



Data-Theoretic Methodology and Computational Platform to Quantify Human Error in Probabilistic Risk Assessment

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SoTeRiA Lab Research Overview

CLASSICAL **ADVANCEMENTS SCIENTIFIC APPROACH** & DIRECTIONS **CONTRIBUTIONS** Physical Failure Mechanisms **Theoretical** Social Failure **Probabilistic Mechanisms** Risk **A**ssessment **Integrated PRA** (PRA) (I-PRA) Methodological [Spatio-Temporal Modeling] **Big Data Analytics**

PRACTICAL APPLICATIONS

Spatio-Temporal LOCA Frequency for GSI-191

Fire PRA

Global Risk Importance Ranking

Organizational Risk Analysis

Monetary Value of PRA

Risk-Informed Emergency Response

Research Motivation

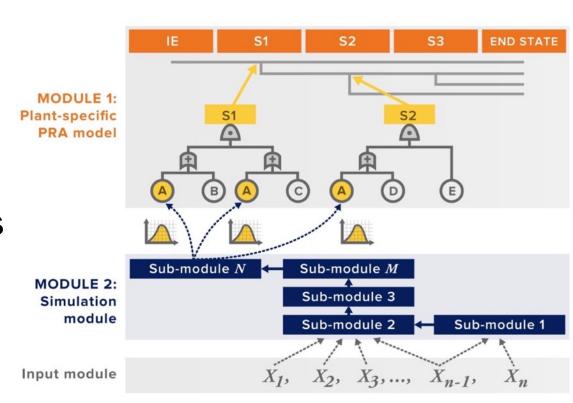
- Organizational factors can either help or hinder safety performance
- Organizational factors have not been explicitly modeled and incorporated into existing HRA and PRA

CHALLENGES:

- 1. Organizational performance modeling is complex
- 2. Organizational data is unstructured
- In 2014, an INPO review of a Nuclear Power Plant's training program revealed that it was 'risky'...
 - Training mechanisms, which influence Training Quality, are not modeled nor connected to PRA, therefore, it was not possible to determine the contribution of programmatic factors to risk
 - It was challenging to identify root causes, address these findings, and improve Training Quality based on risk insights

Integrated PRA Approach

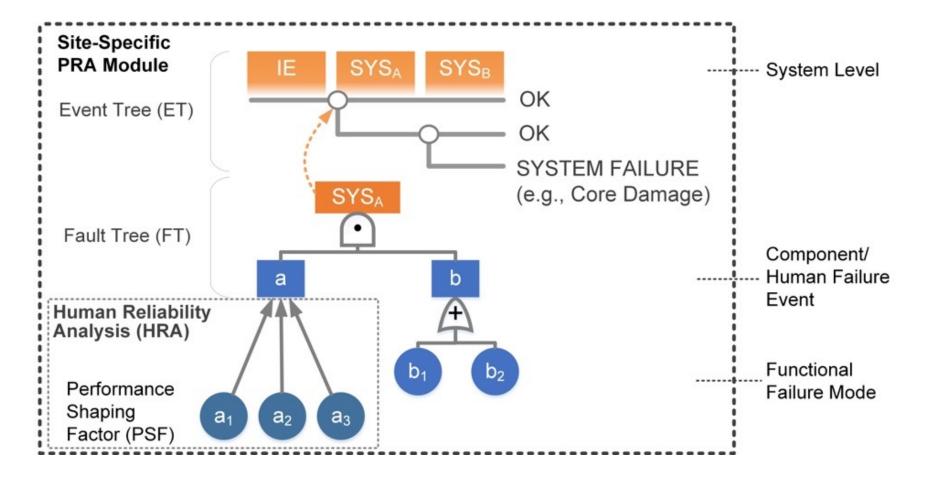
- Simulating
 Underlying Physical
 Failure Mechanisms
- Interface to Make Deterministic Results Probabilistic
- Integrating Results into Existing PRA



Mohaghegh, Z., Kee, E., Reihani, S., Kazemi, R., et al. "Risk-Informed Resolution of Generic Safety Issue 191", ANS PSA 2013 International Topical Meeting on Probabilistic Safety Assessment and Analysis, 2013.

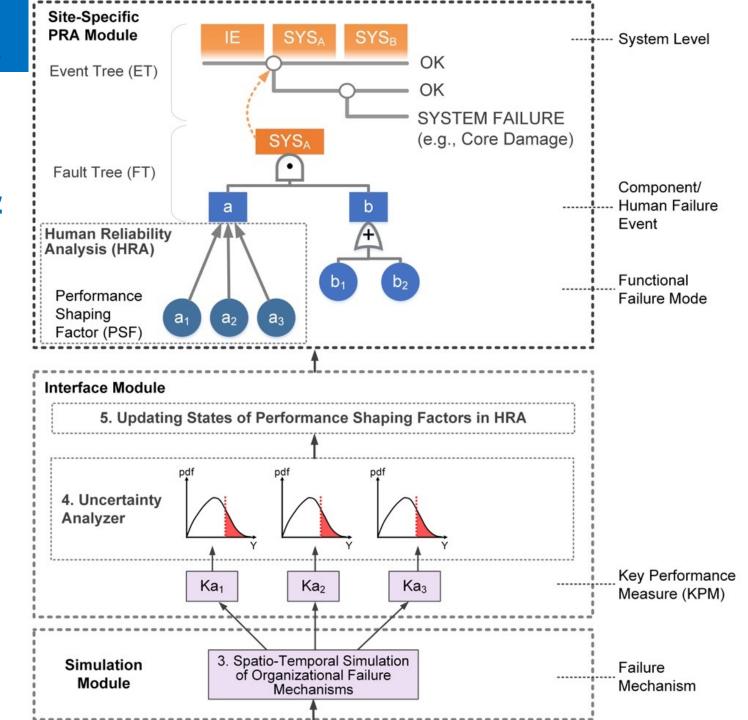
Tatsuya Sakurahara, Zahra Mohaghegh, Seyed Reihani, Ernie Kee, Mark Brandyberry, Shawn Rodgers, "An Integrated Methodology for Spatio-Temporal Incorporation of Underlying Failure Mechanisms into Fire Probabilistic Risk Assessment of Nuclear Power Plants", Reliability Engineering and System Safety (2017), doi: 10.1016/j.ress.2017.09.001

Site-Specific PRA Module



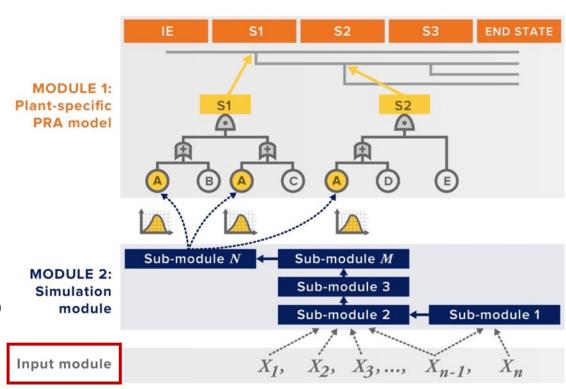
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Interface & Simulation Modules



Integrated PRA Approach

- Data Analysis
- Modeling Underlying Social Failure Mechanisms
- Interface to Make Deterministic Results Probabilistic
- Integrating Results into Existing PRA



Pence J, Sun Y, Mohaghegh Z, Zhu X, Kee E, Ostroff C. Data-Theoretic Methodology and Computational Platform for the Quantification of Organizational Failure Mechanisms in Probabilistic Risk Assessment. 2017 International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA 2017). Pittsburgh, PA: American Nuclear Society; 2017.





A BIG DATA-THEORETIC APPROACH TO QUANTIFY

ORGANIZATIONAL FAILURE MECHANISMS IN PRA

National Science Foundation (NSF)

Science of Organizations Program (SoO)

Big Data Science and Engineering Program (BIGDATA)

PI: Zahra Mohaghegh [Risk & Reliability] CoPI: Cheri Ostroff CoPI: Cathy Blake [Organizational [Computer Science & Science] Management]



Requirements for Incorporating Organizational Factors into PRA

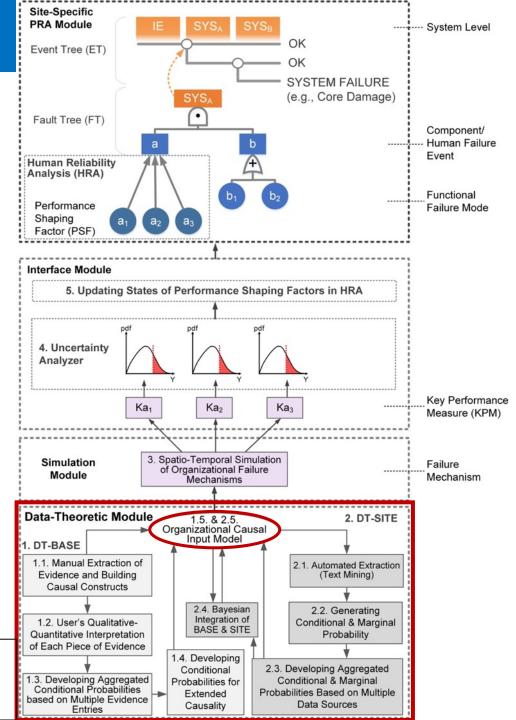
- Integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links;
- (ii) Adaptation of appropriate techniques (i.e., "modeling" and "measurement"), capable of capturing complex interactions of causal factors within their possible ranges of variability and across different levels of analysis, to quantify the theoretical framework.

SoTeRiA Lab

Input Module for Organizational PSFs

Scope of this Study:

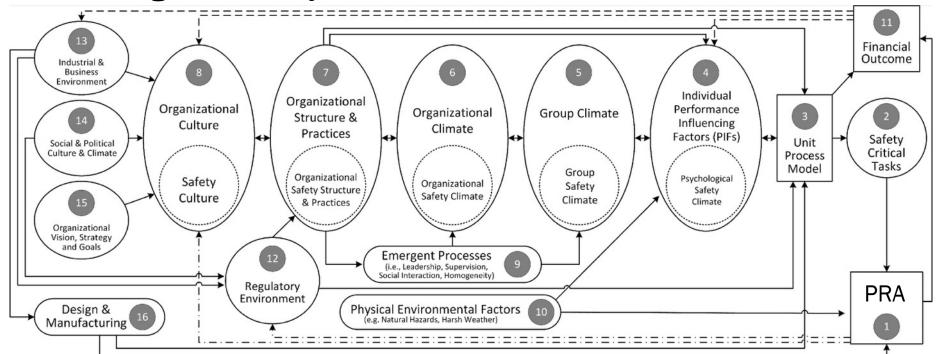
- Formalize Organizational Input Data
- Develop 'Prior' Generic Causal Model:
 - Structures
 - Values
- Update with Plant-Specific Data to Generate Organizational Causal Input Model





Socio-Technical Risk Analysis (SoTeRiA)

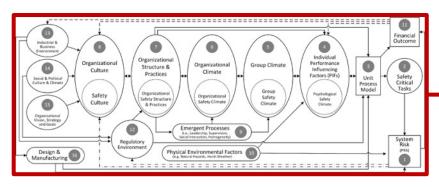
High-Level Systematic Theoretical Framework

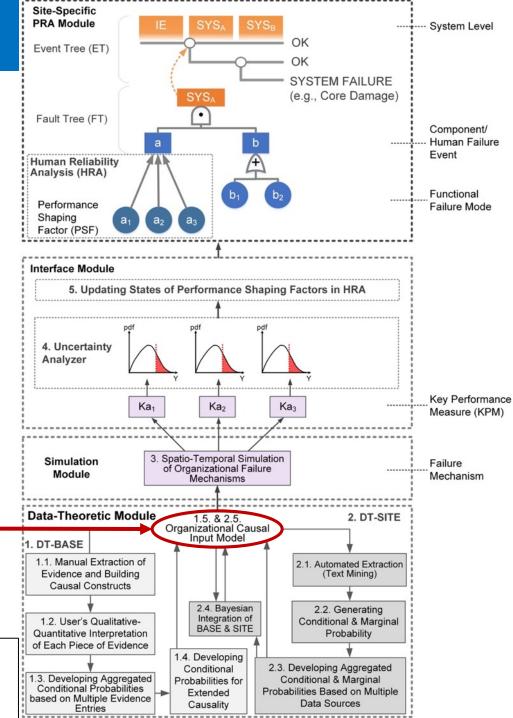


- Integration of Programmatic, Structural, & Social Aspects
- Grounded on Organizational Behavior & Performance Theories
- Explicit Recognition of Causal Relationships at Multiple Levels of Analysis

SoTeRiA Lab

SoTeRiA:
Systematic
Framework for
Organizational
Causal Input
Models





SoTeRiA Lab

Data-Theoretic Module

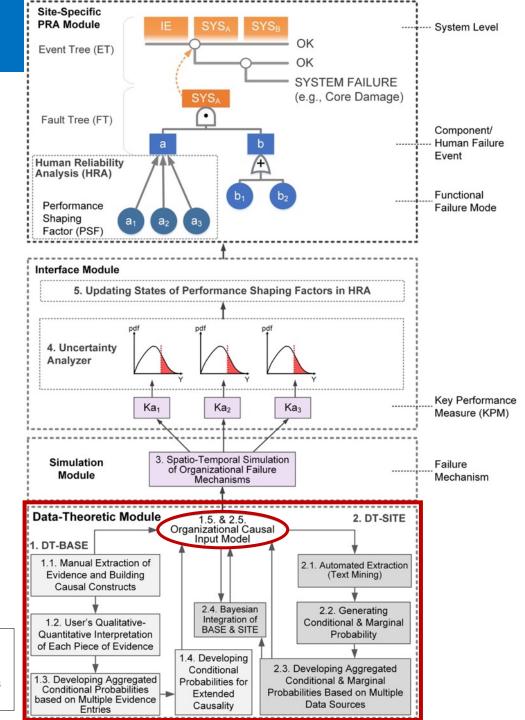
(1) DT-BASE:

- Theory-building process
- Causal modeling in SoTeRiA
- Semi-automated baseline quantification, analyst interpretation of generic information extracted from articles and standards;

(2) DT-SITE:

- Automated data extraction and inference methods (text mining)
- Quantifying SoTeRiA causal elements based on site-specific event databases
- Bayesian updating of the baseline quantification established by DT-BASE

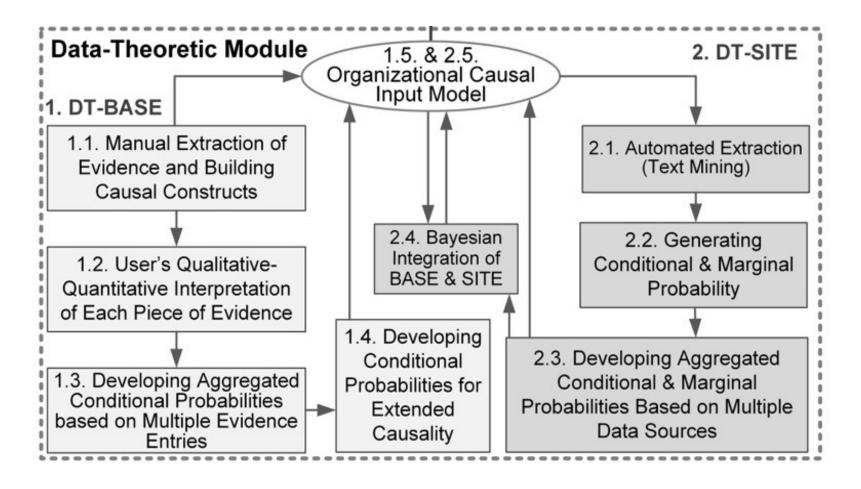
Pence J, Sun Y, Mohaghegh Z, Zhu X, Kee E, Ostroff C. Data-Theoretic Methodology and Computational Platform for the Quantification of Organizational Failure Mechanisms in Probabilistic Risk Assessment. 2017 International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA 2017). Pittsburgh, PA: American Nuclear Society; 2017.



Data-Theoretic Approach

- Theory-building to expand the SoTeRiA causal relationships
- Utilizing SoTeRiA causal relationships to guide data analytics
- Quantifying the SoTeRiA "organizational causal input model" for I-PRA by executing DT-BASE and DT-SITE

Pence J, Sun Y, Mohaghegh Z, Zhu X, Kee E, Ostroff C. Data-Theoretic Methodology and Computational Platform for the Quantification of Organizational Failure Mechanisms in Probabilistic Risk Assessment. 2017 International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA 2017). Pittsburgh, PA: American Nuclear Society; 2017.



Pence J, Sakurahara

T. Zhu X, Mohaghegh

Z, Ertem M, Ostroff

Methodology and

Platform to Quantify

Computational

Organizational

Technical Risk

Engineering and

System Safety

2018.

(Under Review).

Factors in Socio-

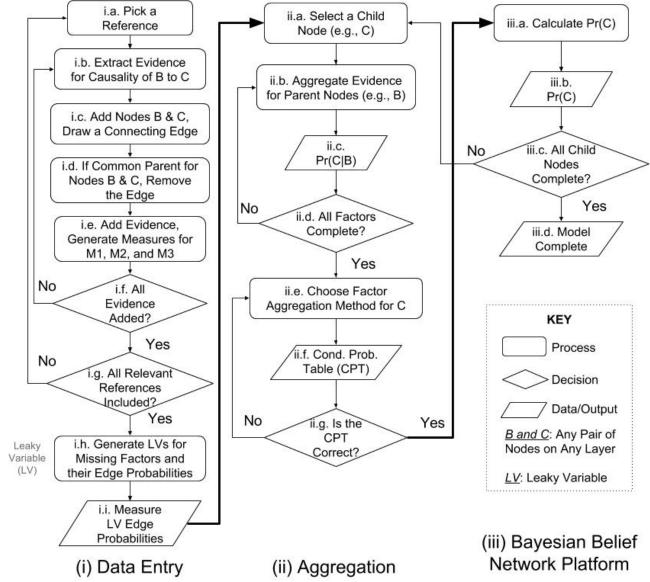
Analysis. Reliability

C. et al. Data-

Theoretic

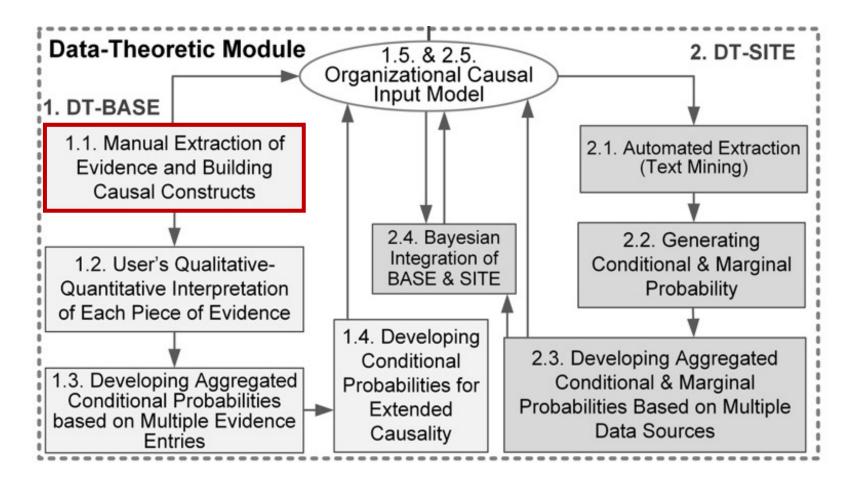
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DT-BASE Computational Flowchart



DT-BASE Steps

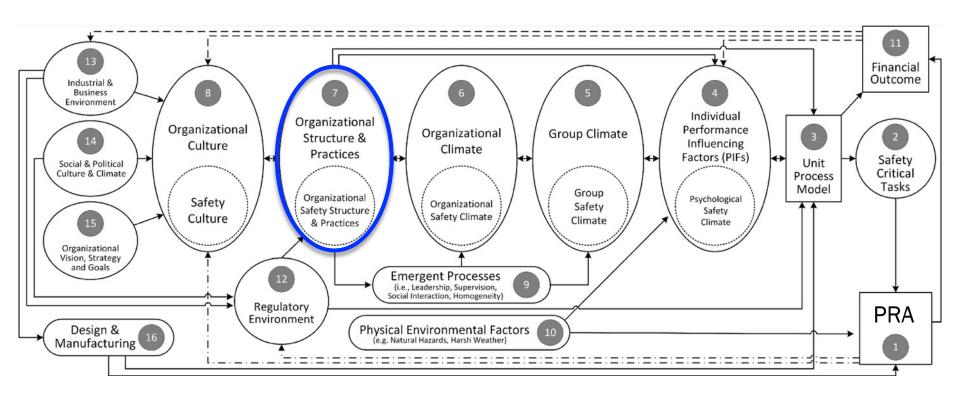
- 1.1. Manual Extraction of Evidence and Building Causal Constructs
 - (Relates to "Data Entry" Phase in the Flowchart)
- 1.2. User's Qualitative-Quantitative Interpretation of Each Piece of Evidence
 - (Relates to "Data Entry" Phase in the Flowchart)
- 1.3. Developing Aggregated Conditional Probabilities based on Multiple Evidence Entries
 - (Relates to "Aggregation" Phase in the Flowchart)
- 1.4. Developing Conditional Probabilities for Extended Causality (Relates to "Aggregation" Phase in the Flowchart)
- 1.5. Integration in a Bayesian Belief Network Computational Platform
 - (Relates to "Bayesian Updating" Phase in the Flowchart)



1.1. Manual Extraction of Evidence and Building Causal Constructs

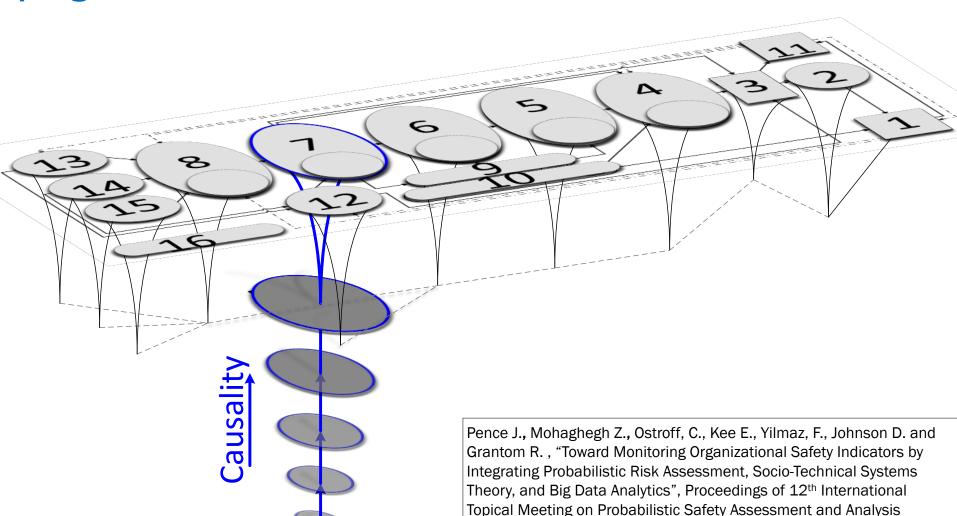
- Step 1: Identifying the unknown of interest, i.e., the selected target node/organizational factor (e.g., training)
- Step 2: Identifying literature (i.e., regulatory and industry standards, academic articles) associated with the selected organizational factor
- Step 3: Locating the selected organizational factor within the SoTeRiA framework
- Step 4: Identifying logical/abstract-level phases (e.g., plan, do, check, act) of programmatic elements
- Step 5: Developing theoretical causal constructs for the organizational mechanisms leading to the performance quality of the selected organizational factor by satisfying theory-building principle

(1.1) Step 3: Locating the selected organizational factor within the SoTeRiA framework

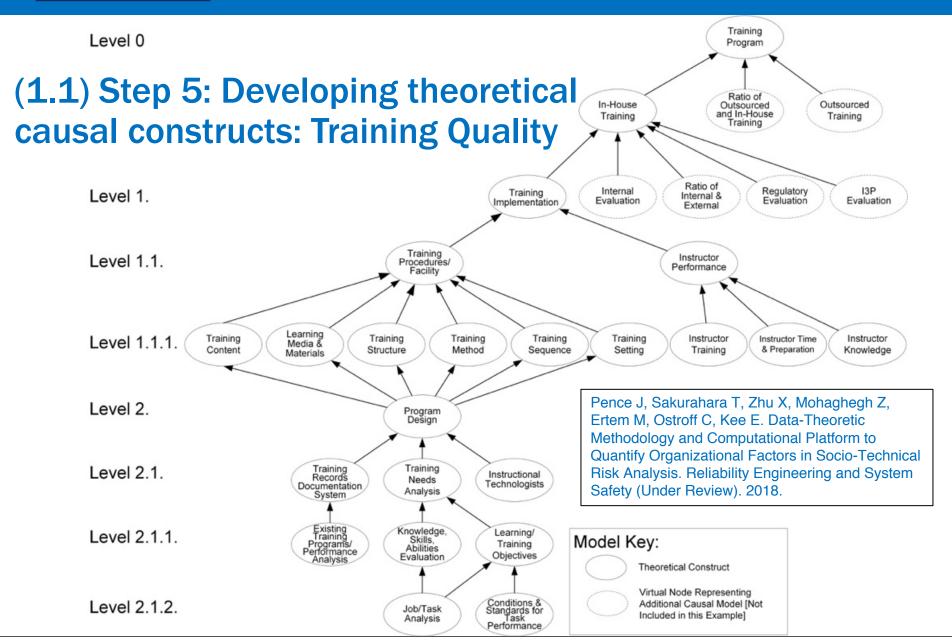


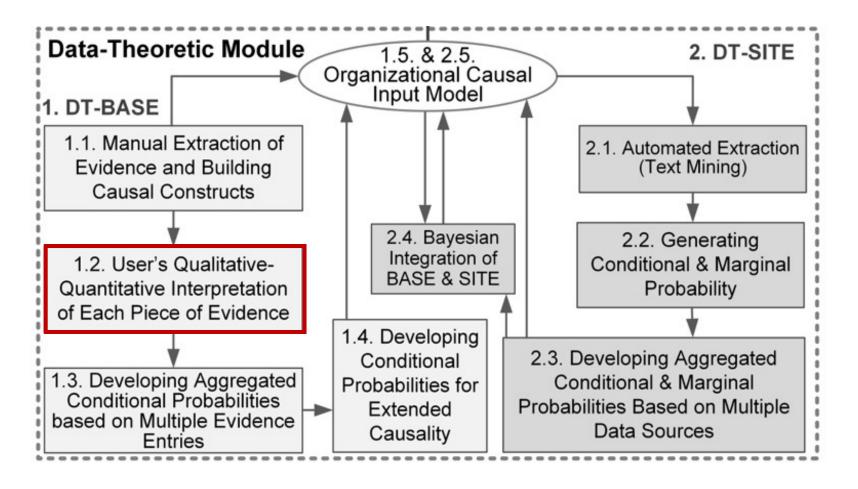
SoTeRiA Lab

(1.1) Step 4: Identifying logical/abstract-level phases of programmatic elements



(PSAM12), 2014



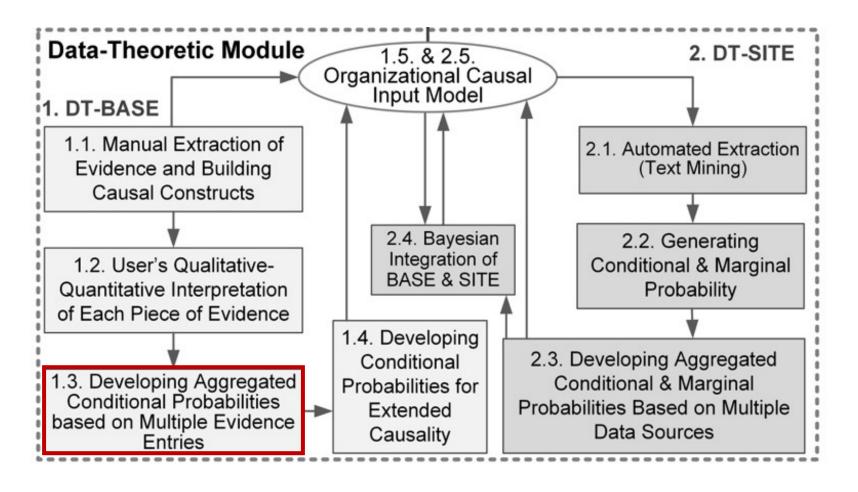




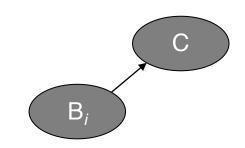
1.2. User's Qualitative-Quantitative Interpretation of Each Piece of Evidence

- Reference Information (.ris)
- Keywords associated with the parent node and child node
- A verbatim copy of the textual statement explaining the causal relationship
- [M_{1, EV}] Credibility of reference source (i.e., Journal Impact Factor)
- $[M_{2,EV}]$ Weight between node B_i and node C indicated in the evidence
- [M_{3, EV}] Analyst confidence level in the subject matter material

Lower Bound	Upper Bound	M1	M2	мз
0.99	1	Virtually Certainly Credible	Virtually Certain	Virtual Certainty in Confidence
0.9	0.99	Very Likely Credible	Very Likely	Very Likely Confident
0.66	0.9	Likely Credible	Likely	Likely Confident
0.33	0.66	Medium Likelihood of Credibility	Medium Likelihood	Medium Likelihood of Confidence
0.1	0.33	Unlikely Credible	Unlikely	Unlikely Confident
0.01	0.1	Very Unlikely Credible	Very Unlikely	Very Unlikely Confident
0	0.01	Extremely Unlikely to be Credible	Extremely Unlikely	Extremely Unlikely to be Confident



1.3. Developing Aggregated Conditional Probabilities based on Multiple Evidence Entries



Conditional probabilities should be aggregated using either Arithmetic (Eq. 1) or Geometric (Eq. 2) aggregation methods:

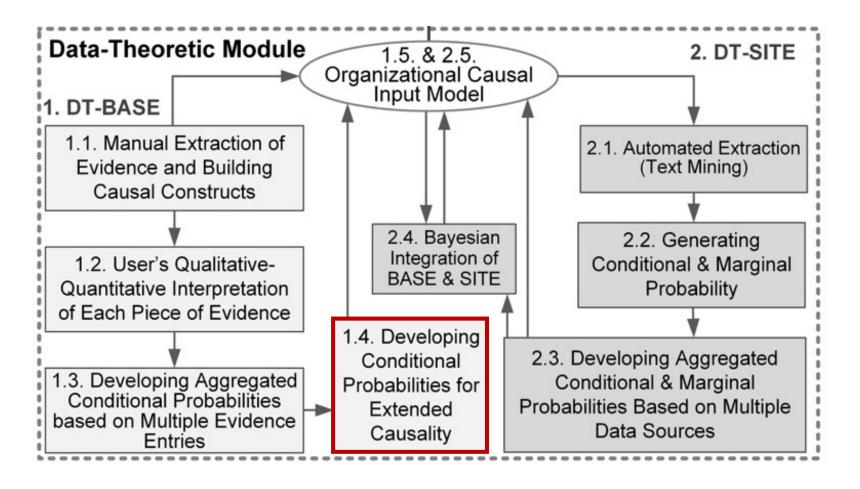
$$\Pr(C|B_i) = \frac{1}{Z} \sum_{j=1}^{K} M_{2,EV_{i,j}} * M_{1,EV_{i,j}} * M_{3,EV_{i,j}} \forall i \in I, \quad (1)$$

$$\Pr(C|B_i) = \prod_{j=1}^{K} M_{2,EV_{i,j}}^{\frac{M_{1,EV_{i,j}} \times M_{3,EV_{i,j}}}{Z}} \quad \forall i \in I,$$
 (2)

where;

$$Z = \sum_{j=1}^{K} M_{1,EV_{i,j}} \times M_{3,EV_{i,j}} \ \forall i \in I.$$
 (3)

Bayesian aggregation is also to be added to the approach



 B_n

 B_2

1.4. Developing Conditional Probabilities for Extended Causality

Noisy-OR:

$$Pr(C|B_1, B_2, ..., B_n) = 1 - \prod_{i \in I} (1 - z_i), \quad (4)$$

Noisy-MAX:

$$Pr(C \le c | \mathbf{b}) = \prod_{i} Pr(C \le c | B_i = b_i, B_{-i} = 0)$$
, (5)

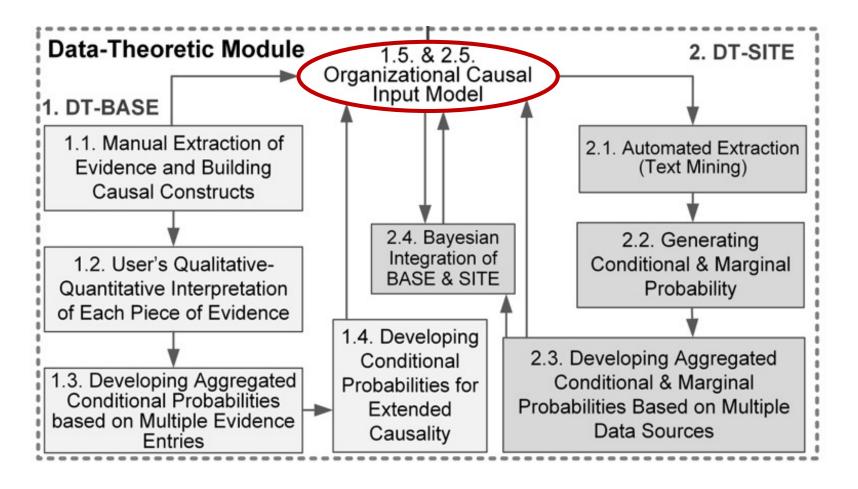
Conditional Probability Table Calculation:

$$\Pr(C|B_1, B_2, \dots, B_n) = \begin{cases} Pr(C = 0|\boldsymbol{b}) & c = 0 \\ Pr(C \le c|\boldsymbol{b}) - Pr(C \le c - 1|\boldsymbol{b}), c > 0 \end{cases} . (6)$$

Leak Variable (Incompleteness Uncertainty):

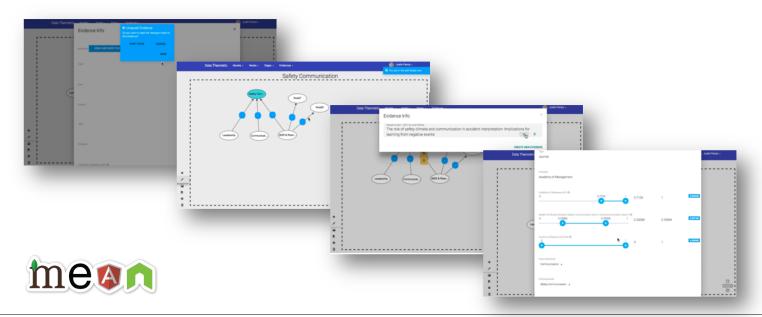
$$z_L = Pr(C|not \ any \ B_i \ exists \ except \ LV), \qquad (7)$$

$$Pr(C|B_1, B_2, ..., B_n, LV) = 1 - (1 - z_L) \prod_{i \in I} (1 - z_i), (8)$$

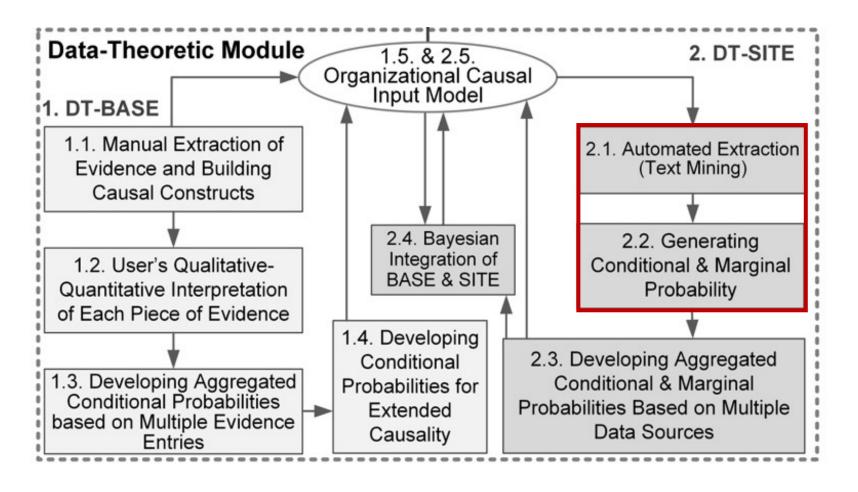


1.5. Integration in a Bayesian Belief Network Computational Platform

- Developed as Open Source Software
- DT-BASE uses MEAN.JS, a full-stack JavaScript open-source solution, which provides the framework for <u>MongoDB</u>, <u>Node.js</u>, <u>Express</u>, and <u>AngularJS</u> based applications.



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2.2. Generating Conditional and Marginal Probabilities for BBN

Preliminary text mining results were developed using the MathWorks Matlab Text Analytics Toolbox™

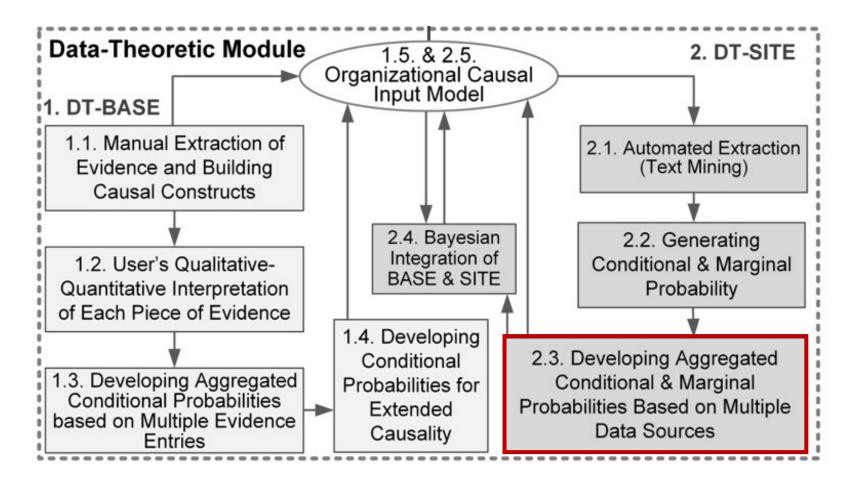
$$Pr(B_1) = \frac{f_{B_1}}{N_{CAP}} \tag{9}$$

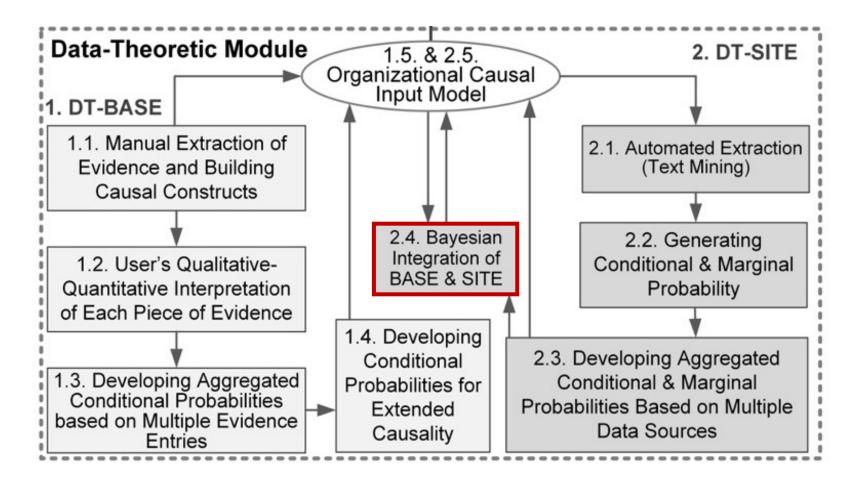
$$Pr(C|B_1) = \frac{Pr(B_1 \cap C)}{Pr(B_1)} \tag{10}$$

$$Pr(B_1 \cap C) = \frac{f_{B_1,C}}{N_{CAP}} \tag{11}$$

$$Pr(C|B_1, B_2) = \frac{Pr(C \cap B_1 \cap B_2)}{Pr(B_1 \cap B_2)}$$
 (12)

$$Pr(B_1 \cap B_2 \cap C) = \frac{f_{B_1, B_2, C}}{N_{CAP}}$$
 (13)





2.4. Bayesian Integration of SITE and BASE Probabilities

$$\pi(p|D_{i}) = \frac{L(D_{i}|p)\pi_{0}(p)}{\int L(D_{i}|p)\pi_{0}(p)dp}, (14)$$

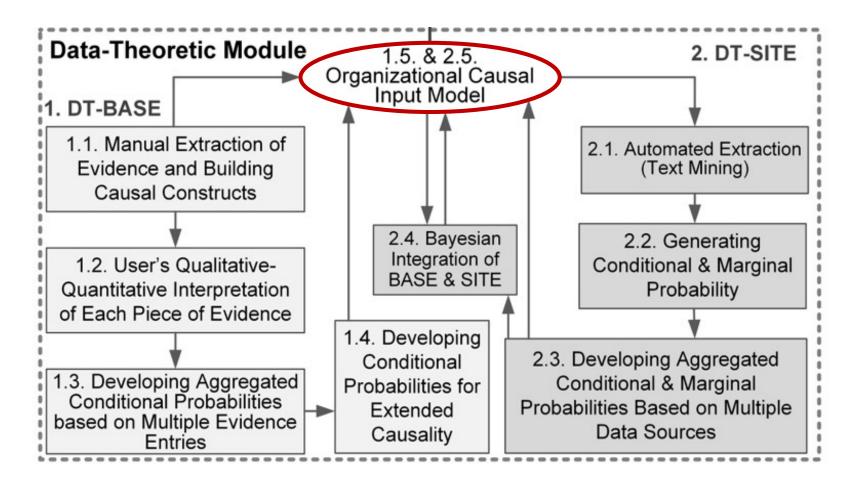
$$L(D_{i}|p) = L(P_{BASE}|p) * L(P_{SITE}|p), (15)$$

$$L(P_{i}|p) = \frac{1}{\sqrt{2\pi}\sigma_{i}P_{i}}exp\left[-\frac{1}{2}\left(\frac{\ln P_{i}-(\ln p+\ln b_{i})}{\sigma_{i}}\right)^{2}\right], (16)$$

$$\sigma_{i} = \frac{1}{\Phi^{-1}(0.95)}\ln\sqrt{\frac{P_{i}}{P_{i}^{'}low}}, (17)$$

For the Training model, upper bound and lower bounds of the target node probability estimates are 0.1 and 0.005, respectively

DA-BASE and DT-SITE models have the common σ_i , because the structure of the causal model developed for DT-BASE is unchanged for DT-SITE





Training Quality Target Node Bayesian Integration

The beta distribution is a convenient choice because; (i) its range is [0, 1], which is consistent with the theoretical range of the P_{TQ} , and (ii) it does not impose strong assumptions on the shape of the probability distribution

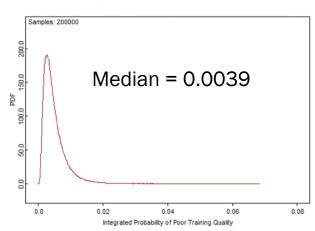
The results from BASE and SITE are treated as two independent pieces of evidence:

$$P^*_{TQ, BASE} = 0.0296$$
 and $P^*_{TQ, SITE} = 0.00023$

$$L(P_{TQ,i}^* \mid P_{TQ}) = \frac{1}{\sqrt{2\pi}\sigma_i P_{TQ,i}^*} exp\left[-\frac{1}{2} \left(\frac{\ln P_{TQ,i}^* - (\ln P_{TQ} + \ln b_i)}{\sigma_i}\right)^2\right], \quad (18)$$

$$(b_i = b_{BASE} = b_{SITE})$$
 is considered equal to one

Bayesian updating performed using the open source program OpenBUGS: Spiegelhalter, D., et al., *OpenBUGS user manual, version 3.0. 2.* MRC Biostatistics Unit, Cambridge, 2007.



Sensitivity Analysis

This study uses a Fussel-Vesely Importance Measure method for Training Quality

$$I_{B_i}^{FV} = \frac{P_{\text{TQ}} - P_{\text{TQ}|B_i = \text{Good Quality}}}{P_{\text{TQ}}}, \quad (19)$$

Level of Causality in Fig. 6	Node (Poor Quality = 0)	Pr (Training Quality = Poor)	FV-IM	Ranking
2.	Training Program Design	0.02169	26.8%	1
1.1.	Training Procedure	0.02203	25.7%	2
1.1.	Instructor Performance	0.02327	21.5%	3
1.1.1.	Training Sequence	0.02609	12.0%	4
1.1.1.	Training Method	0.02609	12.0%	5
1.1.1.	Training Setting	0.02609	12.0%	6
1.1.1.	Training Content	0.02609	12.0%	7
1.1.1.	Training Structure	0.02614	11.8%	8
1.1.1.	Training Media	0.02614	11.8%	9
1.1.1.	Instructor Training	0.02614	11.8%	10
1.1.1.	Instructor Knowledge	0.02617	11.7%	11
1.1.1.	Instructor Time Preparation	0.02617	11.7%	12
2.1.	Training Records Documentation System	0.02657	10.3%	13
2.1.	Training Needs Analysis	0.02670	9.9%	14
2.1.	Instructional Technologist	0.02779	6.2%	15
2.1.1.	Performance Analysis	0.02835	4.3%	16
2.1.1.	Training Objectives	0.02877	2.9%	17
2.1.1.	Knowledge, Skills, and Abilities Evaluation	0.02897	2.2%	18
2.1.2.	Job/Task Analysis	0.02907	1.9%	19
2.1.2.	Conditions & Standards	0.02911	1.8%	20

Interpretation of SA Results

- "Program Design", "Training Procedures/Facility", and "Instructor Performance" are identified as the first, second, and third most important factors, respectively.
 - Among the sub-factors influencing the quality of "<u>Training Procedures/Facility</u>", "<u>Training Sequence</u>" (i.e., logical order, such as instruction, discussion, and testing; beginning, middle, and end of the program), "<u>Training Method</u>" (i.e., strategy of presenting content), "<u>Training Setting</u>" (i.e., classroom, computer, simulator, etc.), and "<u>Training Content</u>" are identified more important than "Training Structure" (i.e., organization of materials by increasing level of difficulty) and "Training Media"
 - Among the sub-factors influencing the quality of "Instructor Performance", the instructor's initial expertise and quality of knowledge, "Instructor Knowledge", is almost as important as "Instructor Training", instructor qualification and certification;
 - Factor Recommendations: Organizations should put enough attention on the quality of hiring process of the instructors and on maintaining qualifications and certifications

Discussion on the Data-Theoretic

- Combines different sources and types of information
 - Articles, Documents, Standards [DT-BASE]
 - Analyst 'Subjective' Interpretation [DT-BASE]
 - 'Objective' Event Data [DT-SITE]
- 2. Guides Data Analytics with Theory
 - SoTeRiA framework and contextual keywords guide data analytics; underlying theory supports the completeness of causal factors, helps avoid potentially misleading results of a solely data-oriented approach
- 3. Data Mining in addition to Expert Opinion [DT-SITE]
 - Organizational factors research is seen as a challenge due to its complexity and perceived lack of data
 - Organizational data have a different nature than equipment. Organizational communications data are a compilation of textual operational experience documents, in unstructured and heterogeneous formats

Next Steps

- (i) Developing advanced safety-oriented text mining applicable for a wide range of unstructured organizational communications
 - Considering lessons learned from other nuclear industry and nuclear regulatory studies
- (ii) Integrating DT-SITE and DT-BASE into one computational platform to improve the Bayesian updating
- (iii) Adding uncertainty analysis into the DT-BASE code
- (iv) Developing methodologies for updating PSFs of existing HRA techniques based on the results of organizational causal modeling
- (v) Applying the Data-Theoretic approach to other factors of SoTeRiA, such as the quality of procedures, and safety culture;
- (vi) Developing Global SA and importance measure analyses to increase the validity of the ranking of factors in the training causal model

Potential SACADA Contributions

- Leverage NSF research to contribute to SACADA
- Develop program-specific causal models for SACADA-relevant Job Performance Measures
 - For example, bridging generic 'Training Program
 Quality' to be 'Task-Specific Training' for different roles
- Research additional organizational PSFs that can be measured via simulator data
- Improve usability and integration for HRA methods





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The DT-BASE computational platform is implementing pgmpy, an open source Python library for probabilistic graphical model analysis (https://github.com/pgmpy/pgmpy). Bayesian inference is performed using OpenBUGS (http://www.openbugs.net). Bayesian Belief Network (BBN) is supported by GeNIe Modeler, BayesFusion, LLC, http://www.bayesfusion.com/.

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