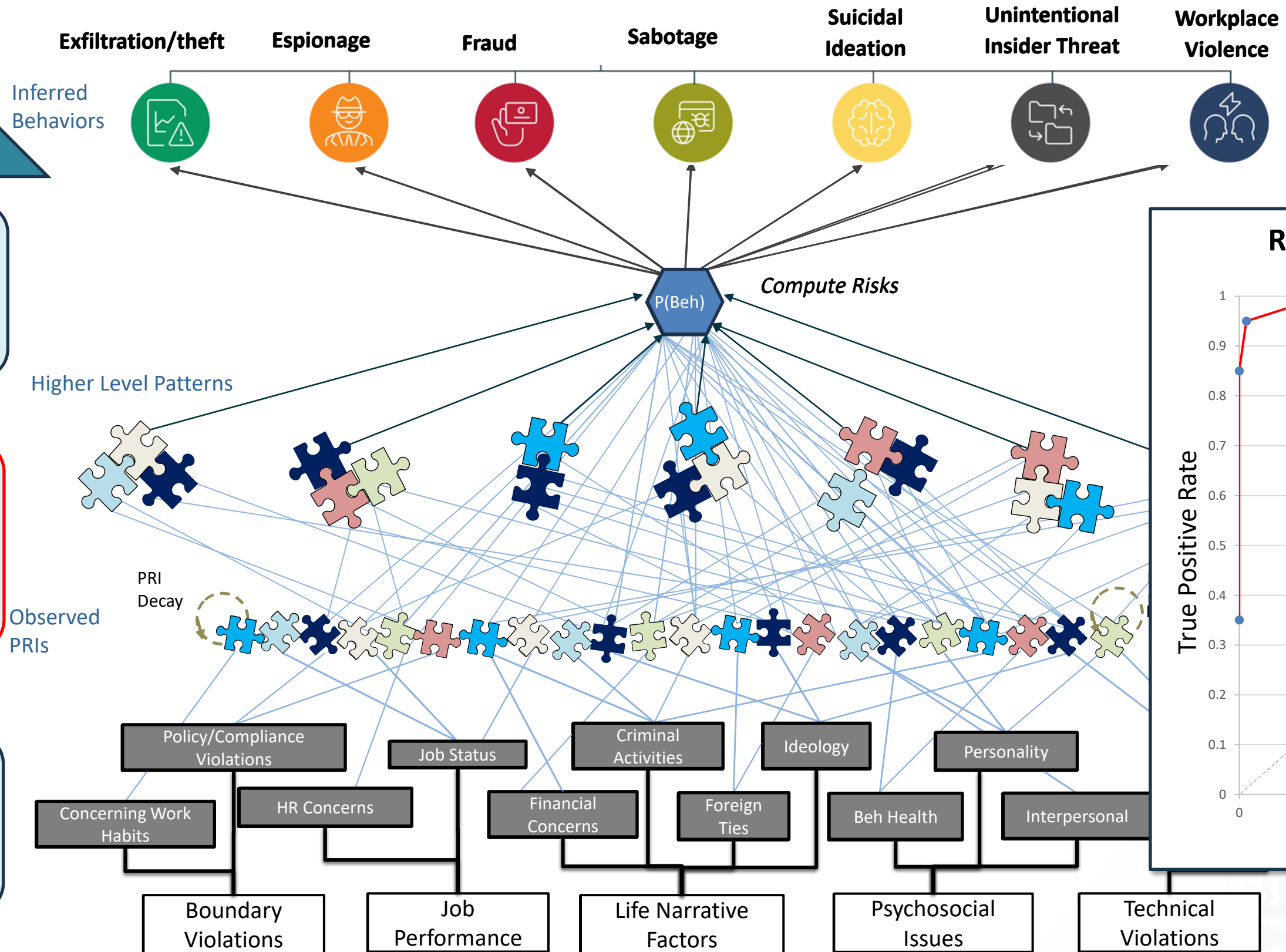
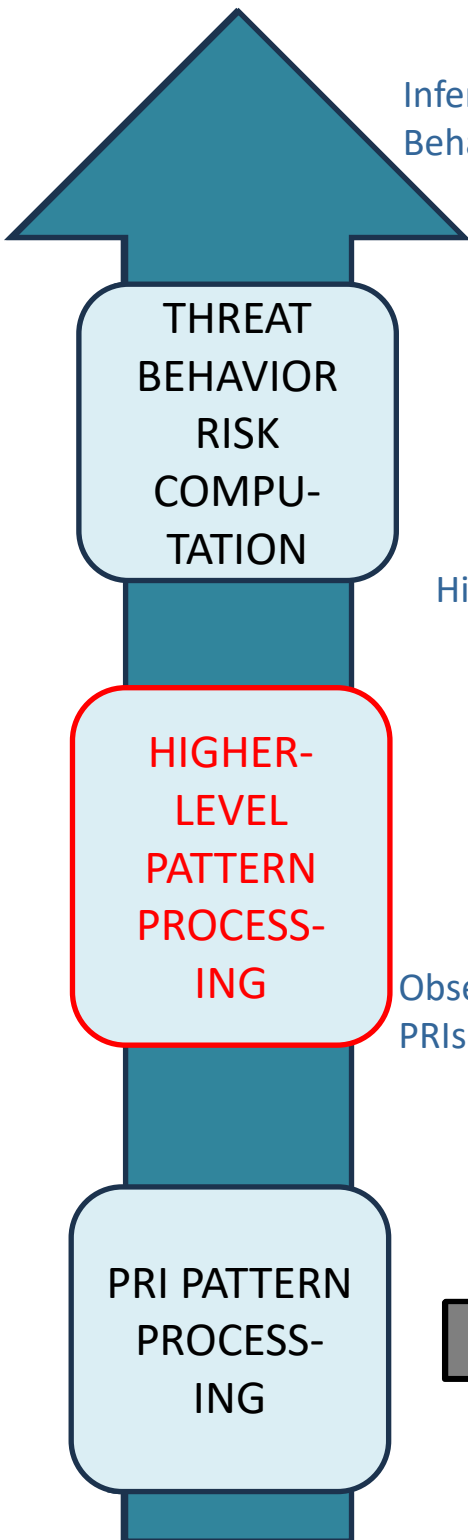
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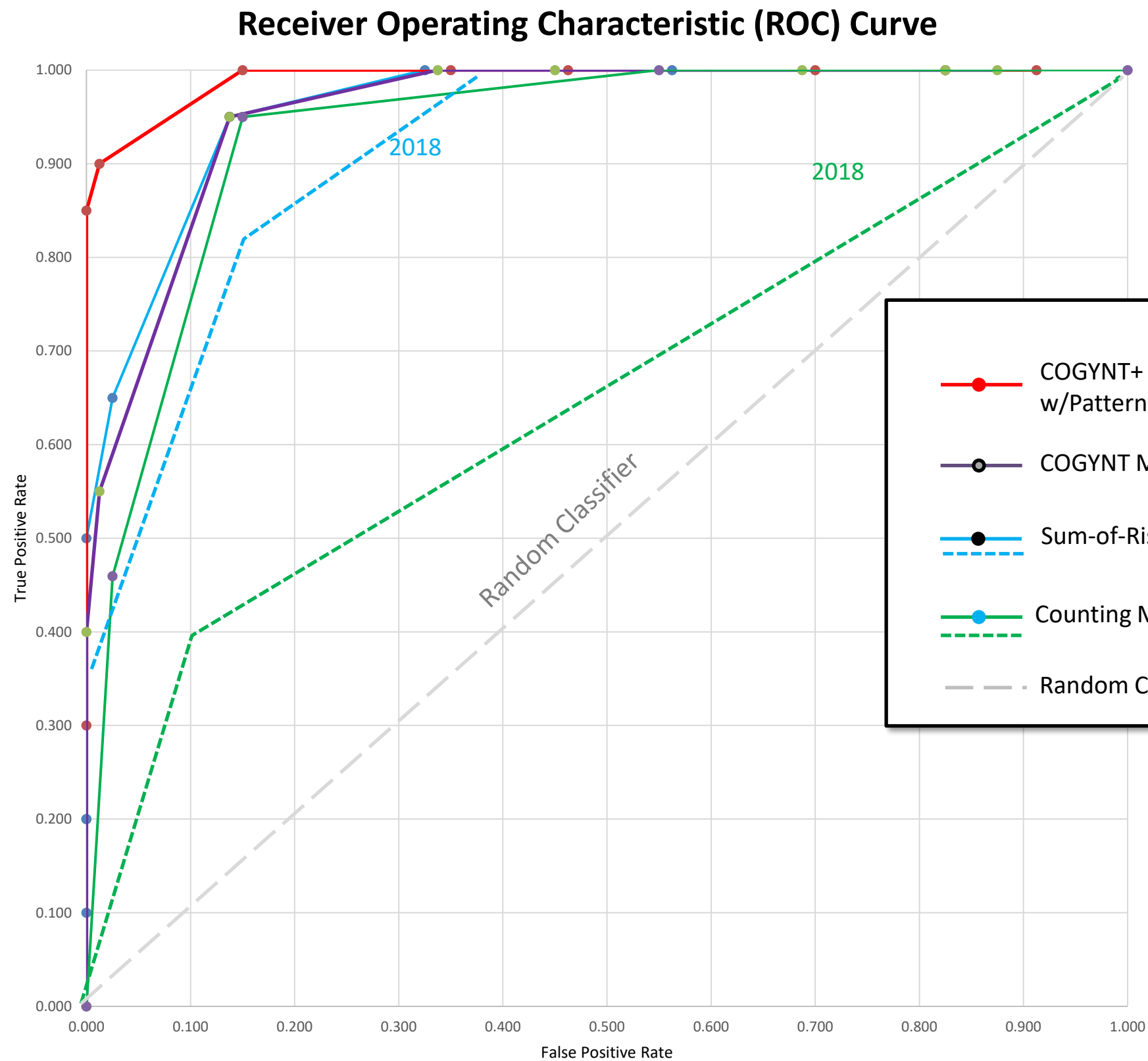
COGYNT *Enhanced* HIERARCHICAL COMPLEX EVENT PROCESSING

Cogynt Enhanced Model processes patterns at a higher level of abstraction



Precision/Recall METRICS	
Precision	1.00
Recall (Hit or True Positive)	0.85
False Positive	0.00
False Negative	0.15
F1	0.92

INCREMENTAL IMPROVEMENTS



Model Comparisons

Metric	COGYNT+	COGYNT (Basic)	Sum-of-Risk	Counting Model
Precision	1.00	0.63	0.63	0.61
Recall (Hit or True Positive)	0.85	0.95	0.95	0.95
False Positive	0.00	0.14	0.14	0.15
False Negative	0.15	0.05	0.05	0.05
F1	0.92	0.76	0.76	0.75

- *Precision: Out of all the cases predicted to be threats, what percentage was a TRUE threat?*
- *Recall: Out of all the TRUE threats, what percentage was predicted to be threats?*

$$F1 = \text{harmonic mean of precision and recall} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

CONCLUSIONS

What we've learned:

- SOFIT PRI ontology provides a solid framework for characterizing and cataloguing risk indicators and contributing factors for insider threat
- PRIs vary in their degree of association with different insider threat behavior types
- PRIs vary in their spans of influence on risk judgments —models may apply different “rates of decay”
- Estimating PRI “weights” or probabilities requires a careful expert knowledge elicitation methodology to avoid “contamination” by different mindsets
- Most predictive models assume that PRIs do not “interact” – that they independently contribute to risk judgments. This lack of pattern processing may limit the effectiveness of predictive models that fail to capture complex PRI patterns, relationships, and interactions
- The enhanced Cogynt model provides a more robust threat assessment paradigm that reflects the complex hierarchical structure used by expert analysts when solving this problem
- These insights and associated research efforts have produced continual improvements.

PATH FORWARD

- There is a strong synergy between the hierarchical nature of the SOFIT PRI knowledge base and the Hierarchical Complex Event Processing (HCEP) capability of Cogility's COGYNT continuous intelligence platform
- Ongoing research with Cogility has led to enhancements in our threat assessment approach that exploit the pattern-based/HCEP processing capabilities of the COGYNT model – enabling us to develop models that reflect more complex PRI patterns, relationships, and interactions
- We're continuing to develop and test these advanced concepts:
 - Refining PRI hierarchical structure
 - Studying PRI calibration methods
 - Testing and evaluating PRI decay models
 - Defining, implementing, and testing pattern processing at higher levels of abstraction

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Questions?

Thank you for your attention



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