THEORIZING AND QUANTIFYING ORGANIZATIONAL AND SOCIAL FACTORS IN PROBABILISTIC RISK ASSESSMENT OF COMPLEX SYSTEMS

BY

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DISSERTATION

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ABSTRACT

Organizational and social factors remain elusive and latent contributors to incidents and accidents in high-consequence industries, such as nuclear power, aviation, oil and gas, and healthcare. Probabilistic Risk Assessment (PRA) is a formal methodology for estimating risk emerging from the interactions of equipment failure and human error. This research is the product of a line of a collaborative study to theorize and quantify the explicit incorporation of organizational and social factors into PRA of complex technological systems, specifically for Nuclear Power Plants (NPPs) to; (a) make risk assessments more accurate, and (b) improve risk management and prevention by identifying and ranking critical organizational/social factors based on their influences on the technical system risk.

For NPPs, PRA can be used to generate three levels of risk information, including risk from reactor core damage (Level 1 PRA), the risk from loss of containment integrity (Level 2 PRA), and risk to the population and environment (Level 3 PRA). This dissertation is the product of multidisciplinary and collaborative PRA research activities, covering six journal manuscripts, and theorizes and quantifies organizational/social factors from two levels of analysis:

1. **Meso-Level**; meso-level organizational factors contribute to incidents or accidents in Level 1 PRA (e.g., Core Damage Frequency (CDF) in NPPs). Chapters 2 to 4 of the thesis cover the following contributions to the meso-level analysis:
    a. Presents a discourse on the incorporation of organizational factors into PRA by summarizing key questions associated with the incorporation of organizational factors into PRA, framing the ongoing debates surrounding the topic, providing a categorical review of literature, and highlighting the directions of research required to reach a resolution for each question;
    b. Expands the granularity of the Socio-Technical Risk Analysis (SoTeRiA) theoretical framework.
    c. Advances the Integrated PRA (I-PRA) methodological framework to operationalize the SoTeRiA theoretical framework by developing the Data-Theoretic (DT) input module, which has two sub-modules: (1) DT-BASE, for developing detailed theory-based causal relationships in the Socio-Technical Risk Analysis (SoTeRiA) theoretical framework, equipped with a software-supported BASEline quantification utilizing information extracted from literature, industry reports, and regulatory standards, and (2) DT-SITE, conducting data analytics to refine and measure the causal factors of SoTeRiA based on

system-specific historical event databases and using Bayesian analysis to update the baseline quantification. The methdology is applied using NPP database.

d. Applies DT-BASE to theorize and quantify a causal model of an NPP's organizational "training system" and performs sensitivity analysis to identify critical factors. The computational platform of DT-BASE eases the execution of theory-building to expand theoretical details in SoTeRiA.The results indicate that among all the causal factors, "Program Design," "Training Procedures/Facility," and "Instructor Performance" are identified as the first, second, and third most important factors, respectively.

e. Applies DT-SITE, using the "training system" causal model from DT-BASE, to conduct text mining of Licensee Event Reports (LERs) from the U.S. nuclear power industry to generate the probability of "poor training quality." Using the results of DT-SITE, the resulting probability of "poor training quality," is estimated as 7.03E-07.

2. **Macro-Level;** macro-level social factors contribute to consequences of emergency response in Level 3 PRA (e.g., population radiological dose exposure). Chapters 5 and 6 of the thesis cover the following contributions to the macro-level analysis:

   a. Develops a macro-level socio-technical risk analysis theoretical framework of factors influencing emergency response to a radiological hazard, considering onsite and offsite response organization performance, socio-technical infrastructure, multi-hazard interactions, and population protective action performance. The advanced theoretical framework contributes to the comprehensiveness of Level 3 PRA by considering a broader set of influencing factors and their multi-level interrelationships, providing opportunities for improved root cause analysis and development of radiological emergency response plans.

   b. Develops an external integration between a radiological hazard and social vulnerability, a commonly used indicator in natural hazard research, and conducts risk importance measure analysis. The results reveal that the Center for Disease Control (CDC) Social Vulnerability Index (SVI) theme contributions to socio-technical risk can vary significantly by location.

   c. Introduces an internally-integrated methodological framework for building and validating an HRA-based Population Departure Time Model (PDTM), and integrating it with the transportation evacuation model to generate model-based Evacuation Time Estimates (ETEs) and evacuation speed estimates as inputs to Level 3 PRA model. This integrated methodology makes an advancement toward the explicit incorporation of social factors into Level 3 through the explicit incorporation of social factors into departure time and evacuation speed estimations. The integrated methodology can help (i) create a more realistic estimation of risk from Level 3 PRA by contributing to a more realistic representation of population evacuation performance and (ii) provide the opportunity to conduct importance ranking of the social factors, influencing departure time and evacuation speed, with respect to their impacts on risk.

d. Applies the internally-integrated methodology for Level 3 PRA in a case study using results from the 2017 Sequoyah SOARCA study.

Lastly, to justify the 'market value' of PRA, and provide incentives for companies to make investments in PRA, for example, investing in the explicit incorporation of organizational/social factors, Chapter 7 of this dissertation analyzes the monetary value of PRA.

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TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

This dissertation is the product of my multidisciplinary and collaborative research activities as a graduate research assistant in the Socio-Technical Risk Analysis (SoTeRiA) Research Laboratory[1] in the Department of Nuclear, Plasma, and Radiological Engineering (NPRE) at the University of Illinois at Urbana-Champaign (UIUC). The SoTeRiA Research Laboratory's focus has been on advancing Probabilistic Risk Assessment (PRA) for complex technological systems, specifically for Nuclear Power Plants (NPPs). As shown in Figure 1.1, the SoTeRiA Research Laboratory's three key areas of scientific contributions include **Area (I)** spatiotemporal coupling of physical failure mechanisms with human/social performance and the incorporation of this coupling into classical PRA using the Integrated PRA (I-PRA) methodology; **Area (II)** incorporating big data analytics into PRA, and **Area (III)** integrating safety risk and financial risk.

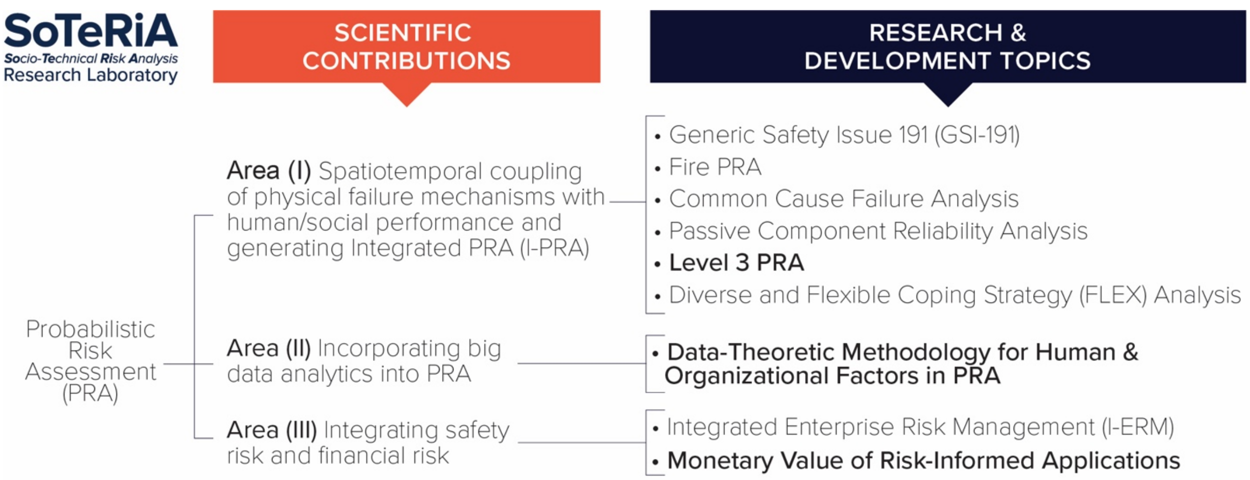

Figure 1.1: SoTeRiA Research Laboratory Scientific Contributions to the Evolution of Probabilistic Risk Assessment (PRA)

The three areas of scientific contributions in Figure 1.1 have been operationalized in multiple research projects (listed under Research & Development Topics in Figure 1.1) in the SoTeRiA Research Laboratory. Among the projects associated with **Area I,** I was involved in "Level 3 PRA," addressing the spatiotemporal coupling of radiological hazard progression with population response (Chapters 5 & 6). With respect to the projects related to **Area II,** I contributed to the research topic of the "data-theoretic methodology for human and organizational factors in PRA," addressing the use of big data

[1] https://soteria.npre.illinois.edu/

analytics for PRA to tackle the challenges associated with the heterogeneous nature of human/social data related to risk scenarios (Chapters 2, 3, & 4)**.** For the projects related to **Area III,** I was involved in the research topic of the "monetary value of risk-informed applications," addressing the interface of financial analysis and safety risk analysis, with consideration of organizational and regulatory factors (Chapter 7). These collaborative research activities were funded from 2015 to 2020 by the National Science Foundation (NSF) under Grant No. 1535167.

In the finalization of the chapters of this thesis, all the feedback and comments received from my Ph.D. committee members, Professors Zahra Mohaghegh, Arden Rowell, Cathy Blake, Dan Morrow, Cheri Ostroff, and Mr. Ernie Kee, on my technical report submitted for my Ph.D. preliminary exam, are incorporated.

Chapter 2 is a published journal article (Pence & Mohaghegh, 2020) and presents a discourse on the incorporation of organizational factors into PRA, a research topic related to **Area II** (in Figure 1.1). The research in this chapter was conducted and published under the guidance of my primary advisor Professor Zahra Mohaghegh. My role in this research was in conducting the categorical review associated with each key question and synthesizing discussions with Professor Mohaghegh for identifying the four key open questions associated with this topic, framing ongoing debates by considering differing perspectives around each question, leveraging the results of the literature review to justify the selection of each question and to analyze the challenges related to each perspective, and highlighting the directions of research required to better address each question. The paper published in this chapter benefited from a review by Dr. Pegah Farshadmanesh (a postdoctoral research associate in the SoTeRiA Laboratory) and an industry expert Ernie Kee (one of my Ph.D. committee members). This chapter sets the stage for Chapters 3 and 4 and discusses the future work that is needed to advance the incorporation of organizational factors into PRA.

Chapter 3 is a published journal article (Pence et al., 2019) and the result of collaborative work that advances an Integrated PRA (I-PRA) methodological framework for operationalizing the Socio-Technical Risk Analysis (SoTeRiA) theoretical framework (Mohaghegh & Mosleh, 2009) to quantify and incorporate underlying organizational/social factors into risk scenarios. The topic of this chapter is related to **Area II** (in Figure 1.1). My role in this research was in the development of the methodology for the Data-Theoretic module of I-PRA, which has two sub-modules: (i) DT-BASE and (ii) DT-SITE. The research of this chapter was conducted and published under the guidance of Professor Zahra Mohaghegh. In addition, other experts and researchers contributed to the content of this chapter, as follows: the development of the DT-BASE computational algorithm was done in collaboration with senior research scientist Dr. Seyed Reihani and graduate research assistant Yicheng Sun. Undergraduate researcher Xuefeng Zhu provided programming support to build the DT-BASE web application. By receiving feedback from Professor Cheri Ostroff (one of my Ph.D. committee members) and in collaboration with Industry Expert Ernie Kee (one of my Ph.D. committee members), I developed a theoretical causal model of the “training system” at an NPP and generated the baseline quantification using DT-BASE. In collaboration with Dr. Mehmet Ertem[2], a postdoctoral researcher in the SoTeRiA Laboratory, Corrective Action Program (CAP) data from an NPP were analyzed to search for training-related concepts as a preliminary demonstration of DT-SITE. Leveraging these results, Dr. Tatsuya Sakurahara, a graduate research assistant[3] in the SoTeRiA Research Laboratory, implemented Bayesian updating to combine DT-BASE and DT-SITE results. Leveraging an importance measure approach developed by Dr. Tatsuya Sakurahara, I conducted the importance measure ranking of causal factors in DT-BASE.

Chapter 4 is a published journal article (Pence et al., 2020) and the result of collaborative work that leverages the training system causal model developed and quantified by DT-BASE in Chapter 3 to focus on the advancement of DT-SITE. The topic of this chapter is related to **Area II** (in Figure 1.1). My role in this chapter was in conducting the literature review and categorization, contributing to the development of the methodological framework for DT-SITE, developing the methodology for collecting and pre-processing unstructured text data from Licensee Event Reports (LERs), identifying theory-based seed terms based on the DT-BASE causal model, annotation of LERs, and leveraging the results of DT-SITE to establish the probability of training-system related events in LERs. The research of this chapter was conducted and published under the guidance of Professors Zahra Mohaghegh and Cathy Blake (one of my Ph.D. committee members). In addition, other experts and researchers contributed to the content of this chapter, as follows: undergraduate researchers, Nalin Gadihoke, and Nimay Desai helped with the development of data extraction tools for the LER database. Dr. Pegah Farshadmanesh, a postdoctoral research associate in SoTeRiA Research Laboratory, supported the development of the DT-SITE methodology. In collaboration with Dr. Pegah Farshadmanesh, we annotated 282 LERs to evaluate seed terms, 200 LERs to develop a gold standard, and estimated inter-rater reliability for both annotations. Industry Expert Ernie Kee supported the interpretation of the LER database. Professor Cathy Blake and her graduate student (Jinmo Kim) supported the data cleaning of extracted LERs, feature generation, and machine learning processes, and performed k-fold cross-validation of DT-SITE. Leveraging the results of DT-SITE, I generated a ratio for finding the unbiased probability of poor training quality, considering the real number of events involving training as a contributor, and an estimation of nuclear industry-wide operator, operations, and maintenance demands during the data collection period.

Chapters 5 and 6 are associated with **Area (I)** (in Figure 1.1) on the research topic of Level 3 PRA. Chapter 5 is a published journal article (Pence et al., 2018b) and the result of collaborative work on

[2] Currently an Assistant Professor at Eskisehir Osmangazi University
[3] Currently a Research Assistant Professor in the SoTeRiA Research Laboratory in NPRE

the development of a Geographic Information System (GIS)-based socio-technical risk map by combining the Center for Disease Control (CDC) Social Vulnerability Index (SVI) with a location-specific radiological hazard. The research of this chapter was conducted and published under the guidance of Professor Zahra Mohaghegh, and first started in a study by Ian Miller (Miller, 2015; Miller et al., 2015), an NPRE graduate student in the SoTeRiA Research Laboratory, for his Master's thesis. I was involved in the origination of the idea of this topic and its execution by Ian Miller. Ian Miller generated the radiological plume model using the MELCOR Accident Consequence Code System (MACCS) and information from the 2012 Surry Power Station (SPS) State-of-the-Art Reactor Consequence Analysis (SOARCA). In collaboration with James Whitacre (a GIS specialist at UIUC), Ian Miller developed a model for creating the MACCS polar grid in GIS for importing peak dose data. As a result, he created an integrated socio-technical risk map. To publish the journal paper cited in Chapter 5, I expanded this research by establishing a macro-level framework theorizing the influence of social factors given a radiological hazard. I also re-ran the methodology using a different database (CDC SVI) to generate an integrated risk map for the SPS. Also, with collaboration with Dr. Tatsuya Sakurahara, I developed and applied an importance measure analysis methodology using CDC SVI data to rank the criticality of social factors with respect to a radiological hazard.

Chapter 6 is a manuscript to be submitted to a journal of risk analysis in April 2020 and is the result of collaborative work to advance and operationalize the macro-level theoretical causal framework from Chapter 5 and presents a new use of Human Reliability Analysis (HRA) for theorizing and quantifying Population Error (PE) associated with population departure time delay. My main role in this chapter was (i) advancing the macro-level theoretical framework and (ii) developing the integrated methodological framework to quantify the theoretical framework, covering multiple phases of hazard-population interactions (i.e., population departure delay, evacuation/transportation, and radiological exposure), and (iii) building and validating the HRA-based Population Departure Time Model (PDTM). The research of this chapter was conducted under the guidance of Professor Zahra Mohaghegh. In addition, other experts and researchers contributed to the content of this chapter, as follows: Dr. Kazumasa Shimada, a visiting researcher from the Japan Atomic Energy Agency (JAEA), supported the development of the integrated methodological framework. Dr. Kazumasa Shimada, in collaboration with Dr. Seyed Reihani and Dr. Tatsuya Sakurahara, ran two elements of the methodological framework using available software codes: the transportation model using the MultiAgent Transport Simulation (MATSim) and Level 3 PRA using MACCS (with information from the 2017 Sequoyah SOARCA study), and developed a computational interface among the HRA-based PDTM, MATSim, and MACCS. Dr. Kazumasa Shimada and Dr. Tatsuya Sakurahara conducted the Morris method screening analysis of MACCS input parameters and advanced the sampling-based uncertainty quantification for MATSim and

MACCS. The content of this chapter benefited from a review by Ha Bui (a graduate research assistant in the SoTeRiA Research Laboratory).

While the goals of the previous chapters are to make risk assessments more accurate and improve risk management and prevention, without a justified representation of the 'market value' PRA, there are not enough incentives for companies to go 'beyond-compliance' and to make investments in PRA, for example, investing in the explicit incorporation of organizational/social factors. Therefore, Chapter 7 introduces a methodology to evaluate the monetary value of PRA. Chapter 7 is a published journal article (Pence et al., 2018a) and is associated with **Area (III)** in Figure 1.1. The benefits of PRA are not only experienced in terms of safety but also through the monetary value achieved through the use of Risk-Informed Performance-Based Applications (RIPBAs) that support decision-making (e.g., expanding the safe operational envelope of NPPs) and can lead to cost savings. Chapter 7 introduces a methodology to evaluate the monetary value of PRA through the systematic causal modeling of the net value of RIPBAs, considering some of the organizational and regulatory factors and demonstrates the methodology for one RIPBA called Risk-Managed Technical Specifications (RMTS). The research of this chapter was conducted and published under the guidance of Professor Zahra Mohaghegh and was first started in a study by a graduate student Marzieh Abolhelm in the SoTeRiA Research Laboratory (Abolhelm et al., 2014). I was involved in the origination of the idea of this topic and its execution by Marzieh Abolhelm. Marzieh Abolhelm collaborated with Dr. Seyed Reihani (research scientist) and Dr. Mehmet Ertem (postdoctoral research associate in the SoTeRiA Research Laboratory) on the development of the methodology, and implementation of the methodology in a case study for RMTS using data from a partnering NPP and with additional feedback obtained from industry expert Ernie Kee. To publish the journal paper covered in Chapter 7, I expanded this research as follows (i) advancing theoretical justifications for evaluating the monetary value of PRA considering RIPBAs, (ii) expanding the theoretical relationship between risk and safety in the SoTeRiA theoretical framework, (iii) advancing the causal model of the net value of RMTS and its interactions with PRA, (iv) updating the details of the systematic scenarios associated with maintenance and regulatory strategies, (v) updating some of the quantitative analysis for the case study. The paper published in this chapter benefited from a critical review by Professor Arden Rowel (one of my Ph.D. committee members).

Chapter 8 provides concluding remarks and summarizes the theoretical and practical relationships among the topics of Chapters 2 to 7.

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CHAPTER 2: A DISCOURSE ON THE INCORPORATION OF ORGANIZATIONAL FACTORS INTO PROBABILISTIC RISK ASSESSMENT: KEY QUESTIONS & CATEGORICAL REVIEW[1]

ABSTRACT

This paper[2] presents a discourse on the incorporation of organizational factors into Probabilistic Risk Assessment (PRA)/Probabilistic Safety Assessment (PSA), a topic of debate since the 1980s that has spurred discussions among industry, regulatory agencies, and the research community. The main contributions of this paper include (1) identifying the four key open questions associated with this topic; (2) framing ongoing debates by considering differing perspectives around each question; (3) offering a categorical review of existing studies on this topic to justify the selection of each question and to analyze the challenges related to each perspective; and (4) highlighting the directions of research required to reach a final resolution for each question. The four key questions are: (I) how significant is the contribution of organizational factors to accidents and incidents? (II) how critical, with respect to improving risk assessment, is the explicit incorporation of organizational factors into PRA? (III) what theoretical bases are needed for explicit incorporation of organizational factors into PRA? and (IV) what methodological bases are needed for the explicit incorporation of organizational factors into PRA? Questions I and II mainly analyze PRA literature from the nuclear domain. For Questions III and IV, a broader review and categorization is conducted of those existing cross-disciplinary studies which have evaluated the effects of organizational factors on safety (not solely PRA-based) to shed more light on future research needs.

2.1. INTRODUCTION

Beginning in the mid-1900s, complex, high-energy, and high-consequence technologies (e.g., Nuclear Power Plants (NPPs)) were developed and grew into profitable industries. In response to the safety concerns of NPPs, in 1975, Probabilistic Risk Assessment (PRA)/Probabilistic Safety Assessment (PSA) was established to evaluate (i) what can go wrong? (ii) how likely is it to go wrong? and (iii) if it does go wrong, what are the consequences? (Kaplan & Garrick, 1981). Contemporarily, and in separate research disciplines, theories on the nature of socio-technical systems emerged, expanding the theoretical scope of "social" performance beyond the individual, to consider the whole organization as part of the

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[1] This chapter is a reprint with permission of the publisher of an article published in Risk Analysis: Pence, J., Mohaghegh, Z., 2020. A Discourse on the Incorporation of Organizational Factors into Probabilistic Risk Assessment: Key Questions and Categorical Review. Risk Analysis n/a. https://doi.org/10.1111/risa.13468

[2] It should be noted that throughout this dissertation, "in this paper" means "in this chapter."

"socio-technical system" (Emery F.E. et al., 1960; Trist, 1981). From the lineage of socio-technical systems theory, "organizational factors" have come to be known as the social aspects (e.g., organizational culture, behavior) and structural features (e.g., safety practices), within the control of an organization, that contribute to organizational performance (Ostroff et al., 2003; Schein, 1990). This paper is the product of a line of research by the authors on the advancement of a socio-technical risk analysis (Mohaghegh, 2007; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2009a, 2009b; Pence et al., 2015; Pence et al., 2014; Pence et al., 2019b; Pence et al., 2017), which explicitly incorporates organizational factors into PRA. In this paper, "explicit" incorporation of organizational factors refers to the model-based or mechanistic (e.g., (Rios, 2004)) integration of organizational performance with PRA. The ideal goals of explicit incorporation of organizational factors into PRA are to (a) make risk assessments more accurate by considering the effects of organizational factors in the estimation of human error and equipment failure probabilities, and (b) improve risk management and prevention strategies by identifying and ranking critical organizational factors based on their influences on the technical system (e.g., Core Damage Frequency (CDF) in NPPs) and their impacts on Risk-Informed Performance-Based Applications (RIPBAs). For example, one RIPBA for NPPs is Generation Risk Assessment (GRA) (Blanchard et al., 2004; Wang et al., 2007)), and the influence of organizational factors could be considered for the elements and structure of production loss scenarios (e.g., Balance of Plant (BOP)) in GRA (Kee et al., 2009). The theoretical and methodological aspects of explicit incorporation of organizational factors are further analyzed in Sections 2.2 to 2.5 of this paper.

This review article presents a discourse on the incorporation of organizational factors into PRA and makes the following contributions:

a) Identifying Four Key Questions: Four key questions associated with the incorporation of organizational factors into PRA are identified based on (1) evidence from academic, industry, and regulatory literature, and (2) authors' research experience in the field of socio-technical risk analysis as well as industry experience on PRA applications. The four key questions are: (I) how significant are the contributions of organizational factors to accidents and incidents? (II) how critical is the explicit incorporation of organizational factors into PRA with respect to improving risk assessment? (III) what theoretical bases are needed for explicit incorporation of organizational factors into PRA? and (IV) what methodological bases are needed for the explicit incorporation of organizational factors into PRA? Sections 2.2 to 2.5 of the paper cover Questions I to IV.

b) Framing Ongoing Debates from Multiple Perspectives: This paper does not provide final answers to the four questions; instead, supported by the existing literature, it frames the existing debate by considering multiple perspectives around each open question to provide conceptual reasoning as to why the risk analysis community may not have come to conclusions for these key questions.

Sections 2.2 to 2.5 begin by listing the differing perspectives related to each question, followed by their explanations and key terms, as well as discussions on the challenges associated with each perspective. Perspectives are given that may seem contestable to the reader – this is to frame the discourse so that differing viewpoints can be used to explore the current state of organizational factors in risk analysis and to identify associated challenges.

c) Reviewing and Categorizing Existing Studies: This paper offers a thorough review of existing studies to justify the selection of each question and analyze the challenges related to each perspective by discussing state-of-the-art approaches in practice and research. For Questions I and II (Sections 2.2 and 2.3), PRA reports and literature, mainly from the nuclear domain, are analyzed. For Questions III and IV (Sections 2.4 and 2.5), a broader review and categorization of existing cross-disciplinary studies that have evaluated the effects of organizational factors on safety (not solely PRA-based studies) is conducted. For Questions III and IV, existing studies from 2008 to 2018[3] are reviewed, categorized, and their gaps are highlighted based on their theoretical (i.e., the underlying organizational theory) and methodological bases of incorporating organizational factors into risk/safety analysis. A summarized review of pre-2008 studies that incorporate organizational factors into risk analysis is provided in this section to set the stage for the review and categorization of existing studies (from 2008 to 2018) in Sections 2.4 and 2.5 of this paper.

d) Highlighting a Research Agenda: This paper highlights the directions of research that need to be taken in order to reach a final resolution for Questions I to IV based on the discourse around each question, viewpoints from multiple perspectives, and insights from a categorical review of existing studies.

Mohaghegh et al., (2007, 2009, 2010) reviewed existing theoretical frameworks and quantitative techniques related to the incorporation of organizational factors into risk models and they categorized them into two generations (Mohaghegh, 2007; Mohaghegh, 2009; Mohaghegh, 2010a, 2010b; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2007, 2009a, 2009b):

- The nature of first-generation theories and quantitative techniques is characterized in terms of "deviations from normative performance" (Rasmussen, 1997). For example, Reason's Swiss Cheese Model (Reason, 1990b, 1997) is a well-known metaphor for describing how organizational effects can contribute to the occurrence of accidents. According to Reason, the accident sequence starts with failed or missing defenses in the organization (e.g., managerial decisions), and these

[3] Some journal articles were available in 2018 but were part of 2019 publication volumes.

defects create latent conditions that are transmitted along organizational pathways. There have been several static quantitative frameworks, based on Reason's concept, that aim at modeling and quantifying the impact of organizational factors on system risk. Examples are WPAM (Davoudian et al., 1994a, 1994b), SAM (Paté-Cornell & Murphy, 1996) and similar models (Øien, 2001), Omega Factor Model (Galán et al., 2007; Mosleh & Golfeiz, 1999), ASRM (Luxhøj, 2004), ORIM (Øien, 2001), I-Risk (Papazoglou et al., 2003), and Causal Modeling of Air Safety (Roelen et al., 2003).

- The second-generation approaches to develop organizational models for risk analysis frameworks focus on modeling the "actual behavior" of organizations. These approaches are evolving and attempt to represent the underlying organizational mechanisms of accidents. On the theoretical side, Rasmussen (Rasmussen, 1997) cites the self-organizing nature of High Reliability Organizations (Rochlin et al., 1987) and Learning Organizations (Senge, 1990; Weick & Sutcliffe, 2001) as concepts useful in analyzing the managerial and organizational influences on risk. The Normal Accident Theory (Perrow, 1984), which views accidents as being caused by interactive complexity and close coupling, can also be considered in the second generation of theories for organizational safety. Second-generation quantitative techniques primarily address the dynamic aspects of organizational influences. For example, Cooke (2004), Leveson (2004), and Marais (2006) use the System Dynamics approach (Forrester, 1961; Sterman, 2000) to describe the dynamics of organizational safety, but these models do not include detailed PRA-style models of the technical system (Cooke, 2004; Leveson, 2004; Marais et al., 2006; Sterman, 2000). Yu et al., (2004) also use a System Dynamics approach to incorporate the effects of organizational factors into nuclear power plant PRA models (Yu et al., 2004). The interconnection between PRA and System Dynamics, however, is not established.

Integrating concepts from multiple disciplines, Mohaghegh et al., (2007, 2009) introduced a set of thirteen principles (Table 2.1) for the field of organizational risk analysis or Socio-Technical Risk Analysis (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a). These principles are distributed in the following four groups; Group I, II, and III relate to theory building, and Group IV relates to developing methodological techniques. In summary, these principles address two requirements for incorporating emergent organizational safety behavior into PRA: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links; (ii) the 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.

Table 2.1: Socio-Technical Risk Analysis Principles (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a)

Groups	Principles
I. Designation & Definition of Objectives	(A) Unknown-of-Interest
	(B) Multidimensional Performance Objectives
II. Modeling Perspective	(C) Safety Performance and Deviation
	(D) Multilevel Framing
	(E) Depth of Causality and Level of Detail
	(F) Model Generality
III. Building Blocks	(G) Basic Unit of Analysis
	(H) Factor Level and Nature
	(I) Factor Selection
	(J) Link Level, Nature, and Structure
	(K) Dynamic Characteristics
IV. Techniques	(L) Measurement Techniques
	(M) Modeling Techniques

Concerning the first requirement, a theoretical framework, called Socio-Technical Risk Analysis (SoTeRiA) (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a), was developed using the theory-building principles (Groups I, II, and III in Table 2.1) and based on a multi-level organizational performance model developed by Ostroff et al., (Ostroff et al., 2013; Ostroff et al., 2003). SoTeRiA is a theoretical causal framework for explicitly integrating both the social aspects (e.g., safety culture) and the structural features (e.g., safety practices) of one organization with technical system PRA. Section 2.4 of this paper provides a review and categorization of studies from 2008 to 2018 with respect to their theoretical bases.

Operationalization and quantification of theoretical frameworks require the development of appropriate techniques (Principle IV in Table 2.1), including modeling and measurement techniques. With respect to modeling techniques (Principle IV-M), Mohaghegh (2007, 2010) developed a hybrid approach (Mohaghegh, 2007, 2010a) by combining a probabilistic method, i.e., Bayesian Belief Network (BBN), and a dynamic simulation-based technique, i.e., System Dynamics, with classical PRA methods, i.e., Event Tree (ET) and Fault Tree (FT), to quantify SoTeRiA. Section 2.5 of this paper provides a review and categorization of studies between 2008 and 2018 with respect to their modeling techniques.

Measurement techniques (Principle IV-L in Table 2.1) relate to data analysis (i.e., data extraction and interpretation) for the factors and the links in the SoTeRiA framework. Review and analysis of measurement methods for organizational factors in risk/safety studies are not included in the scope of this paper. The readers are referred to Mohaghegh (2007) and Mohaghegh and Mosleh (2009b) for a multi-dimensional measurement perspective for organizational factors in safety/risk analysis (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009b). More recent developments of measurement techniques for organizational factors as well as a review of existing studies (from 2008 to 2018) that develop and apply machine learning-related techniques for measuring organizational factors in safety/risk analysis is available in (Pence et al., 2020).

2.2. (QUESTION I) HOW SIGNIFICANT ARE THE CONTRIBUTIONS OF ORGANIZATIONAL FACTORS TO ACCIDENTS AND INCIDENTS?

The ongoing debate about the significance of organizational contributions to accidents and incidents relates to the following three differing perspectives:

- (P.I.1) Organizational factors are not major contributors to incidents or accidents. The major contributors are equipment failures, primarily associated with equipment design flaws rather than due to maintenance program/organizational deficiencies.
- (P.I.2) Organizational factors are reasonable contributors to incidents and accidents, but there are many barriers between them and technical system failures. There are latent failures associated with organizational factors, making the detection and control of organizational deficiencies challenging.
- (P.I.3) Organizational factors are significant contributors to accidents and incidents.

The first perspective (P.I.1) can be framed by an early interpretation of the “defense-in-depth” philosophy (AEC, 1957), which takes a structuralist view of accident progression where multiple physical barriers are seen as the primary defenses in preventing, blocking and containing damage or mitigating consequences of an accident or incident (Chierici et al., 2016; Saleh et al., 2014). The defense-in-depth philosophy was updated after the Three Mile Island (TMI) accident in 1975, identifying organizational factors as root cause contributors (Alvarenga & Frutuoso-e-Melo, 2015; IAEA, 2014b; Omoto, 2015), where it was stated that “the principal deficiencies in commercial reactor safety today are not hardware problems, they are management problems” (Rogovin, 1980). As traditional defense-in-depth definitions have been evolving, engineering-based approaches for identifying the root causes of technological system failures have also needed to change. Initially, analysts considered linear cause-effect modeling (Petroski, 1985), primarily looking “for an intuitive understanding of the physical world” (Carroll, 1995). Such a linear and reductionistic approach has not provided an accurate understanding of the complex causality of accidents or incidents, and the desire to find a single root cause from this first perspective was referred to by Carroll (1995) as root cause seduction (Carroll, 1995). Øien (2001), on the other hand, described post-accident analyses as exercises in "qualitative retrospective hindsight" (Øien, 2001), and indicated that it could be challenging to judge the level of contribution from organizational contributing factors versus non-organizational contributing (purely technical) factors. Therefore, regardless of highlighting the effects of organizational factors in the current defense-in-depth philosophy, there have been some challenges in properly identifying organizational root causes in the aftermath of operational incidents and accidents (Omoto, 2015). These challenges, leading to the emergence of the second perspective (P.I.2), have been mainly due to (i) cultural biases associated with traditional engineering-based mindsets and result from a structuralist view of accident progression, and (ii) a lack of clarity as to the meaning of organizational factors and their paths of influence on incidents/accidents. Achieving clarity as to the meaning of organizational factors and their paths of influence requires the development of theoretical causal frameworks for organizational factors and their connections to safety/risk models. Section 2.4 (associated with Question III) elaborates on the theoretical bases needed for this topic.

Another challenge that is highlighted in the second perspective (P.I.2) relates to the latent nature of organizational factors as it generates (i) a delay in learning from operational experience when it comes to organizational factors and (ii) delayed effects of decision-making outcomes. Latent failures (i.e., resulting from a time lag between errors and consequences (Reason, 1990b)) of organizational factors can generate an incident or accident, given local triggering conditions (Reason, 1990a) (e.g., initiating events). These latent failures of organizational factors can differ in time and space from the actual event and are, therefore, more difficult to identify (IAEA, 1997). The other challenge embedded in the second perspective (P.I.2) is that those in management positions do not like to be blamed, so investigating and reporting on managerial and other organizational weaknesses are limited. As discussed by Perrow (1984), accident investigations typically start with an assumption of operator failure; otherwise, if technical designs were responsible, shutdowns and retrofitting costs would ensue. However, if management were found to be responsible, it would threaten those in charge (Perrow, 1984). Dekker and Nyce (2014) discuss the contradictory nature of having those in power be responsible for assigning causation after an accident (Dekker & Nyce, 2014), referring to Sagan (1994), who stated that "even when failures cannot be hidden, the interpretation of accidents and lessons favored by the most powerful actors will often take precedence… this is why so many technological accidents are blamed on the most proximate cause—human error by operators—rather than deeper causes such as faulty design or mismanagement by higher authorities" (p. 237) (Sagan, 1994). Bier (1999) also adds that "it is important to bear in mind that risk analysts will frequently be employed by exactly the management whose performance must be evaluated, a situation that may create further difficulties for analysts interested in quantifying the effects of management and organizational factors on risk" (Bier, 1999). Underlying these points is another challenge; that there may be a pessimistic perspective on the feasibility of changing organizational factors, so there is less effort put into investigating these root causes.

The third perspective (P.I.3) considers that organizational factors are significant contributors to accidents and incidents. Root cause analyses conducted by diverse industries and governmental agencies show that organizational factors were contributors to incidents and accidents in complex systems (Columbia Accident Investigation Board, 2003; IAEA, 2014a; Johnson, 2004; Kurokawa et al., 2012; Meshkati, 1991; Paté-Cornell, 1993; Vaughan, 2009; Waring, 2015). There have been some longitudinal studies have also been conducted to quantify the degree of influence of organizational factors on NPP incidents and accidents. For example, in 1985, the Institute of Nuclear Power Operations (INPO) conducted an analysis of 180 significant event reports received between 1983 and 1984, and their analysis showed that 92% of root causes were human-related and that the majority had their "origins in either maintenance-related activities, or in fallible decisions taken within the organizational and managerial domains" (Reason, 1990a). Another empirical study was conducted in 2002, when the Nuclear Regulatory Commission (NRC) and Idaho National Engineering and Environmental Laboratory published NUREG/CR-6753, which conducted a review of Licensee Event Reports (LERs) from 1992 to 1997 that were associated with events identified in the Accident Sequence Precursor (ASP) program that had a Conditional Core Damage Probability of 1.0E-5 or more (Gertman et al., 2002). It was found that 37 out of 48 events included human error as a root cause (Gertman et al., 2002). Among the 37 events, 23 were quantitatively evaluated, where it was determined that the average human error contribution to change in risk was 62% (Gertman et al., 2002). Schroer and Modarres (2013) analyzed LERs between the years 2000 and 2011, finding that there were 392 LERs documented events affecting multiple reactor units on a site, and of those entries, 44% were due to organizational dependencies (Schroer, 2012; Schroer & Modarres, 2013). On the other hand, in a 2014 study by the NRC to explore the relationship between safety culture and safety performance in U.S. NPPs, no statistically significant correlation was found between safety climate survey results and measures of accident and incident rates (Morrow et al., 2014).

Based on the review of literature, it can be concluded that the first perspective (P.I.1) is not valid, but both the second perspective (P.I.2) and third perspective (P.I.3) need further analysis to be accurately stated. Although the existing studies clearly acknowledge the influence of organizational factors on incidents/accidents, they could not generate information on the risk importance measures of organizational contributing factors (i.e., the factors under the control of the operating organization) versus those for non-organizational contributors (i.e., those beyond the control of the operating organization, such as flaws in equipment design and material properties). Therefore, it would be challenging to make a solid conclusion on the degree of significance of organizational factors based on these quantitative studies. For example, the risk importance ranking conducted by Gertman et al., (2002) was at the level of human error events and not in respect to the underlying organizational factors. The conclusions of their study indicated that "latent errors, including those associated with maintenance, were important contributors to the significance of the highest conditional core damage probability events that have occurred in recent years" (Gertman et al., 2002). The authors highlighted that "analyses may be needed to better understand the impact of smaller, less-significant errors and the mechanisms by which they are combined to produce larger, more significant effects," and that "dependencies among latent and active human errors should be investigated to determine impacts on failure probabilities" (Gertman et al., 2002). Both challenges, i.e., importance analysis and dependency treatment, can be better addressed by explicit incorporation of organizational factors into risk models (discussed in Section 2.2) and require the development of new methodologies (discussed in Section 2.5). As Gertman et al., (2002) state, "the typical methods used to determine contributors to risk or importance to risk require evaluation of the risk equations generated in a PRA… this limits the results to only the risk elements that are explicitly modeled… a considerable amount of additional analysis is needed to get to contributors that are implicitly in the model through data or assumptions" (Gertman et al., 2002).

In order to reach a final resolution on Question I, there is a need for the explicit incorporation of organizational factors into risk models to help conduct a risk importance ranking (e.g., (Groth et al., 2010; Øien, 2001)) of underlying organizational factors. The concept of explicit incorporation is explained in Section 2.3 (associated with Question II). The resolution of Question I also requires the development of theoretical causal frameworks that (i) help generate an explicit connection of organizational root causes to risk models and (ii) can be leveraged to achieve a higher resolution of data collection for organizational factors contributing to safety-related events, resulting in improved root cause analyses. Section 2.4 (associated with Question III) analyzes the needs associated with the theoretical bases of incorporating organizational factors into risk models. Finally, the resolution of Question I requires methodologies for conducting importance ranking, as well as techniques for categorizing, coding, and counting the underlying organizational factors in industry event data. Section 2.5 (related to Question IV) evaluates the methodological bases that are needed for this topic.

2.3. (QUESTION II) HOW CRITICAL IS THE EXPLICIT INCORPORATION OF ORGANIZATIONAL FACTORS INTO PRA WITH RESPECT TO IMPROVING RISK ASSESSMENT?

The ongoing debate on the criticality of incorporating organizational factors into PRA with respect to the contribution to risk assessment relates to the following differing perspectives:

- (P.II.1) Although the incorporation of organizational factors into PRA could be beneficial for risk management, it is not critical for risk assessment because the effects of organizational factors are already implicitly (or explicitly through some of the external Performance Shaping Factors (PSFs) in HRA) considered in PRA scenarios through both human error and equipment reliability data and assumptions.

- (P.II.2) Explicit incorporation of organizational factors into PRA is critical for risk assessment (in addition to risk management) because this explicit incorporation can help generate a more realistic estimation of human error and equipment failure probabilities.

As mentioned in the introduction, in this paper, explicit incorporation of organizational factors refers to the model-based or mechanistic (e.g., (Rios, 2004)) integration of organizational performance with PRA. There is a reasonable consensus in the research community that the current generation of PRA does not include an explicit representation of organizational factors (Ghosh & Apostolakis, 2005; Modarres et al., 1992; Mohaghegh & Mosleh, 2009a; Renn, 1998). Relating to this topic, the Electric Power Research Institute (EPRI) workshop report (Julius et al., 2002) states that "some organizational factors are currently included in most PRAs and HRAs, either implicitly or explicitly" and discusses the bases for the implicit assumption, as follows: (1) "each individual plant examination (IPE) implicitly assumed that their organizational factors were in line with standard policies for all licensee holders in the US when evaluating the basic human error probabilities even though many organizational factor terms were not explicitly addressed" (e.g., see discussion in (Davoudian et al., 1994b)), (2) "initial models for control room operator actions incorporated generic organizational factors via use of simulator data, models that were based on simulator data, or judgment of the analysts," and (3) "it is reasonable to assume that some organizational factors were considered explicitly in the modeling, particularly in the HRA" (Julius et al., 2002). Julius et al., (2002) also identify five elements in PRA that are "likely to be affected by organizational factors" (Julius et al., 2002) (see Table 2.2). These elements are either related to human reliability or equipment reliability (Julius et al., 2002).

Table 2.2: EPRI Mapping of Organizational Factors into HRA/PRA; Adapted from (Julius et al., 2002)

Causal Structure	Element [Type]	Definition
Human Reliability Analysis (HRA)	Human Error Type [A]	Contributions to safety-related equipment unavailability
	Human Error Type [B]	Actions leading to IE
	Human Error Type [C] (Response)	Actions taken in response to accidents

Table 2.2 (cont.)

Causal Structure	Element [Type]	Definition
	Human Error Type [C] (Recovery)	Actions taken by plant personnel to use equipment, which might not have been initially available.
Equipment Reliability Analysis/CCF Analysis		Equipment failure rates, including common cause failures that can go into the post-initiating event system models and initiating events

The EPRI report by Julius et al., (2002) is an example of references acknowledging the status of the implicit (and partially explicit) incorporation of organizational factors into current classical PRA, highlighted in the first perspective (P.II.1). However, the first perspective (P.II.1) cannot be accepted because this degree of inclusion of organizational factors may not be adequate for a realistic risk assessment, as explained in the following reasons:

a) Organizational PSFs in current HRAs are quantified using expert judgment, generating challenges for the realistic estimation of Human Failure Event (HFE) probabilities. For example, in NUREG-1792, Kolaczkowski et al., (2005) state that although some PSFs help analysts to consider organizational factors (e.g., crew dynamics, characteristics, and potential biases and informal rules), "the state-of-the-art as to how to identify and understand important organizational influences and how to use that information in determining HEPs is not yet adequate" (Kolaczkowski et al., 2005). As another example, Hendrickson et al., (2012) state that "without such techniques to ensure the proper inputs and necessary understanding to properly judge the influencing factors and crew behavior, too much speculation or unsubstantiated judgments may be required by the HRA analyst, leading to undesirable variability in HRA results" (Hendrickson et al., 2012). Therefore, because there is no comprehensive guidance for the treatment of organizational factors in HRA (Hendrickson et al., 2012), over-reliance on subjective expert opinion for determining PSF states may lead to inaccuracies in HRA probabilities. Based on the authors' opinion, in order to have a more accurate quantification of organizational PSFs and not solely rely on expert judgment, there is a need for the explicit modeling of underlying organizational mechanisms associated with organizational PSFs in HRA.
b) Without explicit incorporation of organizational factors into HRA, the treatment of dependencies among PSFs is challenging. The EPRI report by Julius et al., (2002) acknowledges that in traditional HRA methods, "organizational factors appear in these models as PSFs, at the discretion of the analysts, but the full implications of such PSFs in terms of a new form of dependency in operator response, and corresponding impact on operator error probabilities are not considered" (Julius et al., 2002). Several studies have extended classical HRAs by adding additional external PSFs related to

organizational factors (see the review from (Alvarenga et al., 2014) and Section 2.4 for a more detailed analysis of these studies). While these studies move toward improved resolution in HRA models, they are still limited in the treatment of dependencies. Determining the state of an added PSF requires additional consideration of dependencies with other PSFs, and without the consideration of such dependencies, using these models in HRA may result in inaccurate estimations of HEPs. Laumann and Rasmussen (2016) state that "all PSFs should be looked at as organizational factors since it is an organization that could maintain or modify conditions that affect all of these factors" (Laumann & Rasmussen, 2016). Based on this statement and considering the logic of Blackman & Boring (2017) on indirect dependencies in HRA, organizational dependencies should play a much more significant role in the realism of human error probabilities (Blackman & Boring, 2017). This concept, however, goes beyond the scope of traditional HRA guidance and practice (where external organizational PSFs are represented at an abstract level of analysis) and requires model-based/explicit incorporation of underlying organizational mechanisms associated with PSFs.

c) <u>Implicit incorporation of organizational factors would lead to an over-reliance on generic historical data for probability estimations and could not adequately reflect (i) plant-specific information or (ii) organizational changes in estimating HFE or equipment BE (specifically Common Cause Basic Event (CCBE)) probabilities.</u> Most equipment reliability techniques in PRA use data-driven approaches that do not explicitly include underlying physical failure mechanisms or organizational/maintenance models. Ghosh and Apostolakis (2005) state that "many of the mechanisms of organizational contributions to unreliability are not captured (at least not explicitly) in plant PSAs and, hence, are sources of uncertainty and incompleteness in PSAs and may lead the plant to unanalyzed conditions" (Ghosh & Apostolakis, 2005). In this regard, Gertman et al., (2002) state that "latent errors are seldom explicitly modeled in PRAs; instead, they are combined into a single equipment failure event" (Gertman et al., 2002), which is part of a practice where "maintenance records are examined and overall failure rates are ascribed to the various components" (Julius et al., 2002). This means that "some phenomena or failure mechanisms may be omitted because their potential existence has not been recognized or no agreement exists on how a PRA should address certain effects, such as the effects on risk resulting from ageing or organizational factors… furthermore, PRAs typically do not address them" (Drouin et al., 2017). Shen et al., (2012) emphasize that Common Cause Failure (CCF) analysis is an important aspect in PRA because maintenance deficiencies (and other factors in the organizational environment) "which are not modeled explicitly in the PRA, can defeat redundancy and make failures of multiple redundant components more likely than would be the case if these factors were absent" (Shen et al., 2012). One key challenge of implicit consideration of organizational factors in empirical equipment reliability and CCF models is that the historical data do not reflect new maintenance policies, organizational changes, operational changes over time, or unobserved failure mechanisms (i.e., failure mechanisms that have not led to failure or have the potential to lead to failure over time). This is highlighted in the EPRI report by Julius et al., (2002), which states that the "advantage of defining an explicit relationship between organizational factors and the various elements of the PRA is that changes in organizational effectiveness can be accounted for in the estimates of core damage frequency, or the risk of operating the plant" (Julius et al., 2002). Besides, plants may record maintenance events with diverse quality, where "the ease in which the plant-specific data can be interpreted and the subsequent quality of the resulting parameter estimates are a function of how well the plant personnel recorded the necessary information" (Atwood et al., 2003). Similar to equipment failure probabilities, the probability estimation for HFEs is also challenged by an overreliance on generic historical data. As Julius et al., (2002) state, "many of the current HRA methods are not plant specific and therefore cannot reflect effects of organizational change or even the actual plant; it's organization or personnel… there is a need to improve HRA methods to reflect both plant-specific influences and incorporate organizational factors in a more explicit manner into the HRA models" (Julius et al., 2002). In order to improve the realism of estimated probabilities for HFEs, equipment basic events, and more specifically, CCBEs, there is a need for explicit incorporation of underlying physical and organizational failure mechanisms into PRA that can help avoid overreliance on data. As defined by Siu et al., (2015), realism "addresses the degree to which an analysis represents the technical and organizational system relevant to the decision problem" (Siu et al., 2015). Ongoing research by some of the authors of this paper assesses the value of incorporating physical failure mechanisms for CCF analysis (Sakurahara et al., 2019b) and future work will advance this research to underlying organizational factors.

Although the abovementioned deficiencies highlight the value of explicit incorporation of organizational factors for improving risk assessment and support the second perspective (P.II.2), a final resolution to Question II can only be achieved when research is capable of quantitatively identifying "how" critical is the explicit incorporation of organizational factors with respect to the realism of the estimated risk from PRA. This can be done by comparing the estimated risk in a selected scenario from the current classical PRA model to that of a PRA model that has an explicit consideration of key organizational factors. This requires advancing a research agenda for the explicit incorporation of organizational factors. The following two sections highlight the needs, including developing proper theoretical (Section 2.4) and methodological (Section 2.5) bases, to reach this goal.

2.4. (QUESTION III) WHAT THEORETICAL BASES ARE NEEDED FOR AN EXPLICIT INCORPORATION OF ORGANIZATIONAL FACTORS INTO PRA?

The two perspectives that have contributed to the ongoing debate regarding the required theoretical basis for the explicit incorporation of organizational factors into PRA are:

- (P.III.1) For the explicit incorporation of organizational factors into PRA, the need for developing a theoretical model of organizational performance should not be overemphasized.
- (P.III.2) Explicit incorporation of organizational factors into PRA requires theoretically well-defined models of organizational performance.

The first perspective (P.III.1) considers that the explicit incorporation of organizational factors is important, but there is no need for excess emphasis on the theoretical foundations of models; instead, the goal of explicit incorporation should/can be addressed by using surrogate models (or simplistic models) of organizational factors. For example, in classical HRA, organizational factors are aggregated and simplified as organizational-related PSFs. The organizational-related PSFs are mainly based on "lists" of organizational factors (e.g., (Haber et al., 1990; Sasou & Reason, 1999)). In efforts to improve the incorporation of organizational factors, several studies proposed conceptual approaches for adding layers of underlying causality to organizational-related PSFs; for example, using influence diagrams to depict availability of operating instructions, and training quality (Embrey, 1992; Galán et al., 2007) or the aggregated performance of training department and quality assurance department (Mosleh et al., 1997). Since 2008, there have been additional studies with the same purpose of extending PSFs of HRA to incorporate organizational factors. These references are categorized in Section 2.4 as studies that use a "list of factors" as their theoretical basis for modeling organizational influences. The issues with these extended HRA studies are that they are (1) not modeling the underlying organizational mechanisms associated with the PSFs (French et al., 2011), (2) not adequately capturing dependencies among PSFs (as stated in Section 2.3), and (3) over-relying on expert opinion for quantifying organizational PSFs (also explained in Section 2.3); therefore, these models have challenges with respect to achieving the ideal goals (listed in Section 2.1) of incorporating organizational factors into PRA.

On the other hand, the second perspective (P.III.2) emphasizes the development of theoretically well-defined models of organizational performance for the explicit incorporation of organizational factors into PRA. In order to explore the second perspective (P.III.2), this paper conducts a thorough review of the existing studies (from 2008 to 2018) and, leveraging the SoTeRiA theory-building principles (Groups I, II, and III in Table 2.1), analyzes the theoretical bases of organizational models in the existing studies. The review in this section summarizes the literature and categorizes the existing studies based on the maturity of their theoretical bases for organizational factors. The categorization in this section is an advanced version of the categorization developed for studies before 2007 (summarized in Section 2.1), considering the research improvements after 2008. The review does not include studies before 2008, but some of them are used to define the categorization schema. The scope of the review in is not limited to PRA studies; instead, a broader review is conducted of existing cross-disciplinary studies that have evaluated the effects of organizational factors on safety, in general, to shed more light on future research needs.

In this review, the theoretical basis (a in Figure 2.1) of each study is classified by its type of characterization (b in Figure 2.1), type of sub-characterization (c in Figure 2.1), and formalization (d in Figure 2.1). As Figure 2.1 presents, the studies are further grouped into quantified versus not quantified (e in Figure 2.1) to highlight whether (or not) the studies have made the attempt to quantify their developed theoretical frameworks. If quantified, their methods of quantification are analyzed and categorized (Figure 2.2) in Section 2.5. Tables 2.3 and 2.4 summarize the descriptions of the categories highlighted in Figure 2.1, and a complete list of the associated studies is available in a supplementary dataset (available at https://osf.io/c7rmn/), herein referenced as (Pence & Mohaghegh, 2019).

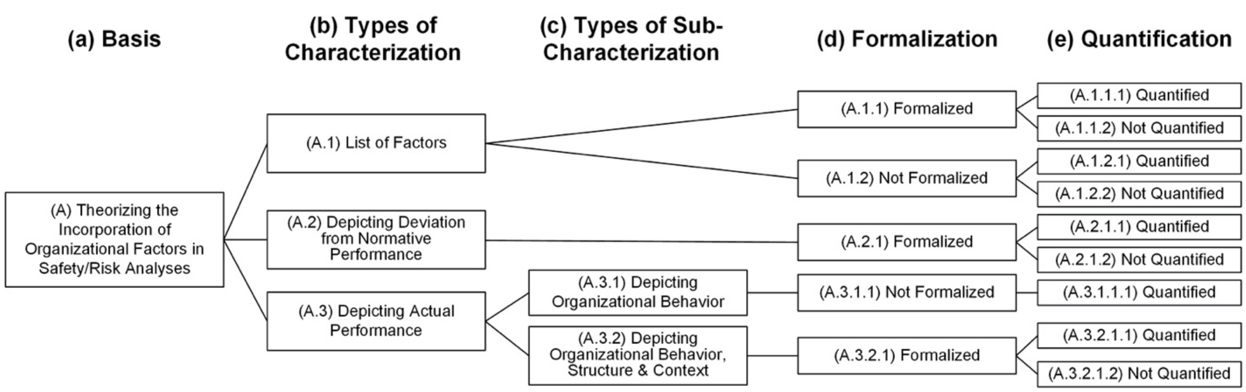

Figure 2.1: Categorization of existing studies (from 2008 to 2018) with respect to their theoretical bases

Table 2.3: Descriptions of Types of Characterization (b in Figure 2.1) and Sub-Characterization (c in Figure 2.1)

Types of Characterization & Sub-Characterization	Descriptions of Types of Characterizations (b in Figure 2.1) and Sub-Characterizations (c in Figure 2.1)
(A.1) List of factors	This characterization represents studies that use lists of factors to identify "what" organizational factors might compose a theory, but are not themselves complete and

Table 2.3 (cont.)

Types of Characterization & Sub-Characterization	**Descriptions of Types of Characterizations (b in Figure 2.1) and Sub-Characterizations (c in Figure 2.1)**
	stand-alone theories (Sutton & Staw, 1995). For example, in safety/risk assessments, lists of factors have been developed for PSFs (e.g., (Swain & Guttmann, 1983)), and Risk Influencing Factors (RIFs) (e.g., (Rosness, 1998; Seljelid et al., 2007)); however, they alone are not theories of human performance. Since theory is a continuum (Weick, 1995), and due to the lack of theoretical development for organizational factors in safety/risk analysis, lists of factors are characterized as simplified theories (associated with perspective III.1 explained at the beginning of this section) in this review paper. Lists of factors can include classifications, which are the "identification and assignment of organization forms to formally recognized classes" (McKelvey, 1978), and the "sorting of objects based on some criteria selected among the properties of the classified objects" (Hjørland & Nissen Pedersen, 2005). Classification schemes "demonstrate how entities are assigned to categories and how categories are differentiated from each another" (Niknazar & Bourgault, 2017). Classification can be a useful practice because it helps to depict the differences among organizations that can be conceptually derived or extracted from data (Rich, 1992b). For example, a classification for organizational factors in NPP safety was developed by Jacobs and Haber (1994), which included twenty factors/dimensions under five categories: culture, communications, decision-making, administrative knowledge, and human resource administration (Jacobs & Haber, 1994). Classifications in the reviewed studies are either derived from (i) experts through elicitation, (ii) group model building, verified by experts or extracted from surveys or verified by surveys or extracted from literature or combined from existing lists of factors or extending existing lists of factors or (iii) identified from operational experience data. Lists of factors can also include taxonomies, which is a specific scheme to express similarity between elements in a hierarchical way, where similarities are grouped into populations, and nested into broader categories (Jeffrey, 1973). According to Rich (1992), hierarchical taxonomies should have at least five nested subgroups if they are to create a meaningful analysis, and a "theoretical empirical process builds the taxonomy on the basis of an underlying theory" (Rich, 1992b). Hempel (1965) defines taxonomy as using types of concepts, for arranging phenomena into categories in an either-or notion (Hempel, 1965) (e.g., either a factor is safety-related or is not safety-related). Taxonomy has also been defined as "an empirical tool for building complex filing systems that allow both the ordering and retrieval of large amounts of data" (Rich, 1992a).

Table 2.3 (cont.)

Types of Characterization & Sub-Characterization	**Descriptions of Types of Characterizations (b in Figure 2.1) and Sub-Characterizations (c in Figure 2.1)**
	Taxonomies in the existing safety studies (Pence & Mohaghegh, 2019) are derived in diverse ways and from diverse sources including existing theoretical frameworks, combining existing factors, combining existing taxonomies, extracting from literature, or verifying by experts.
(A.2) Depicting Deviation from Normative Performance	This characterization considers first-generation theories (see Section 2.1) of "how" organizational factors contribute to deviations from normal performance, but do not depict the actual behavior or structure. This category includes Reason's metaphor for organizational accidents (Reason, 1995, 1997), where defects in processes and interacting elements are considered to influence organizational pathways (e.g., considering Reason's pathogen metaphor (Reason, 1990a)). This category refers to accident causation theories that extend beyond solely human actions to multiple sequential actions or events that contribute to error conditions. Some of the papers in this category use the Human Factors Analysis and Classification System (HFACS) (Wiegmann & Shappell, 2001), which is an advanced version of Reason's Swiss Cheese metaphor, where "types" and "levels" of latent failures are defined in a more detailed way (e.g., preconditions for unsafe acts, unsafe supervision, and organizational influences (Reason, 1990b)). For a discussion on the differences between metaphor and theory, readers are referred to (Le Coze, 2013). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing studies under Category A.2.
(A.3) Depicting Actual Performance	This characterization considers second-generation theories (see Section 2.1) of actual performance. Theories under this characterization attempt to depict "what" mechanisms are "generating behavior in actual dynamic work context" (Rasmussen, 1997), "why" contextual factors (e.g., organizational culture and climate) shape behavior and structure, and "how" they impact actual performance (Mohaghegh, 2007; Ostroff et al., 2013; Whetten, 1989b). The holistic and explicit inclusion of contextual factors, therefore, provides the background for studying behavior and structure leading to actual performance. There are two types of sub-characterization (c in Figure 2.1) for A.3 (A.3.1 and A.3.2), discussed below.
(A.3.1) Depicting Organizational Behavior	Studies in this category use theory that mainly try to "understand, explain, predict, and change human behavior as it occurs in the organizational context" (Wagner et al., 1995). Organizational behavior refers not only to individual or group behavior but individual and group behavior in organizations (Stroh et al., 2003). Some important dimensions

Table 2.3 (cont.)

Types of Characterization & Sub-Characterization	Descriptions of Types of Characterizations (b in Figure 2.1) and Sub-Characterizations (c in Figure 2.1)
	associated with behavioral theories are adaptive behavior (discussed in (Rasmussen, 1997)), complexity and tight coupling (Perrow, 1984), non-linear and interacting behaviors (Leveson, N.G., 2011), and social control perspectives (Rasmussen & Suedung, 2000). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing studies under Category A.3.1.
(A.3.2) Depicting Organizational Behavior, Structure & Context	This sub-characterization refers to the studies that consider a combination of behavioral, structural, and contextual aspects in their theoretical bases of organizational factors. The structural theory of organizations was summarized by Mintzberg (1980), who discussed the five parts of an organization: operating core, strategic apex, middle line, technostructure, and support staff (Mintzberg, 1980). Structural theories encompass the hierarchy, formal rules, policies, procedures (Ostroff, 2018), environments (internal or external), roles, and design of organizations (Mintzberg, 1989). Structural studies of organizations are also moving toward the adoption of network theory (Le Coze, 2013) and social network theory (Barling & Frone, 2004). The structure of an organization is closely related to its context (Pugh et al., 1969), and Ostroff (2018) provides an overview of context in organizational studies and states that “structure and practices are contrived aspects of context” (Ostroff, 2018). Context (Roberts et al., 1978) is defined as the “situational opportunities and constraints that affect the occurrence and meaning of organizational behavior as well as functional relationships between variables” (Johns, 2006). Ostroff (2013) states that “internal context is created within the social collective through its people, structural choices, norms/practices, leadership, and/or use of technology,” proposing four meta-dimensions of organizational context: “physical and technological; structure and practices, culture and climate, and person-based (influential agents, the personal characteristics of others, and collective attitudes and behaviors)” (Ostroff et al., 2013). Ostroff (2013) maintains that organizational structures include hierarchy, formal rules, policies, procedures, and that “all organizations have a structure of authority and regulatory mechanisms that coordinate work effort and provide channels for carrying out organizational decisions” (Ostroff et al., 2013). Category A.3.2 considers theories that account for functional relationships between variables of context, organizational structures, and behaviors. Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing studies under Category A.3.2

As Figure 2.1 shows, criterion (d) considers the formalization of theories under each type of characterization or sub-characterization. The formalized category refers to the case where a formalization process is utilized in the study to bridge qualitative theoretical bases with more formal models. For example, some studies have utilized a process modeling technique to explain the process of transferring theoretical bases from the abstract level to more detailed functional causal levels. Examples of process modeling techniques include; business process modeling (Williams, 1967) and flowcharts (ASME, 1947). Although formalization techniques are related to Principle IV-M (Table 2.1) and belong to modeling techniques (rather than theory-building bases), which are the focus of Section 2.5 of this paper, they are included in this section because they are considered to be the bridging methods that prepare theories to be operationalized by quantitative techniques (reviewed and categorized in Section 2.5). Mohaghegh et al., (2009) state that formalization processes (1) facilitate the use of a quantitative modeling technique (i.e., the techniques that are covered in Section 2.5), (2) are generalizable for diverse types of work processes and organizations, and (3) help to effectively communicate the theoretical model (Mohaghegh et al., 2009). In this paper, those studies that do not use formalization methods or do not explain how they use one of the formalization techniques to generate their models, are considered as Not Formalized. Formalization processes not only facilitate the use of quantitative techniques but also add theoretical justification to the resulting models. It should be noted that some studies use more than one technique for formalization (e.g., combining influence diagram and hierarchical techniques (e.g., (Vinnem et al., 2012)). Six main types of formalization techniques identified in the literature are described in Table 2.4.

Table 2.4: Descriptions of Six Main Formalization Techniques (d in Figure 2.1)

Types of Formalization (d in Figure 2.1)	**Formalization Type Description (d in Figure 2.1)**
1. Causal Loop Diagram	Causal loop diagram refers to a technique to visualize and communicate systems thinking, by creating links and feedback loops between system elements (Forrester, 1961). If these studies proceeded with quantification, they used statistical inference, System Dynamics (SD) (e.g., (Rong et al., 2016)), or the combination of SD and BBN (e.g., (Kazemi et al., 2017)) as their modeling technique (explained in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies that used causal loop diagrams.

Table 2.4 (cont.)

Types of Formalization (d in Figure 2.1)		Formalization Type Description (d in Figure 2.1)
2. Hierarchical Techniques	2.a. Generic Hierarchical Structures	This approach reflects generic hierarchical structures of nested layers of constructs that depict multi-level classifications of factors, including structured taxonomies. If studies used this approach to formalize their theoretical bases and were also quantified, they used BBN (Vinnem et al., 2012), DBN (Ashrafi & Anzabi Zadeh, 2017), ABM (e.g., (Nan & Sansavini, 2016), or statistical inference (e.g., (Zhou et al., 2018)) as their quantitative modeling techniques (covered in Section 2.5). For example, Vinnem et al., (2012) use a combination of generic hierarchical structure and influence diagram (Formalization Type #3) to formalize RIFs (Vinnem et al., 2012) and proceed to quantification using BBN. Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies that used generic hierarchal structure.
	2.b. Hierarchical Organizational Structures	This approach reflects hierarchical organizational structures, depicting authority, rank, and ordered representations of organizations. From the general systems theory perspective, hierarchy is used to arrange the complexity of an organization from its basic (i.e., individual) units to higher levels, developing a level of abstraction to represent each layer (Boulding, 1956). Hierarchical organizational structures can also consider the perspective of social distance, where hierarchy is created by maintaining a distance between groups (e.g., Congress and its constituents) (Bezrukova et al., 2009; Bogardus, 1925). For example, Accimap is a qualitative technique for accident analysis that models the hierarchical structure of levels of decision making (Rasmussen & Suedung, 2000). If studies used hierarchical organizational structures to formalize their theoretical bases and were also quantified, they used Structural Equation Modeling (SEM) (e.g., (Du & El-Gafy, 2012)) or ABM (e.g., (Du & El-Gafy, 2012)) as their quantitative modeling techniques (covered in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies that used hierarchical organizational structures.

Table 2.4 (cont.)

Types of Formalization (d in Figure 2.1)		Formalization Type Description (d in Figure 2.1)
	2.c. Analytic Hierarchy Process (AHP)	Analytic Hierarchy Process (AHP) is a multi-criteria decision-making technique for evaluating alternatives by decomposing problems into hierarchical structures (Saaty, 1987). It should be noted that the Analytic Network Process (ANP) is a similar approach to AHP. However, ANP allows for considering more complex structures, including dependencies and feedback (Saaty, 2004). If studies used AHP (e.g., (Liu et al., 2018)) to formalize their theoretical bases, and were also quantified, they used statistical inference or data envelopment analysis as their quantitative modeling techniques (covered in Section 2.5), where studies that used ANP for formalization (e.g., (Akyuz, 2017; Zhan et al., 2017)) used statistical inference (e.g., (Tseng & Lee, 2009)) or BBN (e.g., (Ping et al., 2018)) as their quantitative modeling techniques (covered in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using AHP.
	2.d. Hierarchical Control Theoretic	This group of studies uses hierarchical control-theoretic approaches, which are grounded on hierarchical control theories (Ashby, 1961), to formalize hierarchical relationships (e.g., (Leveson & Stephanopoulos, 2014)). For example, the System-Theoretic Accident Model and Processes (STAMP) considers that socio-technical systems can be modeled as a hierarchical control structure, considering the constraints, control loops, and processes of the system (Leveson, 2004). The System-Theoretic Process Analysis (STPA) (Leveson, N., 2011) is a hazard analysis technique commonly used with STAMP for identifying inadequacies in control systems and determining the causes of hazards; however, less experimentation has been done for applying STPA for organizational factors. If studies used hierarchical control theoretic approaches to depict the process of formalization of their theoretical bases, they were not quantified. Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies that used hierarchical control theoretic.
3. Influence Diagram		Influence diagrams are directed acyclic graph (DAG) structures with no feedback loops, where nodes (representing factors) are connected by edges (arcs) (Harary, 2005). There are different types of influence diagrams, which can be differentiated by the types of nodes (e.g., decision node, chance node) and edges (e.g., informational influence, conditioning influence) (Howard & Matheson, 2005). If the studies that used qualitative influence diagrams to formalize their theoretical bases proceeded to quantification, they used either BBN (e.g., (Vinnem et al., 2012)), which is a quantitative type of influence diagram, Dynamic BBN (e.g., (Ashrafi & Anzabi Zadeh,

Table 2.4 (cont.)

Types of Formalization (d in Figure 2.1)	Formalization Type Description (d in Figure 2.1)
	2017)), Fuzzy Cognitive Maps (Soner et al., 2015), or Agent Based Modeling (ABM) (e.g., (Stroeve et al., 2011)) as their modeling techniques (covered in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using influence diagrams.
4. Path Diagram	Path diagrams are flowcharts used to describe the causal connections between variables using arrows (Wright, 1921), and are commonly used in Path Analysis and SEM (Tarka, 2018). If studies used Path Diagram to depict the process of formalization of their theoretical bases and were also quantified, they used SEM (e.g., (Mirzaei Aliabadi et al., 2018)), SEM and CFA (e.g., (Fenstad et al., 2016)) or DEA (e.g., (Tseng & Lee, 2009)) as their quantitative modeling techniques (covered in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies that used path diagrams.
5. Structured Analysis and Design Technique (SADT)	SADT is a formalization technique where an activity transforms inputs (I) to outputs (O), given the resources (R) and the control/criteria (C) (Heins, 1993; Marca & McGowan, 1987). If studies used SADT to depict the process of formalization of their theoretical bases and were also quantified, they used BBN or statistical inference as their quantitative modeling technique (covered in Section 2.5). SADT is used to formalize organizational causal theories (Mohaghegh et al., 2009), where the inputs include, but are not limited to, information, hardware, raw materials, and people. Hollnagel (2012) added aspects or features to the SADT approach in the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2012), which is used for formalization in one study, that proceeded to quantification using statistical inference (Asadzadeh & Azadeh, 2014). Other studies used the SADT formalization technique and proceeded with quantification (covered in Section 2.5) using BBN (e.g., (Asadzadeh & Azadeh, 2014; Mohaghegh et al., 2009; Trucco et al., 2008)). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using SADT.
6. Vroom's Expectancy Theory	This theory is used to structure relationships between expectancies (E), instrumentalities (I), states (S), and valences (V) (Vroom, 1964). Vroom's theory of expectancy is used for describing the processes of rational decision making of an individual, based on the strength of desire (i.e., valence) for a given outcome (Sharpanskykh, 2007). For example, Vroom's theory is used to formalize the decision-making options around a specific task in an aviation setting (Sharpanskykh & Haest,

Table 2.4 (cont.)

Types of Formalization (d in Figure 2.1)	Formalization Type Description (d in Figure 2.1)
	2015). If studies used Vroom's expectancy theory to depict the process of formalization of their theoretical bases and were also quantified, they used ABM (e.g., (Sharpanskykh, 2007)) as their quantitative modeling techniques (covered in Section 2.5). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using Vroom's expectancy theory.

The review of the literature in this section supports the value of the second perspective (P.III.2) that emphasizes the importance of generating theoretically well-defined models of organizational performance. The review also provides some resolution on the selection of theoretical bases and highlights that theories under Category A.3.2 in Figure 2.1 (Depicting Behavior, Structure & Context) have a higher degree of maturity. As Sutton and Staw (1995) discuss, studies based on a list of factors (A.1 in Figure 2.1) do not reflect adequate theoretical bases. The issues of using a list of organizational factors associated with PSFs in HRA are also explained at the beginning of Section 2.4. Between the other two types of characterization (b in Figure 2.1), theories of actual performance of organizations can more adequately depict the mechanisms "generating behavior in an actual dynamic work context" (Rasmussen, 1997). Because the language of PRA is built on systematic, scenario-based, functional logic based on "scientific, mechanistic calculations" (Bley et al., 1992), theoretical bases for organizational factors should also move toward mechanistic theorization (i.e., descriptions of the rules that govern the production of the dependent variable) (Rios, 2004). Through mechanistic theoretical bases, which can depict those underlying mechanisms of actual organizational behavior, models can become more than abstractions or metaphors that contribute to parsimoniousness and simplicity by "postulating very few elements… to account for largescale, complex phenomena" (Rios, 2004). Theoretical frameworks associated with Category A.3.2 in Figure 2.1 that depict the relationships between factors of behavior, structure, and context are more capable of providing a mechanistic representation of "why" a set of factors are "expected to be strong predictors" (Sutton & Staw, 1995) of risk/safety outcome. For example, theories that represent actual behavior, structure, and context can establish the underlying root causes of the actual dynamics of culture and climate, which "operate as contextual variables… by setting the stage for the development of normative behavior in organizations" (Ostroff et al., 2013). Among the studies in Category A.3.2, those that showed the feasibility of their theoretical bases, by formalizing as well as quantifying them, are the most promising (see Category A.3.2.1.1 in Figure 2.1, and associated studies in (Pence & Mohaghegh, 2019)).

Although there has been progress in studies in Category A.3.2.1.1, Question III remains open as state-of-the-art theories in this category are still far from achieving the necessary level of comprehensiveness that considers the breadth, depth, and detail of underlying organizational root causes of incidents and accidents. As Whetten (1989b) states, a comprehensive and well-defined theory should include all relevant constructs while being careful to exclude factors that have little effect on the model output (Whetten, 1989a). Here we consider Kozlowski and Klein's (2000, p.27) definition of a construct as "an abstraction used to explain an apparent phenomenon" (Kozlowski & Klein, 2000). In the existing studies under Category A.3.2.1.1, there are three main perspectives on the level of abstraction and apparent phenomena: (i) the individual/agent perspective (e.g., (Sharpanskykh, 2012)), (ii) the organizational/global perspective (e.g., (Li et al., 2009)), and (iii) the combinatory viewpoint (e.g., (Mohaghegh & Mosleh, 2009a)). The individual/agent perspective is a bottom-up perspective, as it emphasizes that local behavior of individual agents/actors emerges to create global effects and cannot be analyzed in the aggregate, whereas the organizational/global perspective is a top-down viewpoint as it considers that organizational structures and global factors (e.g., culture) should be theorized as aggregations that influence local effects. The combinatory perspective considers that the theories for organizational factors in risk analysis must consider both the bottom-up and top-down performance influencing factors in order to identify the interdependencies between emergent group and global phenomena. The existing studies in Category A.3.2.1.1 that are associated with type (i), e.g., (Sharpanskykh, 2012), are limited in their explainability of organizational phenomena. The existing studies associated with type (ii), e.g., (Li et al., 2009), arbitrarily mix levels of analysis without theoretical justification and do not ground the model with a clear connection to human performance or human error. Related to the combinatory perspective in Category A.3.2.1.1, the SoTeRiA theoretical framework (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a) requires more development to add details to the important factors at the individual, group, and organizational levels and would benefit from sensitivity analysis to exclude factors (or sub-factors) that have fewer effects on the emergent outcomes.

Further, for all reviewed studies in Category A.3.2.1.1, and in general for all theoretical frameworks for organizational factors, there is an urgent need to focus on the scientific rigor and reproducibility of organizational theories. Schwaninger and Hamann (2005) state that "in theory building, the quality and robustness of the theoretical propositions developed, i.e., "scientific rigour," should be the principal concern… only hypotheses capable of clashing with facts are regarded as scientifically legitimate" (Schwaninger & Hamann, 2005). This concept raises a challenging question: how can the validity of theories of organizational factors connected to PRA be evaluated? The basis for theoretically well-defined models of organizational factors should begin with similar criteria to model-based HRA methods, for instance; (1) content validity, (2) reliability, (3) traceability (transparency) (e.g., reproducibility (Haas, 2016; King, 1995)), (4) validity (construct validity), (5) adaptability/scalability, and (6) usability (Hendrickson et al., 2012; Mosleh et al., 2010). However, these criteria have not yet been analyzed for modeling organizational factors in PRA and require future research. In support of resolving Question III, the authors plan to conduct research on the many multidisciplinary approaches of theory-building (e.g., (Chermack, 2007; Corbin & Strauss, 2008; Glaser, 1992; Sterman, 2000; Weed, 2005; Weick, 1989)) to address the open issues associated with comprehensiveness and validity of theoretical bases of organizational factors.

2.5. (QUESTION IV) WHAT METHODOLOGICAL BASES ARE NEEDED FOR THE EXPLICIT INCORPORATION OF ORGANIZATIONAL FACTORS INTO PRA?

As Figure 2.1 shows, the existing organizational theoretical frameworks that are used for safety analysis are grouped as quantified or not quantified (e in Figure 2.1). If quantified, their methodological bases of quantification are analyzed in this section. As stated in Section 2.1, the quantification of organizational theoretical frameworks requires the development of appropriate techniques (Principles IV in Table 2.1) including modeling and measurement techniques. This section covers the ongoing debate on the required modeling techniques. A discussion on measurement techniques is available in (Pence et al., 2020).

The two perspectives that have contributed to the ongoing debate regarding the required modeling techniques for the explicit incorporation of organizational factors into PRA are:

- (P.IV.1) PRA techniques (ET and FT) are static; thus, it is not possible to quantify the influence of organizational factors, which are highly dynamic (e.g., considering feedback loops and delays in organizational performance), on risk/safety by explicitly incorporating organizational factors into PRA scenarios.
- (P.IV.2) Combining appropriate techniques with PRA FTs/ETs could generate integrated modeling techniques, capable of quantifying organizational theoretical frameworks that are explicitly connected to PRA elements, leading to the quantification of the effects of organizational factors on risk/safety.

The first perspective (P.IV.1) uses the static nature of modeling techniques in PRA as a justification for the impossibility of analyzing the effect of highly dynamic organizational factors on risk/safety (through explicitly connecting them with PRA scenarios); however, recent progress in simulation-based PRA (Siu, 2019), simulation-based HRA (e.g., (Diaconeasa & Mosleh, 2018)), and Integrated PRA (I-PRA) (Bui, Ha et al., 2019a; Mohaghegh et al., 2013; Sakurahara et al., 2013b;

Sakurahara, T. et al., 2017; Sakurahara, T. et al., 2018; Sakurahara, Tatsuya et al., 2018a; Sakurahara et al., 2014; Sakurahara et al., 2015) reject the validity of the first perspective (P.IV.1).

I-PRA is an example of an integrated modeling technique (relevant to the concept of the integrated modeling technique highlighted in the second perspective (P.IV.2)) that is used for the incorporation of physical failure mechanisms (Sakurahara et al., 2013a; Sakurahara, Tatsuya et al., 2017; Sakurahara, T. et al., 2018; Sakurahara et al., 2014; Sakurahara et al., 2015) The current applications of I-PRA not only have generated the possibility of incorporating the dynamic nature of underlying physical phenomena but also their unified computational platform has facilitated the treatment of dependent failures and CCFs (Sakurahara, Tatsuya et al., 2018b)). Another value of I-PRA is the explicit incorporation of dynamic interactions between physical failure mechanisms and human performance into PRA (Bui et al., 2017; Bui, H. et al., 2019; Sakurahara, T. et al., 2018; Sakurahara et al., 2019a). Pence et al. (2020) demonstrated I-PRA for the incorporation of organizational factors (Pence et al., 2020).

As Mohaghegh et al., (2009) state, the intention of integrated approaches is to combine appropriate modeling techniques, capable of capturing complex interactions of organizational causal factors within their possible ranges of variability and across different levels of analysis, to quantify the theoretical organizational frameworks and to integrate them with the PRA ETs/FTs in order to analyze the effects of organizational factors on risk/safety. To further evaluate the second perspective (P.IV.2) and to analyze the characteristics and types of modeling techniques that are needed to be integrated for quantifying organizational theoretical frameworks associated with risk/safety analysis, this paper conducts a categorical review of the existing studies (from 2008 to 2018) and evaluates their modeling techniques. The review in this section summarizes the literature of modeling techniques and categorizes the existing studies (Figure 2.2). The review does not include studies before 2008, but some of them are used to define the categorization schema. The scope of review is not limited to PRA studies; instead, a broader review is conducted of existing cross-disciplinary studies, which evaluates the effects of organizational factors on safety, in general, is conducted to shed more light on future research needs.

In this review, the modeling technique basis (a in Figure 2.2) in each study is classified by its type of characterization (b in Figure 2.2), type of sub-characterization (c in Figure 2.2), and operationalization techniques (d in Figure 2.2). Table 2.5 summarizes the descriptions of the types of characterization (b) highlighted in Figure 2.2, and a complete list of associated studies is available in the supplementary data (Pence & Mohaghegh, 2019) for this paper.

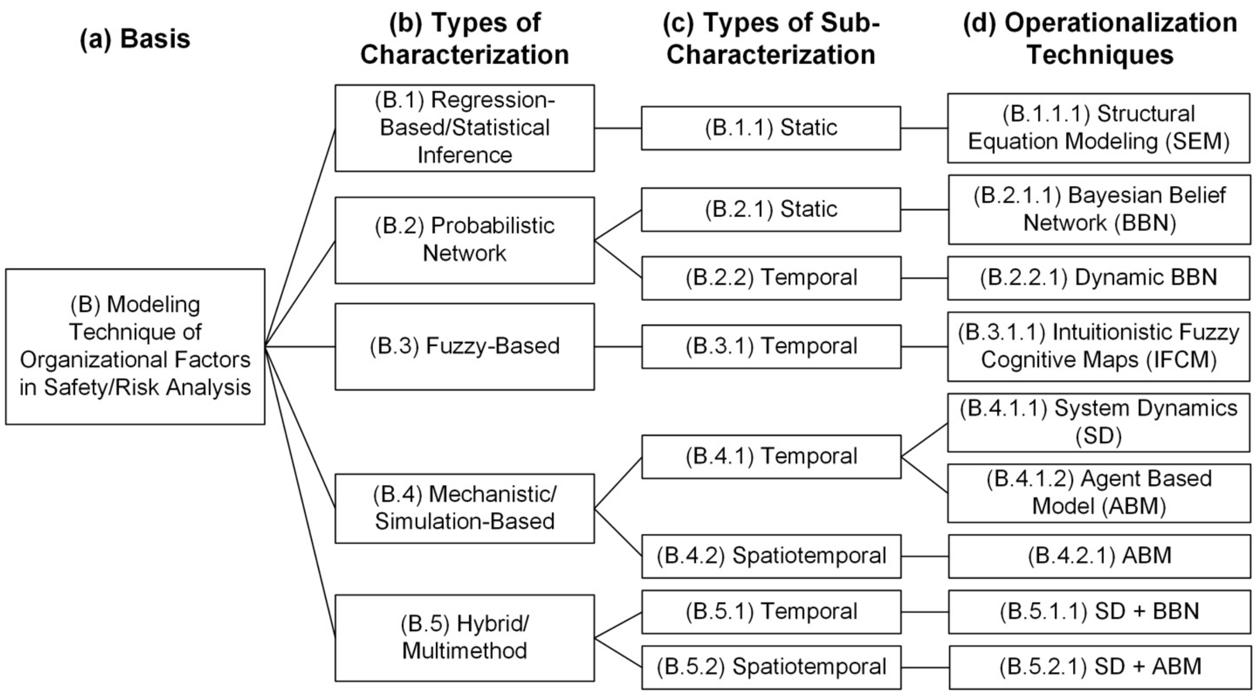

Figure 2.2: Categorization of existing studies (from 2008 to 2018) with respect to their bases for modeling techniques

Table 2.5: Descriptions of Types of Characterization (b in Figure 2.2)

Types of Characterization (b in Figure 2.2)	**Descriptions of Characterization Type (b in Figure 2.2)**
(B.1) Regression-Based/Statistical Inference	The aim of techniques under this type of characterization is to evaluate relationships using statistical analyses of actual data to distinguish causation from spurious correlation (Simon, 1954). The process involves defining a set of variables and their relationships, then testing all of the relations simultaneously. This is practiced by applying various techniques such as Path Analysis (Wright, 1934), SEM (McLntosh & Gonzalez-Lima, 1994), and Confirmatory Factor Analysis (CFA) (Mueller & Hancock, 2001). Despite some differences among these techniques, the underlying concept is that the analyst calculates the covariance among the variables in a proposed model (using the actual data) and compares it with the expected covariance (the restriction that the modeler places). The comparison indicates to what extent the model fits the actual data. As Figure 2.2 shows, the regression-based/statistical inference techniques are static, i.e., there is no explicit inclusion of time in their governing equations. There are a variety of operationalization techniques in the existing studies associated with regression-based/statistical inference, which are summarized under Category B.1.1.1 in

Table 2.5 (cont.)

Types of Characterization (b in Figure 2.2)	Descriptions of Characterization Type (b in Figure 2.2)
	(Pence & Mohaghegh, 2019). Since the underlying principle of these techniques is the same, and in order to avoid the complexity of the figure, Figure 2.2 only includes SEM as a representative technique.
(B.2) Probabilistic Network	The dominant probabilistic technique, used in the reviewed studies, is Bayesian Belief Network (BBN) also known as Bayesian Networks, Belief Nets, Causal Nets, or Probability Nets. BBNs "are directed acyclic graphs in which the nodes represent propositions (or variables), the arcs signify direct dependencies between the linked propositions, and the strengths of these dependencies are quantified by conditional probabilities" (Pearl, 1986). The use of BBNs in safety/risk analysis has grown significantly in the past 30 years. The supplementary data (Pence & Mohaghegh, 2019) for this paper includes studies (from 2008 to 2018) that use BBN for analyzing the effects of organizational factors on safety; however, for a general review of BBN applications in HRA, readers are referred to (Mkrtchyan et al., 2015). As Figure 2.2 shows, BBN (B.2.1.1) is categorized as a static probabilistic technique, while Dynamic BBN (DBN) (B.2.2.1) is a temporal/dynamic probabilistic technique. Dynamic BBN applies the same concept as BBN but includes the dimension of time (Dean & Kanazawa, 1989). A DBN can dynamically model probability distributions over semi-infinite collections of random variables, without changing the network over time (Murphy & Russell, 2002). Arcs/edges within one slice of time are considered instantaneous causation, and in DBN, arcs can skip across slices of time, meaning that parent nodes can be in the same time slice or in a previous time slice to the child node (Murphy & Russell, 2002).
(B.3) Fuzzy-Based	Another dynamic/temporal modeling technique, utilized in the existing studies, is Intuitionistic Fuzzy Cognitive Maps (IFCM) (Iakovidis & Papageorgiou, 2011; Papageorgiou & Iakovidis, 2009) (B.3.1.1)). Fuzzy modeling techniques leverage a "nonlinear mapping of an input data (feature) vector into a scalar output (i.e., it maps numbers into numbers)" (Mendel, 1995) using fuzzy set theory and fuzzy logic (Klir & Yuan, 1996). A fuzzy set is "a class of objects with a continuum of grades of membership" (Zadeh, 1965), and fuzzy logic is the coordination of mathematical and/or imprecise or ambiguous information (i.e., nonlinear models) (Ross, 2005). Fuzzy modeling techniques map crisp/precise inputs into crisp outputs using four components: rules, fuzzifier, inference engine, and defuzzifier (Mendel, 1995; Ross, 2005). Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using fuzzy-based method.

Table 2.5 (cont.)

Types of Characterization (b in Figure 2.2)	Descriptions of Characterization Type (b in Figure 2.2)
(B.4) Mechanistic/ Simulation-Based	The mechanistic/simulation-based approaches that are used in the existing studies are categorized into temporal/dynamic and spatiotemporal, where both time and space are explicitly included in the governing equations of the model. SD (B.4.1.1) is a dynamic simulation-based technique that has been used by several existing studies (e.g., (Gajdosz et al., 2013)). SD is used for modeling nonlinear behavior and dynamics of complex systems considering stocks, flows, feedback loops, time delays, table functions and a set of equations (Forrester, 1994; Forrester, 1997; Forrester, 2007; Sterman, 2000). Another technique under the mechanistic and simulation-based method is ABM that has either temporal (B.4.1.2) (e.g., (Sharpanskykh & Stroeve, 2011)) or spatiotemporal (B.4.2.1) (e.g., (Lu et al., 2016)) properties. This modeling technique is based on a set of equations or rules that govern the behavior of individual agents that create emergent observables (Grimm & Railsback, 2013). ABMs have autonomous multi-level agents that can have a discrete number of states varying over time and space, depending on the rulesets employed in the model. Supplementary data (Pence et al., 2019a) for this paper provides a complete list of existing safety studies using mechanistic/simulation-based approaches.
(B.5) Hybrid/ Multimethod	Hybrid/multimethod techniques refer to the cases, where a combination of two different types of methods is used to get benefit from diverse modeling technique capabilities. For example, some studies (e.g., (Mohaghegh, 2010a)) used a combination of SD and BBN which is a temporal method, and another study (e.g., (Liang et al., 2018)) integrated ABM and SD, which is a spatiotemporal method.

Although the reviews of literature in this section support the value of perspective (P.IV.2), there are still some open questions regarding the selection of modeling techniques that need to be integrated with PRA. The review highlights that the choice of modeling techniques highly depends on (i) the amount of data, (ii) amount of detailed knowledge about the phenomena, and (iii) the nature of underlying theoretical bases. Regression/statistical inference techniques require vast amounts of data, especially when the scope of organizational processes/factors increases. BBN has several advantages as a modeling technique for organizational factors: (a) it is a suitable technique where objective data are lacking and the use of expert opinion and soft evidence is required, (b) it can be linked mathematically to classical PRA techniques (ET and FT), and (c) has several of formalization techniques that are mentioned in Section 2.4, e.g., SADT and Influence Diagram, which can be converted to BBN (Mohaghegh et al., 2009). However, the static nature of BBN could generate limitations for modeling organizational factors.

The literature review in this section highlights the importance of selecting a modeling technique that can capture the temporal aspects of organizations. Mohaghegh et al., (2009) state that dynamic effects of organizations must be explicitly modeled to capture the (1) delay in influences, (2) temporal changes in factors and links (e.g. temporal cycles) (e.g., entrainment (Ancona & Chong, 1992)), (3) composite time effects (e.g., time scale variation and feedback loops), or (4) the changes in direction and strength of links as functions of time. As discussed in Section 2.2, organizational factors are latent factors established prior to an accident with the potential to influence human error or equipment failure. For example, Julius et al., (2002) state that "it has been noted that (organizational) changes may cause delayed effects with the major effect occurring after two years" (Julius et al., 2002). From this perspective, the dynamics of organizations are not similar to the dynamic tasks in HRA (e.g., (Swain & Guttmann, 1983), but instead are related to the underlying context, structure, and behavior of the organization over a longer timescale than the PRA mission time. With respect to the "latency" of organizational failures, the calibration of the timescale of organizational factors remains an ongoing area of research.

Although DBNs "allow feedback loops and recurrent regulatory structures to be modeled while avoiding the ambiguity about edge directions common to static Bayesian networks" (Grzegorczyk & Husmeier, 2009), they have some deficiencies. For example, the transient modeling approach in DBNs has limitations for modeling long-term time scales (e.g., lifecycle), because of the computational complexity generated by large causal models. Further, existing DBN tools are limited in their ability to control the granularity of multiple timescales, which presents challenges in supporting the multi-level analysis of organizational factors. With respect to IFCM techniques, they are limited by a lack of time delay between nodes and cannot handle more than one relationship between nodes (Papageorgiou & Salmeron, 2013).

On the other hand, the temporal methods that are mechanistic/simulation-based (i.e., B.4.1.1, B.4.1.2, and B.4.2.1 in (Pence & Mohaghegh, 2019)) are limited in their ability to be connected with PRA elements. Besides, the modelers sometimes do not have detailed knowledge regarding all elements of organizational mechanisms associated with safety/risk and this makes using a purely mechanistic/simulation-based modeling technique quite challenging or impossible. In this case, hybrid modeling techniques, or multimethod techniques, Categories B.5.1.1 and B.5.2.1 in (Pence & Mohaghegh, 2019), provide the most desirable techniques for the explicit incorporation of organizational factors into safety/risk analysis. For example, Mohaghegh proposed an integration of SD and BBN (Category B.5.1.1), where BBN is used for those parts of the organizational phenomena that enough information is not available to build a simulation-based model using SD and there are uncertainties associated with those parts/aspects of the phenomena (Mohaghegh et al., 2009).

Another type of mechanistic/simulation-based technique is ABM (Category B.4.1.2 in (Pence & Mohaghegh, 2019)) which can depict the temporal dimension of an organization. A recent study (Bui, Ha et al., 2019b) has connected an ABM-based model of human performance (for the external control room of power plants) to PRA; however, ABM models of organizational factors have not yet been connected to PRA elements. Where models that use SD deal with continuous processes, ABMs deal mostly in discrete time (Borshchev & Filippov, 2004). For ABM, to approach real-time analysis, discretization would require an infinite number of time steps, creating a tradeoff between numerical accuracy and simulation speed (Barnes & Chu, 2015). One of the modeling benefits of ABM is the possibility of depicting the spatial dimension, in addition to time (Category B.4.2.1 in (Pence & Mohaghegh, 2019)). The authors have begun to theorize the spatial dimension of human and organizational factors in socio-technical risk analysis (Pence & Mohaghegh, 2015); however, the criticality of explicitly modeling space for organizational safety/risk analysis is still an open area of debate.

Another criterion that influences selecting a specific type of mechanistic/simulation-based modeling technique relates to the nature of theoretical bases. As discussed in Section 2.4, there are three theoretical perspectives associated with theories of actual behavior, structure and context, the (i) individual/agent perspective, (ii) organizational/global perspective, and (iii) combinatory viewpoint. The individual/agent perspective can be better operationalized using ABM techniques, which are decentralized or bottom-up models (i.e., global system dynamics are not defined) (Borshchev & Filippov, 2004), where individual agents monitor variables locally, so they are not averaged over time (Parunak et al., 1998). For the organizational/global perspective, SD is a better candidate modeling technique as it can consider global structural dependencies and their associated data and equations (Borshchev & Filippov, 2004), which result in an averaging of critical system variables, assumptions of homogeneity, and lumping parameters (Parunak et al., 1998).

From the combinatory viewpoint, hybrid/multimethod techniques are better candidates as they allow the modeler to use different modeling techniques for different aspects of organizational performance. For example, the hybrid category of SD and ABM (Category 5.2.1 in (Pence & Mohaghegh, 2019)) enables the combination of individual (i.e., bottom-up) and system-level (i.e., top-down) dynamics, where individual processes can change a system state, alter system information, and in turn affect individual agents in a continuous cycle of information exchange (Liang et al., 2018). Hybrid/Multimethod modeling techniques allow for the combination of multiple theoretical perspectives through the integration of probabilistic, rule-based behavior, and equation-based modeling techniques. Each combination of modeling techniques (e.g., SD and BBN, SD and ABM), can have a variety of integrated designs (Swinerd & McNaught, 2012; Vincenot et al., 2011; Wallentin & Neuwirth, 2017), and therefore, future research is needed to explore the accuracy and efficiency of hybrid/multimethod configurations, especially the challenges associated with their uncertainty quantification and computational demand.

2.6. CONCLUDING REMARKS

This paper is the product of a line of research by the authors to explicitly incorporate organizational factors into Probabilistic Risk Assessment (PRA)/Probabilistic Safety Assessment (PSA). In this paper, "explicit" incorporation of organizational factors refers to the model-based or mechanistic integration of organizational performance with PRA. The ideal goals of explicit incorporation of organizational factors into PRA are to; (a) make risk assessments more accurate in order to avoid underestimating or overestimating risk, and (b) improve risk management and prevention strategies by identifying and ranking critical organizational factors based on their influences on the technical system (e.g., Core Damage Frequency (CDF) in NPPs) and their impacts on Risk-Informed Performance-Based Applications (RIPBAs). Plant-specific, configuration-specific RIPBAs leverage the investment in developing and maintaining PRA by utilizing risk information and performance data in operational decision making to help create cost savings for NPPs while maintaining safety. Risk information and performance data are used in decision-making for operational flexibility, efficiency, and strengthening regulatory-plant cooperation. Explicit models of organizational factors could be incorporated into RIPBAs such as Risk-Informed Asset Management (RIAM) (Liming & Kee, 2002), Risk-Informed Business Modeling (Liming & Grantom, 2000), and Risk-Informed Project Prioritization (Koc et al., 2009), and other RIPBAs (e.g., (Liming, 2015)). In RIAM, for example, organizational factors can be used in the development of probabilistic models for corporate management decisions related to change management, asset allocation for plant improvements, and plant-wide maintenance planning.

This review article presented a discourse on the incorporation of organizational factors into PRA and made the following contributions: (1) identifying four key open questions associated with this topic; (2) framing ongoing debates by considering differing perspectives around each question; (3) offering a thorough review and categorization of existing studies on this topic to justify the selection of each question and to analyze the challenges related to each perspective by discussing state-of-the-art approaches in practice and in research (for supplementary data of the literature review see (Pence & Mohaghegh, 2019)); and (4) highlighting the directions of research that need to be taken in order to reach a final resolution for each question. The following summarizes Questions I to IV, their associated perspectives, the conceptual reasoning as to why the risk analysis community may not have come to conclusions for these key questions, the challenges associated with each, and the directions of research that need to be taken in order to reach a final resolution:

(Question I) How significant are the contributions of organizational factors to accidents and incidents?

- Perspective (P.I.1): Organizational factors are not major contributors to incidents or accidents. The major contributors are equipment failures, primarily associated with equipment design flaws rather than due to maintenance program/organizational deficiencies.
- Perspective (P.I.2): Organizational factors are reasonable contributors to incidents and accidents, but there are many barriers between them and technical system failures. There are latent failures associated with organizational factors, making the detection and control of organizational deficiencies challenging.
- Perspective (P.I.3): Organizational factors are significant contributors to accidents and incidents.

Based on the review of literature, it can be concluded that the first perspective (P.I.1) is not valid, but both the second perspective (P.I.2) and third perspective (P.I.3) need further analysis to be accurately stated. Although the existing studies acknowledge the influence of organizational factors on incidents/accidents, they could not generate information on the risk importance measures of organizational contributing factors (i.e., the factors under the control of the operating organization) versus those for non-organizational contributors (i.e., those beyond the control of the operating organization, such as flaws in equipment design and material properties). Therefore, it would be challenging to make a solid conclusion on the degree of significance of organizational factors based on these quantitative studies.

In order to reach a final resolution on Question I, there is a need for the explicit incorporation of organizational factors into risk models to help conduct risk importance ranking of underlying organizational factors. The resolution of Question I also requires the development of theoretical causal frameworks that (i) help generate an explicit connection of organizational root causes to risk models and (ii) can be leveraged to achieve a higher resolution of data collection for organizational factors contributing to safety-related events, resulting in improved root cause analyses. Question III analyzed the needs associated with the theoretical bases of incorporating organizational factors into risk models. Finally, the resolution of Question I requires methodologies for conducting importance ranking, as well as techniques for categorizing, coding, and counting the underlying organizational factors in industry event data. Question IV evaluated the methodological bases that are needed for this topic.

(Question II) How critical is the explicit incorporation of organizational factors into PRA with respect to improving risk assessment?

- Perspective (P.II.1): Although the incorporation of organizational factors into PRA could be beneficial for risk management, it is not critical for risk assessment because the effects of organizational factors are already implicitly (or explicitly through some of the external

Performance Shaping Factors (PSFs) in HRA) considered in PRA scenarios through both human error and equipment reliability data and assumptions.

- Perspective (P.II.2): Explicit incorporation of organizational factors into PRA is critical for risk assessment (in addition to risk management) because this explicit incorporation can help generate a more realistic estimation of human error and equipment failure probabilities.

The first perspective (P.II.1) cannot be accepted because the degree of inclusion of organizational factors in current PRAs and HRAs may not be adequate for a realistic risk assessment for the following reasons: (a) organizational PSFs in current HRAs are quantified using expert judgment, generating challenges for the realistic estimation of HFE probabilities, (b) without explicit incorporation of organizational factors into HRA, treatment of dependencies among PSFs is limited, and (c) implicit incorporation of organizational factors would lead to overreliance on historical generic data for probability estimations and could not adequately reflect (i) plant-specific information or (ii) organizational changes in estimating HFE or equipment basic events (specifically CCBE) probabilities. Although the abovementioned deficiencies highlight the value of explicit incorporation of organizational factors for improving risk assessment and support the second perspective (P.II.2), a final resolution to Question II can only be achieved when research is capable of quantitatively identifying "how" critical is the explicit incorporation of organizational factors with respect to the realism of the estimated risk from PRA. This can be done by comparing the estimated risk in a selected scenario from the current classical PRA model to that of a PRA model that has an explicit consideration of key organizational factors. This requires advancing a research agenda for the explicit incorporation of organizational factors.

(Question III) What theoretical bases are needed for the explicit incorporation of organizational factors into PRA?

- Perspective (P.III.1): For the explicit incorporation of organizational factors into PRA, the need for developing a theoretical model of organizational performance should not be overemphasized.
- Perspective (P.III.2): Explicit incorporation of organizational factors into PRA requires theoretically well-defined models of organizational performance.

The first perspective (P.III.1) cannot be fully accepted because overly simplified models are (1) incapable of modeling the underlying organizational mechanisms, (2) not adequately capturing dependencies among underlying organizational mechanisms, and (3) over-relying on expert opinion for quantification; therefore, these models have challenges with respect to achieving the ideal goals (listed in Section 2.1) of incorporating organizational factors into PRA. The review of literature in Section 2.4 supports the value of the second perspective (P.III.2), emphasizing the importance of generating theoretically well-defined models of organizational performance, and providing some justification that theories Depicting Behavior, Structure & Context (Category A.3.2 in Figure 2.1) have a higher degree of maturity. However, Question III remains open because state-of-the-art theories in this category are still far from achieving the necessary level of comprehensiveness that considers the breadth, depth, and detail of underlying organizational root causes of incidents and accidents. This perspective raises a challenging question: how can the validity of theories of organizational factors connected to PRA be evaluated? The basis for theoretically well-defined models of organizational factors should at least begin with similar criteria to model-based HRA methods, for instance; (1) content validity, (2) reliability, (3) traceability (transparency) (e.g., reproducibility), (4) validity (construct validity), (5) adaptability/scalability, and (6) usability. However, these criteria have not yet been analyzed for modeling organizational factors in PRA and require future research.

Establishing appropriate theoretical bases for organizational factors in safety/risk scenarios will help (1) reduce the overreliance on data that do not adequately reflect plant-specific information on organizational changes in the estimation of human failure events or equipment reliability, (2) establish a scientific connection between cognitive-based HRA and underlying organizational factors, and (3) use the underlying pathways of causality in root cause analysis to uncover deeper layers of deficiencies (e.g., managerial factors as root cause contributors) that can be used in RIPBAs.

(Question IV) What methodological bases are needed for the explicit incorporation of organizational factors into PRA?

- Perspective (P.IV.1): PRA techniques (ET and FT) are static; thus, it is not possible to quantify the influence of organizational factors, which are highly dynamic (e.g., considering feedback loops and delays in organizational performance), on risk/safety by explicitly incorporating organizational factors into PRA scenarios.
- Perspective (P.IV.2): Combining appropriate techniques with PRA FTs/ETs could generate integrated modeling techniques, capable of quantifying organizational theoretical frameworks that are explicitly connected to PRA elements, leading to the quantification of the effects of organizational factors on risk/safety.

Recent progress in simulation-based PRA, simulation-based HRA, and Integrated PRA (I-PRA) can be used to reject the validity of the first perspective (P.IV.1). The literature review in Section 2.5 supports perspective (P.IV.2); however, there are still some open questions regarding the selection of modeling techniques that need to be integrated with PRA. The selection of an appropriate technique highly depends on (i) the amount of data, (ii) amount of detailed knowledge about the phenomena, and (iii) the nature of underlying theoretical bases. For example, techniques such as BBN have been demonstrated as suitable for mathematically linking to classical PRA, but their static nature could generate limitations for modeling organizational factors. Therefore, it is important to select a modeling technique that can capture the temporal aspects of organizations. Mechanistic/simulation-based are limited in their ability to be connected with PRA elements, especially when modelers do not have detailed knowledge regarding all elements of organizational mechanisms associated with safety/risk. In this case, hybrid modeling techniques, or multimethod techniques, Categories B.5.1.1 (integration of SD and BBN) and B.5.2.1 (integration of SD and ABM) in (Pence & Mohaghegh, 2019), provide the most desirable techniques for the explicit incorporation of organizational factors into safety/risk analysis because they allow the modeler to use different modeling techniques for different aspects of organizational performance. One of the modeling benefits of ABM is the possibility of depicting the spatial dimension, in addition to time; however, the criticality of explicitly modeling space for organizational safety/risk analysis is still an open area of debate.

Another criterion that influences selecting a specific type of mechanistic/simulation-based modeling technique relates to the nature of theoretical bases. Hybrid/Multimethod modeling techniques also allow for the combination of multiple theoretical perspectives through the integration of probabilistic, rule-based behavior, and equation-based modeling techniques. Each combination of modeling techniques can have a variety of integrated designs, and therefore, future research is needed to explore the accuracy and efficiency of hybrid/multimethod configurations, especially the challenges associated with their uncertainty quantification and computational demand. Modeling techniques for organizational factors require further advancement in order to address: (a) what temporal fidelity is necessary for organizational performance models? (b) Is spatial fidelity important for understanding organizational contributions to risk? (c) how practical (i.e., computationally expensive) are predictive modeling methods? (d) how can organizational performance models be validated? Forthcoming publications by the authors will explore these and other open questions discussed in this paper.

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CHAPTER 3: DATA-THEORETIC METHODOLOGY AND COMPUTATIONAL PLATFORM TO QUANTIFY ORGANIZATIONAL FACTORS IN SOCIO-TECHNICAL RISK ANALYSIS[1]

ABSTRACT

Organizational factors, as literature indicates, are significant contributors to risk in high-consequence industries. Therefore, building a theoretical framework equipped with reliable modeling techniques and data analytics to quantify the influence of organizational performance on risk scenarios is important for improving realism in Probabilistic Risk Assessment (PRA). The Socio-Technical Risk Analysis (SoTeRiA) framework theoretically connects the structural (e.g., safety practices) and behavioral (e.g., safety culture) aspects of an organization with PRA. An Integrated PRA (I-PRA) methodological framework is introduced to operationalize SoTeRiA in order to quantify the incorporation of underlying organizational failure mechanisms into risk scenarios. This research focuses on the Data-Theoretic module of I-PRA, which has two sub-modules: (i) DT-BASE: developing detailed causal relationships in SoTeRiA, grounded on theories and equipped with a semi-automated baseline quantification utilizing information extracted from academic articles, industry procedures, and regulatory standards, and (ii) DT-SITE: conducting automated data extraction and inference methods to quantify SoTeRiA causal elements based on site-specific event databases and by Bayesian updating of the DT-BASE baseline quantification. A case study demonstrates the quantification of a nuclear power plant's organizational "training" causal model, which is associated with the training/experience in Human Reliability Analysis, along with a sensitivity analysis to identify critical factors.

3.1. INTRODUCTION AND STATEMENT OF OBJECTIVES

Organizational factors can either help or hinder safety performance (Reason, 1990), and they have been identified as significant contributors to incidents (NRC, 2008) and major accidents (CSB, 2014; IAEA, 1992, 2014). Probabilistic Risk Assessment (PRA) (NRC, 1975), a formal methodology for estimating risk emerging from the interactions of equipment failure and human error, utilizes Human Reliability Analysis (HRA) (Mosleh, A. & Chang, 2004; Swain & Guttmann, 1983) for modeling and quantifying human error in risk scenarios. Despite the overwhelming evidence from the fields of organizational psychology and management science that strongly relates organizational factors such as safety culture, leadership style and priorities, and reward practices to safety, injuries, and accidents (Beus

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et al., 2010; Haber, S.B. et al., 1990; Haber, S. et al., 1991; Hofmann & Morgeson, 1999; Nahrgang et al., 2011; Zohar & Luria, 2005), organizational performance models are not explicitly incorporated into HRA or PRA (Forester et al., 2009; Ghosh & Apostolakis, 2005). HRA provides an estimation of individual human error based on the states of internal Performance Shaping Factors (PSFs) (e.g., fatigue, cognitive mode) and external PSFs (e.g., physical work environment, teamwork, managerial and organizational factors) (Swain & Guttmann, 1983). The external organizational PSFs in HRA techniques are represented at an abstract level of analysis that does not "explicitly" consider underlying mechanisms. "Explicit" incorporation/ consideration of underlying mechanisms refers to the model-based integration of organizational performance and processes with HRA to analyze the effects on human error due to changes in underlying organizational contributing factors. It has been argued that "all PSFs should be looked at as organizational factors since it is an organization that could maintain or modify conditions that affect all of these factors" (Laumann & Rasmussen, 2016). However, due to the complexity of organizational performance modeling, the integration of organizational mechanisms with PSFs of HRA has been a challenging topic. This paper is a product of a line of research to incorporate organizational factors into HRA and PRA to (1) explicitly assess the risk due to specific organizational weaknesses, (2) find and rank the critical organizational root causes of failure, which help efforts to take effective corrective action, and (3) avoid the possibility of underestimating the risk associated with human error. This figure provides a literature review of studies in the field of risk analysis, specifically associated with PRA, that evaluated the influence of organizational factors on technological system risk and safety.

In the last two decades, many researchers have studied organizational factors in the context of risk analysis by evaluating; their role in historical incidents and accidents (Ghosh & Apostolakis, 2005; Kontogiannis & Malakis, 2012), their classification (Haber, S.B. et al., 1990) and use in regulatory applications (Marcus et al., 1990), their implicit consideration in existing HRA guidance (Alvarenga et al., 2014; Laumann & Rasmussen, 2016; Li et al., 2012), their application in frameworks for equipment reliability (Øien, Knut, 2001) considering multi-level phenomenology (Modarres et al., 1992; Vinnem et al., 2012), and their potential use as performance indicators (EPRI, 2001; Nichols & Marcus, 1990). In Mohaghegh's review of existing theoretical frameworks and quantitative techniques related to the incorporation of organizational factors into risk models, she categorizes them in two generations (Mohaghegh, 2007; Mohaghegh, 2009; Mohaghegh, 2010a, 2010b; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2007; Mohaghegh & Mosleh, 2009a, 2009b). The nature of first-generation theories and quantitative techniques is characterized in terms of "deviations from normative performance" (Rasmussen, 1997). For example, Reason's Swiss Cheese Model (Reason, 1990, 1997) is a well-known metaphor for describing the organizational effects on the occurrence of accidents. According to Reason, the accident sequence starts with failed or missing defenses in the organization (e.g., managerial decisions), and these defects create latent conditions that are transmitted along organizational pathways. Similarly, there have been several static quantitative frameworks, based on this theoretical concept, that aim at modeling and quantifying the impact of organizational factors on system risk. Examples are WPAM (Davoudian et al., 1994a, 1994b), SAM (Paté-Cornell & Murphy, 1996) and similar models (Øien, Knut, 2001), Omega Factor Model (Galán et al., 2007; Mosleh, Ali & Golfeiz, 1999), ASRM (Luxhøj, 2004), ORIM (Øien, Knut, 2001), I-Risk (Papazoglou et al., 2003), and Causal Modeling of Air Safety (Roelen et al., 2003). The second-generation approaches to develop organizational models for risk analysis frameworks focus on modeling the 'actual behavior' of organizations. These approaches have been evolving and attempt to represent the underlying organizational mechanisms of accidents. On the theoretical side, Rasmussen (Rasmussen, 1997) cites the self-organizing nature of High Reliability Organizations (Rochlin et al., 1987) and Learning Organizations (Senge, 1990; Weick, K. & Sutcliffe, 2001) as concepts useful in analyzing the managerial and organizational influences on risk. The Normal Accident Theory (Perrow, 1984), which views accidents caused by interactive complexity and close coupling, can also be considered in the second generation of theories for organizational safety. Second-generation quantitative techniques primarily address the dynamic aspects of organizational influences. For example, Cooke (2004), Leveson (2004), and Marais (2006) use the System Dynamics approach (Forrester, 1961; Sterman, 2000) to describe the dynamics of organizational safety, but these models do not include detailed PRA-style models of the technical system (Cooke, D.L., 2004; Leveson, 2004; Marais et al., 2006; Sterman, 2000). Yu et al. (2004) also use a System Dynamics approach to incorporate the effects of organizational factors into nuclear power plant PRA models (Yu et al., 2004). The interconnection between PRA and System Dynamics, however, is not established.

More recently, concepts from resilience engineering have been added to the second-generation socio-technical models. While the concept of resilience is beneficial for describing the adaptive nature of organizations (Vogus & Sutcliffe, 2007), the benefits of resilience compared to a reliability approach in risk analysis have not yet been adequately analyzed (Hollnagel et al., 2013). The theoretical relationships between resilience and organizational safety in high-consequence industries remain underdeveloped and require further research; however, it should be acknowledged that various factors (e.g., capabilities of organizations (Dekker, 2014)) from resilience engineering can be useful to enhance organizational safety methods (Haavik et al., 2016; Øien, K et al., 2010). Recent studies in safety and risk analysis continue to emphasize the need for organizational modeling techniques, with a systematic perspective, that can include a broader set of influencing factors (IAEA, 2014) and is capable of capturing an organization's adaptive performance, emergent phenomena, and success paths (Hollnagel, 2014).

Integrating concepts from multiple disciplines, Mohaghegh introduced a set of thirteen principles (Table 3.1) for the field of organizational risk analysis or Socio-Technical Risk Analysis (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a). These principles are distributed in the following four categories; Categories I, II, and III relate to theory building, and Category IV relates to developing methodological techniques. In summary, these principles address two requirements for incorporating emergent organizational safety behavior into PRA: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links; (ii) the 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.

Table 3.1: Socio-Technical Risk Analysis Principles (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a)

Categories	Principles
I. Designation & Definition of Objectives	(A) Unknown-of-Interest
	(B) Multidimensional Performance Objectives
II. Modeling Perspective	(C) Safety Performance and Deviation
	(D) Multilevel Framing
	(E) Depth of Causality and Level of Detail
	(F) Model Generality
III. Building Blocks	(G) Basic Unit of Analysis
	(H) Factor Level and Nature
	(I) Factor Selection
	(J) Link Level, Nature, and Structure
	(K) Dynamic Characteristics
IV. Techniques	(L) Measurement Techniques
	(M) Modeling Techniques

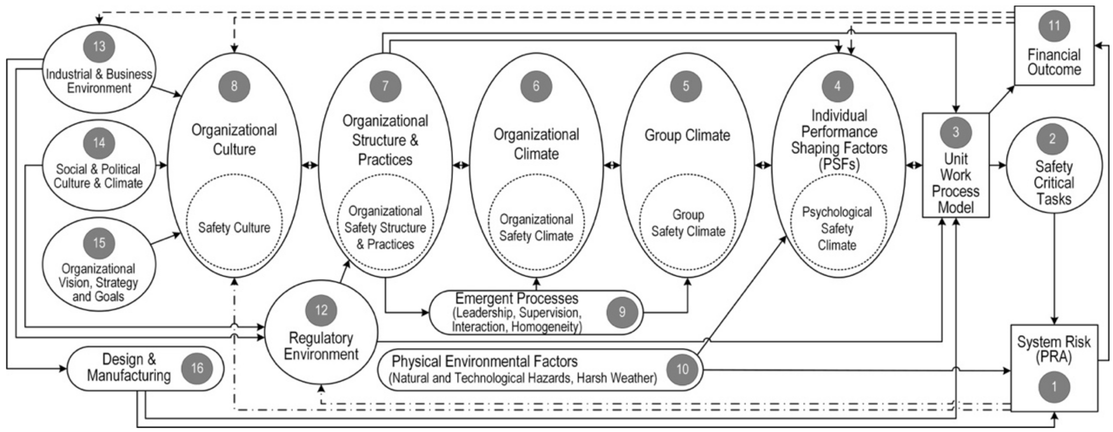

Figure 3.1: Socio-Technical Risk Analysis (SoTeRiA) Theoretical Framework (Mohaghegh, 2007)

With respect to the first requirement, a theoretical framework, called Socio-Technical Risk Analysis (SoTeRiA) (Figure 3.1) (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a), was developed based on the theory-building principles (Categories I, II, and III in Table 3.1) and based on a multi-level organizational performance model developed by Ostroff (Ostroff, Cheri et al., 2013; Ostroff, Cheri et al., 2003). SoTeRiA is a theoretical causal framework for explicitly integrating both the social aspects (e.g., safety culture; Node 8 in Figure 3.1) and the structural features (e.g., safety practices; Node 7 in Figure 3.1) of one organization with technical system PRA (i.e., Node 1 in Figure 3.1). The SoTeRiA framework is further explained in Section 3.2.1, but for more details on the development of SoTeRiA, readers are directed to Refs. (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a).

Operationalization and quantification of SoTeRiA required the development of appropriate techniques (Principles IV in Table 3.1), including "modeling" and "measurement" techniques. With respect to modeling techniques (Principle IV-M), Mohaghegh and Mosleh developed a hybrid approach (Mohaghegh, 2010a; Mohaghegh et al., 2009) by combining a probabilistic method, i.e., Bayesian Belief Network (BBN), and a deterministic/dynamic simulation technique, i.e., System Dynamics, with classical PRA methods, i.e., Event Tree (ET) and Fault Tree (FT), to quantify SoTeRiA. This paper introduces the Integrated PRA (I-PRA) methodological framework (explained in Section 3.2.1 and instantiated in Figure 3.2) that is an advancement of the original work by Mohaghegh and Mosleh (Mohaghegh et al., 2009) and is based on an adaptation of the I-PRA approach which has been already applied for incorporating physical failure mechanisms into PRA for GSI-191 (Mohaghegh, Zahra et al., 2013) and fire PRA (Sakurahara, Tatsuya et al., 2017; Sakurahara et al., 2015).

Measurement techniques (Principle IV-L in Table 3.1) relate to data analytics (i.e., data extraction and interpretation) for the factors and the links in the SoTeRiA framework. Mohaghegh and Mosleh (Mohaghegh & Mosleh, 2007; Mohaghegh & Mosleh, 2009b) highlighted the importance of integrating subjective and objective measurement techniques for SoTeRiA. In the application of SoTeRiA, one of the challenges was the unstructured nature of data for organizational risk analysis. This research develops a Data-Theoretic approach, which is the focus of this paper and builds the data input module of the I-PRA framework. The Data-Theoretic is an approach where "data analytics" are guided by "theory." Theory enhances the accuracy and completeness of "causality" being analyzed from data and helps avoid potentially misleading results from solely data-oriented approaches.

Section 3.2.2 covers the foundation, methodology, and computational platform for the Data-Theoretic approach. The Data-Theoretic approach not only contributes to the development of new measurement techniques for the SoTeRiA framework but also makes theoretical contributions to SoTeRiA. The SoTeRiA framework (Figure 3.1) covers high-level paths of causality while still requiring further theory building to generate more detailed causal factors, sub-factors, and their interactions. The computational platform of the Data-Theoretic approach eases the execution of theory-building principles to expand theoretical details in SoTeRiA. As an example, the Data-Theoretic approach is applied for the organizational training processes of a Nuclear Power Plant (NPP) (Section 3.3), and a theoretical causal model is built and quantified for "training," which is one of the factors related to Node 7 in SoTeRiA (Figure 3.1). The training quality would influence the state of Experience/Training PSF in HRA, and consequently, would affect the risk estimated from the I-PRA framework. The scope of this paper is on one organization, and future work by the authors will address multiple organizations and inter-organizational factors.

3.2. INTEGRATED PROBABILISTIC RISK ASSESSMENT METHODOLOGY FOR SOCIO-TECHNICAL RISK ANALYSIS

The central risk assessment technique used in this research is Probabilistic Risk Assessment (PRA). This systematic risk methodology was originally developed for the nuclear power industry (NRC, 1975) and has grown into a technical discipline with a wide range of applications. In classical PRA, a static PRA logic, consisting of ET and FT (see the site-specific PRA module in Figure 3.2), represents the causal relationships among the Initiating Events (IEs), system failures (e.g., SYS_A, SYS_B), component failures (e.g., basic event "b"), and human failure events (e.g., basic event "a") that can result in undesirable system end states (e.g., core damage in NPPs) (U.S. Nuclear Regulatory Commission, 1983). These static PRA techniques have limitations in their capabilities to account for the dynamic evolution of risk scenarios (Siu, 1994).

To overcome the limitations of classical PRA, dynamic PRA (also referred to as simulation-based PRA) methodologies have been developed (Aldemir, 2013; Hsueh & Mosleh, 1996; Siu, 1994). Although a fully-dynamic PRA may generate more realism in risk modeling, it would not be economically efficient or practical for NPPs in the short term because (i) classical PRA is widely utilized by both the nuclear industry and the regulatory agency and would require a significant amount of time and resources to transition to fully-dynamic PRA, and (ii) the need for reaching the degree of realism that a fully-dynamic PRA could generate has not yet been scientifically justified for either the industry or the regulatory agency. Therefore, as a more feasible short-term alternative, the authors developed the Integrated PRA (I-PRA) methodological framework (Figure 3.2). I-PRA generates a "unified" computational framework to integrate simulation modules of underlying failure mechanisms associated with areas of concern (e.g., fire, seismic) with classical PRA (i.e., logic-based ET, FT). I-PRA is equipped with an interfacing methodology, including uncertainty analysis, Bayesian updating and dependency treatment, to more comprehensively capture information on the relationships between PRA scenarios and the underlying failure mechanisms. For instance, the influences of underlying contributing factors (e.g., material properties, room configuration) on the plant risk metrics (e.g., core damage frequency) are explicitly captured through I-PRA unified platform; hence, the importance measure analysis for the input parameters at the failure mechanism level, more directly related to the design parameters than the PRA basic events, can be performed. Development of a unified computational framework, which seamlessly integrates the plant PRA model with the underlying failure mechanisms, can also improve the treatment of dependent failures in PRA (as discussed in another publication by the authors (Sakurahara, Tatsuya et al., 2018b)). Another advancement of I-PRA is the "explicit" incorporation of interactions between physical failure mechanisms and human performance (Bui et al., 2017; Sakurahara, Tatsuya et al., 2018a). For example, a fire-induced scenario at NPPs is a socio-technical process involving two-directional interactions between fire progression and human actions for manual fire detection and suppression: (i) influences of fire progression (e.g., dense smoke, high temperature) on the human performance and (ii) influences of manual action (e.g., spray of suppressant, activation of smoke purge) on fire progression. In the existing Fire PRAs, those physics-human interactions are "implicitly" treated by a simplified and conservative approach based on the competition between two timings, time-to-cable-damage and time-to-suppression (NRC & EPRI, 2005). In contrast, I-PRA creates an "explicit" interface between a Computational Fluid Dynamics (CFD)-based fire model (Fire Dynamics Simulator; FDS) and the human performance model through modifications to the Heat Release Rate (HRR) curve. The methodological development of I-PRA, mainly for the incorporation of physical failure mechanisms and their interface with human performance, is covered in the authors' previous publications for several applications, such as (1) risk-informed resolution of Generic Safety Issue 191 (GSI-191) (Kee et al., 2016; Mohaghegh, Z. et al., 2013; O'Shea & Mohaghegh, 2016), (2) Fire PRA (Sakurahara, Tatsuya et al., 2018a; Sakurahara, T. et al., 2018; Sakurahara et al., 2015), and (3) Seismic PRA (Farshadmanesh et al., 2018).

This paper adapts I-PRA for the quantification and operationalization of SoTeRiA (Figure 3.1) to quantify the incorporation of organizational failure mechanisms into classical PRA. The I-PRA framework (Figure 3.2) quantifies the incorporation of underlying organizational failure mechanisms (i.e., simulation module in Figure 3.2) into risk scenarios in classical PRA (i.e., the site-specific PRA module in Figure 3.2). Section 3.2.1 explains key modules of I-PRA, in relationship with different nodes in the SoTeRiA framework, to clarify how I-PRA is designed to operationalize SoTeRiA. The focus of this paper is on the Data-Theoretic module of I-PRA that is explained in detail in Section 3.2.2. The implementation of the Data-Theoretic approach for NPPs is included in Section 3.3.

3.2.1. Integrated PRA Modules to Quantify the SoTeRiA Framework

The SoTeRiA framework (Figure 3.1) theorizes multiple levels of 'internal' mechanisms, including individual, unit, group, and organization (Nodes 2 to 9 of Figure 3.1), and their interactions with the 'external' environment, including physical, regulatory, business, and sociopolitical climates (Nodes 10 to 16 in Figure 3.1), along with their causal influences on technical system risk (PRA; Node 1). Because different organizations can have unique organizational designs at multiple levels of performance (e.g., management, supervisor, team), it is the analyst's choice to determine the boundary among levels (e.g., between unit and group).

Based on SoTeRiA, the first step in developing a socio-technical risk model is to build the scenarios for the technical "system risk" (Node 1 in Figure 3.1). The system risk is modeled in the site-specific PRA module in I-PRA (Figure 3.2). The second step is to identify the safety critical tasks (Node 2 in Figure 3.1) that affect the elements of risk scenarios. For example, maintenance performance is a safety critical task since it affects hardware failure. The next step is to model the work processes (e.g., maintenance work processes) that lead to safety critical performance. This helps create the "unit process model" (Node 3 in Figure 3.1). Next, human performance models for individuals involved in the work processes of the unit process model need to be developed. This research is not implying the development of a separate model for each human; instead it considers modeling each team (who conducts similar tasks in its work processes) in the aggregate. For example, regarding a group of maintenance technicians performing similar categories of tasks in the maintenance unit, team performance would be modeled in the aggregate level. Lastly, the organizational aspects such as safety culture (Node 8 in Figure 3.1) and safety climate (Nodes 5 and 6 in Figure 3.1), and structural features such as safety practices (Node 7 in Figure 3.1) of the supporting organization are linked to human performance models.

Another safety critical task includes operator performance that can be associated with a unit (e.g., an operator action in a main control room) or that can refer to an individual action in risk scenarios. In the I-PRA framework (Figure 3.2), an operator action, basic event "a," stands for an example of a safety critical task, although I-PRA can cover other safety critical tasks (e.g., maintenance performance) related to the site-specific PRA. Node 4 in Figure 3.1, "individual Performance Shaping Factors" (PSFs) refers to the PSFs in the HRA of I-PRA (Figure 3.2), and the remaining organizational nodes in the SoTeRiA framework (Figure 3.1) help model organizational failure mechanisms (#1.5, #2.5 and #3) in I-PRA.

As Figure 3.2 shows, I-PRA is a multi-level risk assessment framework that begins with the Data-Theoretic module extracting and formalizing the organizational data required for the simulation of underlying organizational mechanisms (#3) that affect the states of PSFs (e.g., a_1, a_2, and a_3) and that, therefore, influence the probability of human errors (e.g., event “a” in the FT) in the site-specific PRA module. Through the interface module, the “spatio-temporal simulation of organizational failure mechanisms” (#3) is connected to the associated PSFs in the site-specific PRA module. In the interface module, the uncertainties associated with input data are characterized and propagated by the uncertainty analyzer (#4 in Figure 3.2) to make the simulation module probabilistic and ready to be connected to the site-specific PRA model.

The Data-Theoretic module uses the high-level causal relationship of SoTeRiA (Figure 3.1) as a preliminary causal structural shell in Element 1.5 to guide the analyst when adding more detailed causal constructs. Elements 1.1 to 1.4 of DT-BASE are the steps for adding more detailed causal constructs and quantifying the targeted causal model in Element 1.5. The scope of the targeted causal model in Element 1.5 can include adding details to one node of Figure 3.1 or adding details to multiple nodes of Figure 3.1 while preserving the high-level interconnections among those nodes (based on the causal connection of SoTeRiA in Figure 3.1). In this paper, the scope of the targeted causal model is Training, which is related to Node 7 in Figure 3.1. The targeted causal model that is gradually built and quantified through Elements 1.1 to 1.4 of DT-BASE forms the organizational causal input model in Element 1.5 as the input to DT-SITE. The quantification of the organizational causal input model is updated through DT-SITE Elements 2.1 to 2.4 to generate an updated version of the same causal model in Element 2.5, ready to provide input for the simulation module. In other words, the organizational causal input model in Element 2.5, a targeted-scope model of SoTeRiA (Figure 3.1) with more detailed levels of causality, gives the input information (i.e., the causal structures and their associated measures) for the spatio-temporal simulation module (#3), where the analyst can add temporal and/or spatial dimensions.

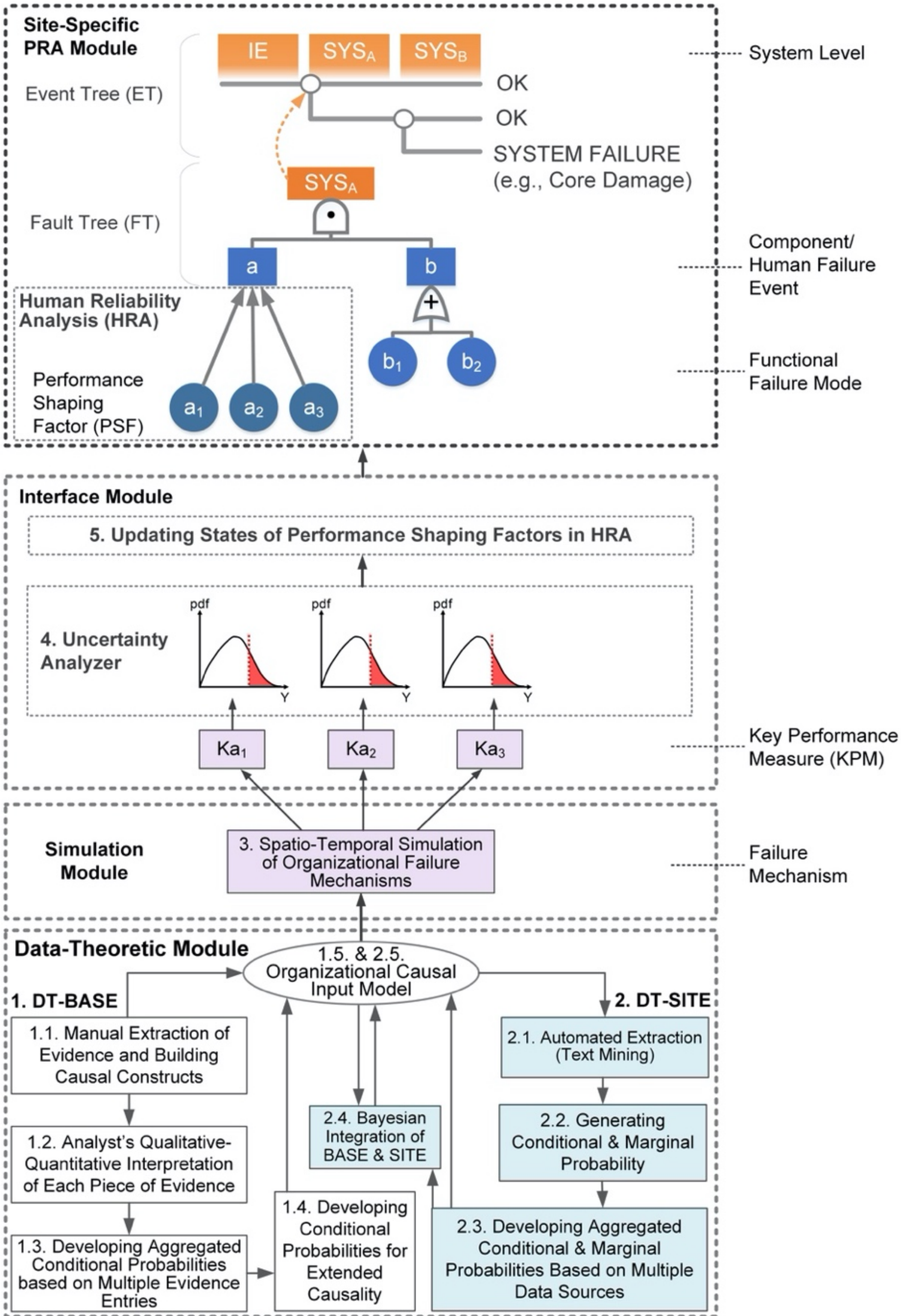

Figure 3.2: Integrated Probabilistic Risk Assessment (I-PRA) Methodological Framework for Socio-Technical Risk Analysis

For example, the hybrid modeling approach by Mohaghegh and Mosleh (Mohaghegh et al., 2009) added the temporal dimension to the quantification of SoTeRiA by combining the System Dynamics technique with BBN. Ongoing research by the authors is focusing on the incorporation of spatial aspects, in addition to temporal, to socio-technical risk analysis (Bui et al., 2016; Bui et al., 2017; Pence et al., 2015a; Pence et al., 2015b).

The modeler has the choice of connecting the quantified organizational causal input model (#2.5 in Figure 3.2) directly to the PSFs through the interface module or of making it temporal or spatio-temporal in the simulation module and then letting the simulation outputs pass to the interface module. This choice depends on criteria such as the level of available resources (e.g., computational resource, data availability) and the desired level of accuracy and resolution in the system risk estimation. The authors recommend that the first phase of risk estimation be done without adding spatio-temporal dimensions, followed by advanced risk Importance Measure analysis (Sakurahara, T. et al., 2017) to determine the risk significance of each failure mechanism. In the next phase, the spatio-temporal dimensions can be added to the risk-significant failure mechanisms identified by the risk Importance Measure analysis.

The key performance measures (e.g., Ka_1, Ka_2, Ka_3 in Figure 3.2) refer to the measured performance outputs of the organizational model that help define the states of PSFs. For example, the quality of organizational training affects the state of training/experience PSF in HRA. Thus, the estimated quality of training from the organizational model is a key performance measure associated with the training/experience PSF in I-PRA. In the interface module, by having the probability distributions of the key performance measures resulting from the uncertainty analysis, the probability of each state of PSFs (e.g., low, nominal, high) is generated (#5 in Figure 3.2) by estimating the probability that the associated key performance measure exceeds threshold values (See discussion in Section 3.3.3). This paper focuses on the development of the Data-Theoretic module, explained in Section 3.2.2, and its application (Section 3.3) for modeling the quality of NPP training. A more detailed explanation and advancement of other modules of the I-PRA framework is the focus of Chapter 4.

3.2.2. Methodological and Computational Developments for the Data-Theoretic Module of Integrated PRA

The role of the Data-Theoretic module in the I-PRA framework is the execution of measurement techniques (Principle IV-L in Table 3.1) to extract and interpret organizational data associated with the structure and state (or value) of factors, sub-factors, and links in the SoTeRiA framework. Based on the evaluation of measurement techniques for organizational safety/risk frameworks (Mohaghegh & Mosleh, 2009b), two common categories of methods including “subjective” and “objective” are listed. In the subjective measurement, the state of a factor is based on employees’ perception. The subjective measurement is often taken by surveys or interviews conducted with the entire organization, a random sample, or specific members (e.g., supervisors and managers). In contrast, the objective measurement refers to the case where a person (or a group) measures the factor using checklists and/or by inspections and auditing (compliance-based). Auditors only get a snapshot of the organization, and often a limited number of subjects are audited. Perception surveys (subjective measurements) can capture some aspects of the reality that are overlooked by objective auditing. However, subjective measures also have their own limitations and biases. For example, employees' perceptions can be influenced by supervisors' interpretations (Mohaghegh & Mosleh, 2009b). Individual-level subjective measurements through surveys are usually limited to a set of factors; otherwise, they can be time consuming and expensive. Correlation between individual-level and organizational-level aggregation (Ostroff, C., 1993) relies on in-group agreement (Klein et al., 1994); however, when factors are 'elusive' and unknown to individuals at the time of subjective measurement, it is not possible to gather meaningful data for highly granular organizational factors. Previous studies have introduced empirical data analysis for associating organizational factors with performance indicators (Nichols & Marcus, 1990) and cause codes (Schroer & Modarres, 2013) from industry data, however, these methods do not use theory to guide their analysis, and are not designed to be integrated with HRA or PRA methods. Readers are referred to Ref. (Mohaghegh & Mosleh, 2009b) for a more detailed review of methods for measuring organizational factors at different levels of analysis. Neither a subjective or objective measurement approach alone has been proven to be a reliable approach for measuring the systematic multi-level relationships of organizational factors, and therefore, hybrid integration of these methods is required (Mohaghegh & Mosleh, 2009b). In order to address this challenge, this research proposes a new measurement method called the Data-Theoretic approach, having its preliminary development published in Ref. (Pence et al., 2017).

The Data-Theoretic module of I-PRA executes the Data-Theoretic approach, covering two main parts: (1) DT-BASE (#1 in Figure 3.2; the white boxes on the left in the Data-Theoretic module) that focuses on the development of detailed causal relationships in SoTeRiA, based on a theory-building process (explained in Section 3.2.2.1.1) and equipped with a semi-automated baseline quantification utilizing analyst interpretation of generic information extracted from articles and standards; (2) DT-SITE (#2 in Figure 3.2; the light blue boxes on the right in the Data-Theoretic module) that relates to conducting automated data extraction and inference methods (text mining) to quantify SoTeRiA causal elements based on site-specific event databases and by Bayesian updating of the baseline quantification established by DT-BASE. The Data-Theoretic approach is advancing measurement techniques for organizational factors in the following ways:

1. It guides “data analytics” with “theory.” The problem with solely data-oriented approaches is that, due to the lack of guidance from an underlying theory, analysts can be misled by data, creating what Lazer (2014) calls “big data hubris,” mistaking correlation for causation and “algorithm dynamics issues,” when an algorithm is not capable of capturing the theoretical construct of interest (Lazer et al., 2014). In the Data-Theoretic approach, the theoretical causal structure of the SoTeRiA framework (Figure 3.1) and the contextual keywords of each node in SoTeRiA guide data analytics; therefore, the underlying theory supports the completeness of causal factors, the accuracy of their causal relationships, and helps avoid the potentially misleading results of a solely data-oriented approach. Bar-Yam (2013) emphasized that (a) big data is critical for addressing complex systems, (b) theoretical modeling is essential to the scientific process for understanding complex systems, and (c) theory makes data more useful (Bar-Yam, 2013).
2. It combines different sources and types of information, for example (i) information pieces from academic literature, practical industry procedures, and regulatory standards are integrated through DT-BASE elements, (ii) analysts’ “subjective” interpretation of information in DT-BASE is combined with “objective” event data extracted in DT-SITE, and (iii) “generic” information obtained in DT-BASE is integrated with “site-specific” information extracted in DT-SITE.
3. It uses text mining (in DT-SITE), in addition to expert opinion (in DT-BASE), as a measurement technique. Although lack of data has been mentioned as one of the key reasons for making slow progress in the incorporation of organizational factors into PRA (Ghosh & Apostolakis, 2005; Li et al., 2012), this research provides a new perspective by highlighting that data is available for organizational factors; however, the data has a nature that is different from tabular equipment reliability data. Archival data, documents, and texts serve as primary organization-level data. The Communicative Constitution of Organization (CCO) is a widely-accepted multidisciplinary perspective of organizational communication theory, which asserts that “organizations are constituted (and maintained) through human communication” (Cooren et al., 2011). For example, organizational documents in circulation at NPPs are tangible data structures that move forward through space and time, and these documents are what constitute the organization (Ashcraft et al., 2009; Güney & Cresswell, 2012; Taylor et al., 1996). The extraction, interpretation, and analysis of communicative symbols present a new opportunity for analyzing organizational safety performance and risk contribution. Through the communication process, organizations produce, synthesize, and store a large volume of textual information used for regular business activities and compliance purposes. This large and complex volume of information (big data) needs a new measurement technique to analyze its contents. Data of organizational communications are a compilation of operational experience documents such as Corrective Action Program (CAP) entries, Licensee Event

Reports (LERs), Root Cause Analysis (RCA) documents, and maintenance logs. Because these documents are unstructured and heterogeneous, it is necessary to incorporate data analytic techniques such as text mining for socio-technical risk analysis (Pence et al., 2015a; Pence et al., 2014). Text mining is widely used for big data due to its ability to extract information from unstructured textual information (Berman, 2013; Ding et al., 2011; Tao et al., 2013).

Sections 3.2.2.1 and 3.2.2.2 explain the status of methodological and computational developments for DT-BASE and DT-SITE, respectively.

3.2.2.1. DT-BASE Elements of the Data-Theoretic Module

The following sub-sections explain the five methodological elements of DT-BASE, including:

- Manual Extraction of Evidence and Building Causal Constructs (# 1.1 in Figure 3.2)
- Analyst's Qualitative-Quantitative Interpretation of Each Piece of Evidence (#1.2 in Figure 3.2)
- Developing Aggregated Conditional Probabilities based on Multiple Evidence Entries (#1.3 in Figure 3.2)
- Developing Conditional Probabilities for Extended Causality (#1.4 in Figure 3.2)
- Integration in a Bayesian Belief Network Computational Platform (#1.5 in Figure 3.2)

The above methodological elements are computationally implemented following the flowchart in Figure 3.3, which has three phases: (i) Data Entry, (ii) Aggregation, and (iii) Bayesian Belief Network Platform. Figure 3.3 maps DT-BASE elements (the box at the top of Figure 3.3) to the computational flowchart sequence (below the box in Figure 3.3) and uses color-coding to show the relationships between DT-BASE elements and flowchart phases. Elements #1.1. and #1.2 of DT-BASE are executed in phase (i) of the flowchart (Figure 3.3). Elements #1.3 and #1.4 of DT-BASE are conducted in phase (ii) of the computational flowchart. Phase (iii) of the flowchart (Figure 3.3) executes element #1.5 of DT-BASE.

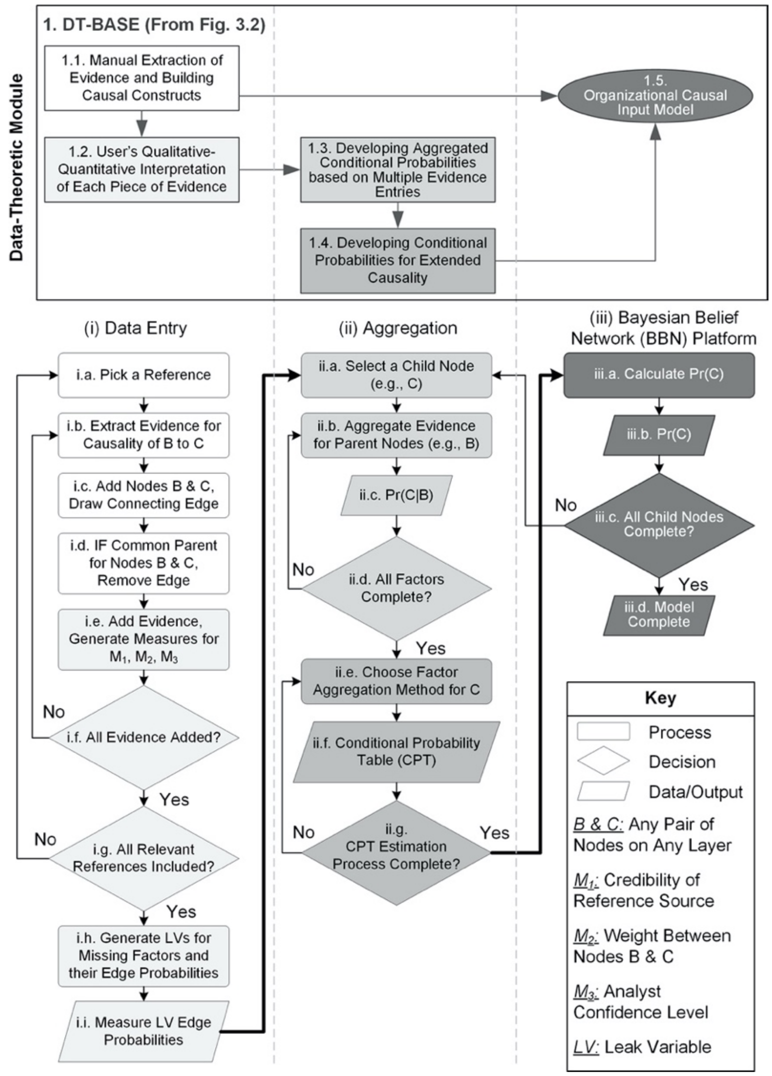

Figure 3.3: DT-BASE Module on the Top of the Figure Surrounded by a Solid Black Line and the Associated Computational Flowchart Below Each Phase: (i) Data Entry (Associated with 1.1 and 1.2 in Figure 3.2); (ii) Aggregation (Associated with 1.3 and 1.4 in Figure 3.2), and (iii) BBN (Associated with 1.5 in Figure 3.2)

3.2.2.1.1. Manual Extraction of Evidence and Building Causal Constructs (Element #1.1 in Figure 3.2)

For element #1.1 of DT-BASE (Figure 3.2), the SoTeRiA framework (Figure 3.1) provides the initial causal structure, and the analyst utilizes a theory-building process, along with their interpretation of "evidence" extracted from references, to expand causal constructs associated with the nodes in SoTeRiA. In this paper, "evidence" means a textual statement in a reference that supports the causal construct between two factors (e.g., cause "B_i" (i=1, 2, …n) or the parent node, effect "C" or the child node, and the edge (causal link) between B_i and C in Figure 3.4).

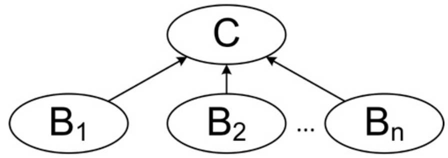

Figure 3.4: Causes (Parent Nodes) and Effect (Child Node) in a Simple Theoretical Causal Construct

Theory building (e.g., (Chermack, 2007; Corbin & Strauss, 2008; Weed, 2005)) does not have a purely rule-based prescriptive process, and therefore, this element of DT-BASE (#1.1) cannot be fully automated. The theory-building process in this research not only utilizes the socio-technical risk analysis principles (Principles I, II, II, and IV-M in Table 3.1) (Mohaghegh, 2007), but also is consistent with Sterman's (2000) conceptualization of an iterative learning process (Sterman, 2000) and reflects Weick's (1989) perspective on the intuitive nature of theory-building (Weick, K.E., 1989). Element #1.1 of DT-BASE has the following five-step manual theory-building process as well as computational features that help in structuring the causal model:

- Step 1: Identifying the unknown of interest, i.e., the selected target node/organizational factor (e.g., training). This step refers to Principle I.A. in Table 3.1.
- Step 2: Identifying the literature (i.e., regulatory and industry standards as well as academic articles) associated with the selected organizational factor.
- Step 3: Locating the selected organizational factor within the SoTeRiA framework (Figure 3.1). For example, "training" is an organizational factor associated with Node 7 in SoTeRiA.
- Step 4: Identifying logical abstract-level phases (e.g., plan, do, check, act) evolving and leading to the performance quality of the selected organizational factor. This helps develop causal levels at the abstract level of analysis.
- Step 5: Developing theoretical causal constructs for the organizational mechanisms leading to the performance quality of the selected organizational factor by satisfying theory-building principles (Principles II and III in Table 3.1) and by utilizing semi-formal process modeling techniques (e.g., business process modeling (Williams, 1967), flowcharts (ASME, 1947), etc.). Although semi-formal modeling techniques are related to Principle IV-M (Table 3.1) that is focused on modeling techniques (rather than theory building), they can be considered as the bridging techniques that help turn a theory into a causal model equipped with a formal modeling technique (e.g., BBN). Semi-formal process modeling techniques help expand the causalities from the abstract level of analysis (developed in Step 4) to more detailed functional and task levels. We refer the readers to Mohaghegh and Mosleh (Mohaghegh et al., 2009) for the details on the application of semi-formal process modeling techniques for the development of multi-level causalities. In this research, the Structured Analysis and Design Technique (SADT) (Heins, 1993; Marca & McGowan, 1987) (Figure 3.5) is used as the

selected process modeling technique due to its (1) ease of conversion from a ‘semi-formal’ to ‘formal’ (e.g., BBN) technique, (2) ease of communicating the model and results, and (3) the generality of the technique for different organizational factors (Mohaghegh, 2007). In SADT, the activity transmits the inputs (I) to the outputs (O), given the resources (R) and the control/criteria (C) (Mohaghegh et al., 2009). The inputs can include, but are not limited to, information, hardware, raw materials, and people. Outputs are the products of the process. Resources are the things needed to perform the activity, such as tools, equipment, and people. Controls/criteria include requirements such as job control mechanisms, constraints, procedures, applicable rules and regulations, and standards that are used to direct, control, and judge the conduct of an activity. The SADT input-output structure can be converted to a BBN causal structure, as demonstrated by Mohaghegh and Mosleh (Mohaghegh et al., 2009), and is implemented in Section 3.3 of this paper to build and quantify the training causal model.

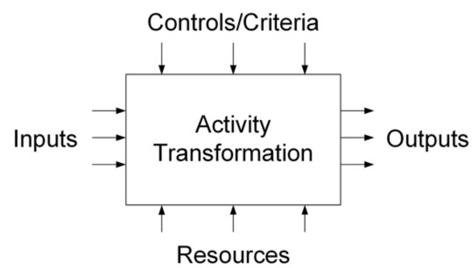

Figure 3.5: Structured Analysis and Design Technique (Marca & McGowan, 1987)

The computational feature of element #1.1 of DT-BASE is a part of the data entry phase (i.a., i.b., i.c., and i.d.) in Figure 3.3 and helps the analyst add the causal constructs, in the right location and at the right level of analysis, to gradually build the final structure of the organizational causal input model (delivered to element #1.5 in Figure 3.2). As Figure 3.3 shows, the analyst picks a reference (e.g., from academic literature, practical industry procedures, or regulatory standards), and based on their interpretation of each piece of evidence and following the theory-building steps (Step 3 to Step 5 listed above), they add the causal construct to the model.

Section 3.3.1. further explains element #1.1 by applying it in the case study to build the causal model for training in NPPs.

3.2.2.1.2. Analyst’s Qualitative-Quantitative Interpretation of Each Piece of Evidence (Element #1.2 in Figure 3.2)

Once element #1.1 of DT-BASE (Figure 3.2) has been executed for a causal construct (i.e., a minimum of two nodes and an edge in Figure 3.4), the analyst is prompted through element #1.2 to enter a set of information based on their interpretation of the evidence supporting the causal construct. The computational execution of element #1.2 is included in the data entry phase (i.e., i.h., i.i.) of Figure 3.3. Because SoTeRiA is explicitly modeling "performance quality" for each node, the analyst first defines the "states" of each node based on their potential quality states (or the existence of a specific quality); for example, "good/high" (or true or existent) (State 1) and "bad/poor/low" (or false or absent) (State 2). For each causal construct, the analyst is then prompted to enter the following information:

- Reference information: The analyst imports reference information (.ris file) or enters the title, year, authors' names, type of publication, publisher, etc. into data fields. In DT-BASE, evidence dependencies are managed through a bibliometric analysis which cross-compares reference information to find potential overlaps and avoids double counting of evidence. Current dependencies considered are: same author or authors, same institution, and concurrent publications (i.e., which may indicate similar subject populations or case studies). This information is presented to the analyst to guide them to remove potential information dependencies based on the entered references. In other words, the current scope of dependency treatment is "binary", meaning that, if a potential overlap is identified between two references, they are counted only once; otherwise, both of them are included in the DT-BASE.
- Keywords associated with the parent node and child node (see Figure 3.4): The relevant keywords for each node are created as tags in the entry. Multiple keywords can be added to represent the context of a factor. Synonyms and alternative industry-specific phrasing should be included to account for the textual context in other data sources.
- A verbatim copy of the textual statement explaining the causal relationship: The exact statement, which supports the relationship between the two nodes, is copied as supporting evidence.

Next, the analyst is prompted to provide the following subjective quantitative values associated with the piece of evidence:

- **[$M_{1, EV}$]** Credibility of the reference source (e.g., Journal Impact Factor): The weight or impact factor of the publication, based on a "low estimate point" and a "high estimate point" from zero to one, where the current value used is the median.
- **[$M_{2, EV}$]** Weight between node B_i and node C indicated in the evidence: The analyst's interpretation of the author's statement about the strength of causal influence of B_i on C. $M_{2, EV}$ is represented by a numerical scale from zero to one. For the example of B_i (State 1) affecting C (State 1) (see Figure 3.4), $M_{2, EV}$ refers to the conditional probability of C, given B_i, as in, $Pr(C \mid B_i)$. Language may include that "it is very likely B_i causes C." It is also possible that the reference has a numerical analysis and that the results show the strong or weak influence of B_i on C.

- **[$M_{3, EV}$]** Analyst confidence level in the subject matter material: The analyst's familiarity with the two nodes and their causal relationship. $M_{3, EV}$ ranges from zero to one.

In order to support consistency among different analysts with respect to their judgments for M_1, M_2, and M_3, this research utilizes a set of natural language expressions that are associated with probabilities, initially developed by Wallsten (Wallsten et al., 1986) and adapted by the International Panel on Climate Change (IPCC) (Mastrandrea et al., 2010; Stocker, 2014). The IPCC probability language has seven categories of probability values to describe a degree of belief in a proposition; "virtually certain, very likely, likely, medium likelihood, unlikely, very unlikely, extremely unlikely" (Morgan, 2014; Stocker, 2014). The categories and ranges are shown in Table 3.2. Because these categories were developed for the context of climate change and have not been calibrated or measured to specifically address NPP contexts, future research is needed to conduct sensitivity analysis to determine whether changing categorical bin thresholds make a significant difference to PRA results, and if so, additional effort is needed to calibrate these bins for nuclear power industry applications. For example, future work will consider specific questions to assist individuals in assessing their confidence likelihood for M_3.

Table 3.2. Mapping Between Probability Words and Probability Values (Adapted from (Stocker, 2014))

Lower Bound	Upper Bound	M1	M2	M3
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

Table 3.2 (cont.)

Lower Bound	Upper Bound	M1	M2	M3
0	0.01	Extremely Unlikely to be Credible	Extremely Unlikely	Extremely Unlikely to be Confident

As step (i.i.) of the data entry phase of Figure 3.3 shows, to introduce a measure of incompleteness uncertainty into the causal model, a Leak Variable (LV) is introduced at each 'layer' of causality. The LV stands for nodes that are not included in the model. The analyst can enter a value for LV edge probability. The meaning of LV edge probability is explained in Section 3.2.2.1.4, where it is used in the extended causality equation. The analyst can create as many evidence entries as literature supports. The next step of the DT-BASE approach performs aggregation as each piece of evidence is added.

3.2.2.1.3. Developing Aggregated Conditional Probabilities based on Multiple Evidence Entries (Element #1.3 in Figure 3.2)

Element #1.3 of DT-BASE, which relates to the second phase (ii.b.) of the computational flowchart (Figure 3.3), focuses on the estimation of aggregated conditional probabilities when the analyst's interpretations of multiple evidence entries are elicited for the same conditional probability. In Element #1.2, based on each piece of information $EV_{i,j}$, the analyst provides $M_{2,\,EV_{i,j}}$ that indicates the strength of the causal relationship between the factors B_i and C and can be treated as an estimate of the conditional probability $Pr(C|B_i)$, if there is only one piece of information available. In Element #1.3, the aggregated estimate of $Pr(C|B_i)$ is estimated by combining $M_{2,\,EV_{i,j}}$ derived from multiple pieces of information $EV_{i,j}; j \in \{1, \ldots, K\}$.

To compute the aggregated conditional probabilities, this research uses two axiomatic approaches for aggregating multiple experts' probability estimates that have been commonly used in PRA: arithmetic mean (Eq. 3.1) and geometric mean (Eq. 3.2) (Cooke, R. & Shrader-Frechette, 1991; Kaplan, 2000), formulated as follows:

$$Pr(C|B_i) = \sum_{j=1}^{K} w_{EV_{i,j}} M_{2,\,EV_{i,j}} \quad \forall i \in I\,, \qquad (3.1)$$

$$Pr(C|B_i) = \prod_{j=1}^{K} M_{2,\,EV_{i,j}}^{w_{EV_{i,j}}} \quad \forall i \in I\,, \qquad (3.2)$$

where $w_{EV_{i,j}}$ is the normalized weight, representing the relative quality of different pieces of information (Kaplan, 2000). Considering that quality of $M_{2,\,EV_{i,j}}$ estimate is influenced by both (i) quality of the original evidence (e.g., literature), measured by $M_{1,\,EV_{i,j}}$, and (ii) quality of the analyst who interpreted the original evidence, measured by $M_{3,\,EV_{i,j}}$; $w_{EV_{i,j}}$ is formulated as a function of $M_{1,\,EV_{i,j}}$ and $M_{3,\,EV_{i,j}}$:

$$w_{EV_{i,j}} = \frac{M_{1,\,EV_{i,j}} \times M_{3,\,EV_{i,j}}}{\sum_{j=1}^{K} M_{1,\,EV_{i,j}} \times M_{3,\,EV_{i,j}}} \quad \forall i \in I, j = 1, \ldots, K \quad (3.3)$$

The selection between the arithmetic mean (Eq. 3.1) and geometric mean (Eq. 3.2) could depend on the applications. For instance, as suggested by Morton et al. (Morton et al., 2014), the arithmetic mean may generate a misleading output when there is a large dispersion between the experts' assessment as the extreme estimates dominate the result; under such a situation, the geometric mean can generate a more stable and reasonable output that captures the 'center' of the group's opinion. More detailed guidelines for when to use which aggregation method need to be developed in future research.

In these aggregation equations, index 'i' (i=1, 2,…, I) is used to denote one instance (parent node) that has a shared effect on C, pertaining to one causal relationship (i.e., $Pr(C|B_i)$ in Figure 3.4). Index 'j' (j=1, 2,…, K) denotes one evidence entry that is related to the causal relationship between B_i and C. K stands for a total number of evidence entries. The analyst decides between the two aggregation methods. In Eq. 3.3, the normalization factor Z is developed to normalize the weight for each piece of evidence based on the combination of $M_{1,EV}$ and $M_{3,EV}$ so that the resultant value obeys probability axioms.

3.2.2.1.4. Developing Conditional Probabilities for Extended Causality (Element #1.4 in Figure 3.2)

Element #1.4 of DT-BASE focuses on the estimation of the conditional probability of the child node given multiple parent nodes (i.e., $Pr(C|B_1, B_2, \ldots, B_n)$ in Figure 3.4) based on the aggregation of estimated values from element #1.3 (i.e., $Pr(C|B_1)$, $Pr(C|B_2)$, ..., $Pr(C|B_n)$). The estimated conditional probabilities build the Conditional Probability Table (CPT), which is an input to the next step of the methodology, i.e., the Bayesian Belief Network (BBN) platform (element #1.5 explained in Section 3.2.2.1.5). Element #1.4 of DT-BASE is made computational in the second phase (ii.d.) of the flowchart shown in Figure 3.3.

In element #1.2 (Section 3.2.2.1.2), the analyst is asked to elicit information for each piece of evidence of the causal relationship between one parent (B_i) and the child node (C), implicitly assuming that a single parent can lead to the child (C). This assumption is related to the concept of Independence of Causal Influence (ICI) (Dıez & Druzdzel, 2006; Pearl, 2014). Therefore, a common aggregation model that is used in element #1.4 of DT-BASE is the Noisy-OR (Dıez & Druzdzel, 2006; Galán et al., 2007; Heckerman & Breese, 1996; Mkrtchyan et al., 2016; Pearl, 2014) that governs the following relationship:

$$Pr(C|B_1, B_2, \ldots, B_n) = 1 - \prod_{i \in I}(1 - z_i), \quad (3.4)$$

where, "i"shows all configurations of parent nodes that are present, and z_i is the probability of C given that only cause B_i is present (i.e., $Pr(C|B_i)$), utilizing the probabilities being aggregated in Section 3.2.2.1.3.

For multi-state variables, the Noisy-OR representation of causal influence can be extended to the Noisy-MAX representation with the same ICI assumption. Diez's definition of Noisy-MAX (Díez & Galán, 2003) is as follows:

$$Pr(C \leq c|\boldsymbol{b}) = \prod_i Pr(C \leq c|B_i = b_i, B_{-i} = 0), \quad (3.5)$$

where; $\boldsymbol{b}$ is a configuration of parent nodes and B_{-i} represents all factors other than B_i. It should be noted that $Pr(C \leq c|B_i = b_i, B_{-i} = 0)$ also considers conditional influence towards C given that only cause B_i is present. The CPT can then be computed by applying the following equation to each configuration of the parent nodes:

$$Pr(C|B_1, B_2, \ldots, B_n) = \begin{cases} Pr(C = 0|\boldsymbol{b}) & c = 0 \\ Pr(C \leq c|\boldsymbol{b}) - Pr(C \leq c - 1|\boldsymbol{b}), & c > 0 \end{cases}. \quad (3.6)$$

Using Eq. 3.4 and Eq. 3.6, the CPT can be calculated for binary-state nodes using Noisy-OR and for multi-state nodes using Noisy-MAX, respectively.

The effects of LV and the associated incompleteness uncertainty can be considered by defining an edge probability that refers to the conditional probability of C, given that not any of B_i exists and only LV exists (Dıez & Druzdzel, 2006), as it is shown in Eq. 3.7. In that case, the aggregated conditional probability is estimated from Eq. 3.8.

$$z_L = Pr(C|not\ any\ B_i\ exists\ except\ LV), \quad (3.7)$$

$$Pr(C|B_1, B_2, \ldots, B_n, LV) = 1 - (1 - z_L)\prod_{i \in I}(1 - z_i), \quad (3.8)$$

It should be noted that the Noisy-OR method and the concept of ICI generate limitations for capturing factor interactions (Mkrtchyan et al., 2016). Future research will evaluate the possibility of using more advanced methods to address these limitations.

3.2.2.1.5. Integration in a Bayesian Belief Network Computational Platform (Element #1.5 in Figure 3.2)

In element #1.5 of DT-BASE (Figure 3.2), the results of quantitative interpretations and measurements that are generated in elements # 1.2, #1.3, and #1.4 of DT-BASE, are combined with the causal model structure constructed in element #1.1 to develop organizational causal input model (built in the BBN environment) that provides input for the spatio-temporal simulation module of the I-PRA framework. As mentioned in Section 3.2.2.1.1., a semi-formal modeling technique (i.e., SADT) is used in element #1.1 of DT-BASE to transition theoretical constructs to a formal modeling technique structure (i.e., BBN's probabilistic modeling environment). Other aspects of modeling techniques (associated with Principle IV-M) such as space and time will be executed in the simulation module (#3) of I-PRA.

Element #1.5 is executed in the third phase of the computational flowchart (Figure 3.3), where information is integrated into a BBN platform to calculate the probability of the final target node (i.e., the child node in the last layer of the causal model) based on the CPT developed in phase (ii) of Figure 3.3. BBN, widely used in HRA research, provides graphical formalism and structure, a probabilistic representation of uncertainty, structuration of interrelationships, accommodation of diverse data sources, and representation of belief for factor influences (Mkrtchyan et al., 2015, 2016) in the organizational causal input model (#1.5 in Figure 3.2). Readers are referred to Ref. (Nielsen & Jensen, 2009) for more background on BBN.

The computational platform of DT-BASE is an open-source web application powered by the MEAN full-stack framework (MongoDB, ExpressJS, AngularJS, NodeJS) (Haviv, 2016). DT-BASE is developed as a web application to enable a scientific network for collaborative model building where analysts can build and share modular theoretical models. Using a client-server architecture, multiple analysts can collaborate on a single causal model.

3.2.2.2. DT-SITE Elements of the Data-Theoretic Module

As the I-PRA framework (Figure 3.2) shows, the output of element #1.5 of DT-BASE, the organizational causal input model, provides the causal factors, their related keywords, and causal relationships as inputs for the elements of DT-SITE. At this stage of the research, the causal model structure that is developed at the end of DT-BASE (element #1.5) does not change based on the data analysis in DT-SITE, but its quantification is updated using the DT-SITE analysis. Depending on the scope and availability of site-specific data, it is possible that some nodes in the updated organizational causal input model (element #2.5) are only quantified by DT-BASE, while others are quantified by Bayesian integration of DT-BASE and DT-SITE analyses. Future research will evaluate the value of adding an element in DT-SITE to consider updating the causal model (i.e., adding/deleting nodes or causal paths) based on the data analysis in DT-SITE.

Currently, DT-SITE has the following five methodological elements:

- Automated Extraction of Information; Text Mining (#2.1 in Figure 3.2)
- Generating Conditional and Marginal Probabilities for BBN (#2.2 in Figure 3.2)
- Developing Aggregated Conditional and Marginal Probabilities based on Multiple Data Sources (#2.3 in Figure 3.2)

- Bayesian Integration of SITE and BASE Probabilities (# 2.4 in Figure 3.2)
- Integration in a Bayesian Belief Networks Computational Platform (#2.5 in Figure 3.2)

DT-SITE is still in an early stage of development, and its computational platform has not yet been integrated with DT-BASE in the Data-Theoretic Module. The following sub-sections explain the purpose of each of the current five elements of DT-SITE, and Section 3.3 demonstrates its limited-scope implementation for the NPP case study.

3.2.2.2.1. Automated Extraction of Information; Text Mining (Element #2.1 in Figure 3.2)

The DT-SITE element for the automated extraction of information includes the following two steps:

i. Information Searching: Factors, causal relationships, keywords, and contextual statements from element #1.5 of DT-BASE are used to guide the text mining (Aggarwal & Zhai, 2012), to extract semantic 'safety-oriented' terminology from organizational communications. This step implements computational approaches for pre-processing unstructured textual information to ensure that extracted information maintains conformity to the original texts. At this stage of research, text mining is designed for one specific type of database, i.e., the NPP incident reporting system called the Corrective Action Program (CAP), which is also used in Section 3.3 for the case study. Ongoing research by the authors is focused on the development of more advanced text mining that can be applied to other safety-related databases.

ii. Frequency Development: To convert the outputs of the information searching step to frequencies, depending on the type and format of the database, specific subjective and objective interpretations should be included in the computational process. Also, each database needs to be normalized into performance period timeframes. For instance, the CAP database of NPPs can receive thousands of entries in a year. Each CAP entry refers to one incident (or one safety-related issue) that is represented by a row in a table. For each entry, multiple contributing causes are possible and are written in a text narrative. Using the DT-BASE causal factors (from element #1.5 of Figure 3.2) as the keywords included in the 'input file' of the text mining code, the process is guided to find the number of occurrences of a construct (or multiple constructs) in each CAP entry. For simplification, at this stage of research, the following assumption is made; a factor is counted only once as a contributor despite the number of times it appears in the narrative of one entry. For example, f_{B_1}, which stands for the frequency of factor "B_1," refers to the number of CAP entries including factor B_1 in the data collection period (e.g., one year); $f_{B_1,C}$ represents the number of CAP entries which include both B_1 and C in the data collection period; and $f_{B_1,B_2,C}$ represents the number of CAP entries which simultaneously include B_1, B_2, and C in the data collection period.

3.2.2.2.2. Generating Conditional and Marginal Probabilities for BBN (Element #2.2 in Figure 3.2)

In this element of DT-SITE, frequencies developed in element #2.1 are used to estimate marginal and conditional probabilities associated with the CPT values of the BBN model developed in element #1.5 of DT-BASE. For instance, consider one parent node B_1 and a child node C. The marginal probability of node B_1, $Pr(B_1)$, can be estimated from the frequency outputs of text mining using Eq. 3.9:

$$Pr(B_1) = \frac{f_{B_1}}{N_{CAP}}, \qquad (3.9)$$

where N_{CAP} represents the total number of CAP entries in the same data collection period as f_{B_1}.

Meanwhile, the conditional probability of the child node C, given a specific state of the parent node B_1, $Pr(C|B_1)$, are defined in Eq. 3.10;

$$Pr(C|B_1) = \frac{Pr(B_1 \cap C)}{Pr(B_1)}. \qquad (3.10)$$

On the right-hand side of this equation, the estimate of the denominator, Pr (B_1), is obtained from Eq. 3.9. The numerator, $Pr(C \cap B_1)$, refers to the probability of joint occurrence of B_1 and C, and can be estimated based on Eq. 3.11:

$$Pr(B_1 \cap \ C) \ = \frac{f_{B_1,C}}{N_{CAP}}. \qquad (3.11)$$

When there is more than one parent node in the BBN, for example, three parent nodes in Figure 3.4, Eq. 3.12 represents the conditional probability, of which the numerator can be estimated based on the frequency data obtained by the text mining using Eq. 3.13;

$$Pr(C|B_1, B_2) = \frac{Pr(C \cap B_1 \cap B_2)}{Pr(B_1 \cap B_2)}, \ (3.12)$$

$$Pr(B_1 \ \cap \ B_2 \ \cap C) = \frac{f_{B_1,B_2,C}}{N_{CAP}}. \ (3.13)$$

It should be noted that the probabilities estimated by the approach shown in this section are biased by (or conditioned on) the number (and quality) of CAP entries, and this bias is further explained in Section 3.3.3.

3.2.2.2.3. Developing Aggregated Conditional and Marginal Probabilities based on Multiple Data Sources (Element #2.3. in Figure 3.2)

The mathematical structure of aggregating conditional and marginal probabilities, estimated from multiple databases, would be similar to the Arithmetic (Eq. 3.1) or Geometric (Eq. 3.2) aggregation methods used in Section 3.2.2.1.3. Similarly, the analyst will have the option to give credibility and importance weights to each database. Since at this stage of the research only one data source (the CAP database of an NPP) has been used, this element of DT-SITE has not yet been implemented. Possible challenges of element #2.3 would be dealing with dependencies among diverse data sources or conflicting information among the data sources. Future research will address these challenges.

3.2.2.2.4. Bayesian Integration of DT-BASE and DT-SITE Probabilities (Element #2.4 in Figure 3.2)

In this element of DT-SITE, each conditional probability, estimated from element #2.3, is combined with the associated conditional probability estimated from the DT-BASE that is stored in the BBN of the organizational causal input model (#1.5). This helps develop the updated conditional probabilities and leads to the generation of the updated organizational causal input model (#2.5 in Figure 3.2). In other words, the updated organizational causal input model (#2.5) has the same causal structure developed from element #1.5, but it has the updated (i.e., integration of SITE and BASE) conditional probabilities. Note that it also has the marginal probabilities estimated from element #2.3 of DT-SITE. The mathematical mechanism for integrating conditional probabilities from DT-SITE and DT-BASE is Bayesian updating, as described in Eq. 3.14:

$$\pi\left(p|\underline{D}\right) = \frac{L\left(\underline{D}|p\right)\pi_0(p)}{\int L\left(\underline{D}|p\right)\pi_0(p)dp} \quad , (3.14)$$

where $\pi_0(p)$ refers to the prior distribution of an unknown quantity, p, referring to the conditional probability of interest that is needed to be updated. $L\left(\underline{D}|p\right)$ stands for the likelihood function for a set of new evidence, given that the true value of the unknown quantity is p, and $\pi\left(p|\underline{D}\right)$ is the posterior (updated) distribution of p, given the set of new evidence $\underline{D}$. In this research, the DT-SITE and DT-BASE estimations of p is treated as two pieces of evidence to help find the updated value for the conditional probability; hence, $\underline{D} = \{\hat{p}_{BASE}, \ \hat{p}_{SITE}\}$ where $\hat{p}_{BASE}$ and $\hat{p}_{SITE}$ are the estimate of p generated by DT-BASE and DT-SITE, respectively. With the assumption of independence between the estimations from DT-SITE and DT-BASE, the likelihood function, $L\left(\underline{D}|p\right)$, can be formulated as the product of two likelihood functions:

$$L\left(\underline{D}|p\right) = L(\hat{p}_{BASE}|p) * L(\hat{p}_{SITE}|p). \quad (3.15)$$

In this formulation, $L(P_{BASE}|p)$ represents a measure of accuracy of the DT-BASE estimation, and $L(P_{SITE}|p)$ is a measure of accuracy of the DT-SITE estimation with respect to the conditional probability of the specific construct. Depending on the type of knowledge available regarding the accuracy of measurements in DT-BASE and DT-SITE, a mathematical model needs to be chosen for the likelihood functions. One example of such a likelihood function is demonstrated in Section 3.3.2, where the DT approach is applied to a case study for the training causal model.

3.3. APPLICATION OF THE DATA-THEORETIC APPROACH TO DEVELOP AND QUANTIFY THE TRAINING CAUSAL MODEL IN NUCLEAR POWER PLANTS

The focus of this section is on the implementation of the Data-Theoretic approach (Data-Theoretic Module in Figure 3.2) for a single factor – "training" – as an exemplar among the myriad of factors at the 'organizational-level' of analysis (i.e., the overall training program that supports different groups at an NPP). Based on an independent third-party review at an NPP, 'training quality' was identified as risk-significant. Because it has not been explicitly modeled and integrated with PRA, understanding the contribution of training quality to risk needed additional modeling. The results of this research help model the underlying organizational mechanisms associated with the training/experience PSF in HRA. Ref. (Whaley et al., 2012) states that, if training is considered to be a performance driver, "this PSF might also include the quality of the training provided." The goal of this research is to go beyond the qualitative judgment derived from HRA workbook estimations and to develop a plant-specific distribution of training quality utilizing plant CAP data.

In this research, the training causal model (Figure 3.6) is developed and quantified based on theoretical literature and using industry and regulatory guidelines and plant database, receiving validation on the structure and contents from training experts at an NPP. By Bayesian integration of generic and site-specific information, the plant-specific distribution of the training quality (Figure 3.7) estimation is generated. More thorough validation regarding the estimated probabilities relates to the Probabilistic Validation methodology (Sakurahara, Tatsuya et al., 2018a) under development by the authors for the I-PRA framework. Probabilistic Validation is a methodology to characterize and propagate sources of epistemic uncertainty (e.g., parameter uncertainty, model uncertainty, statistical convergence, analyst's epistemic uncertainty about M1, M2, M3, etc.) in an integrated manner to construct the total epistemic uncertainty, associated with the model output, as a measure for the degree of validity of the probability estimated from the model. The following subsections cover the implementation of DT-BASE and DT-SITE elements.

3.3.1. Applying DT-BASE Elements to Model and Quantify Training Quality in Nuclear Power Plants

This section explains the implementation of DT-BASE elements (#1.1 to #1.5 in Figure 3.2) for the development of the "training" theoretical causal model and its generic quantification. As it is stated in Section 3.2.2.1.1, the theory-building process in element #1.1 starts with five key steps that are applied in the following:

- Step 1: Identifying the unknown of interest: The unknown of interest is the target node "Training," which stands for the organization's ability to provide adequate training to its workforce, based on the programmatic, process-based approaches implemented at the NPP. "Training Program" is placed at the target node (Level 0) of the causal model (Figure 3.6) and is divided into in-house and outsourced training. In this research, we focus on causal modeling of in-house training. For simplification, the causal model developed in the scope of this paper does not cover some of the contributing factors such as student performance, availability of student time, availability of simulator time, cultural factors, or management attitudes towards training. Therefore, in the quantification phase, a LV (introduced in Section 3.2.2.1.2) is considered at each layer of the causal model to represent model uncertainty, which implicitly considers the potential of excluding some factors in the causal model.
- Step 2: Identifying the literature related to training: Starting with the language of industry and based on NPP documentation, diverse training categories were identified, such as electrical maintenance, mechanical maintenance, chemistry technician, etc. The NPP implements a Systematic Approach to Training (SAT), and therefore, each theoretical construct associated with SAT was used as an initial search term to identify relevant literature from industry, regulatory and academic sources, expanding the scope of search terms. The criteria for adding sub-factors was if they were supported by either industry, regulatory or academic sources (i.e., written evidence could be found to support the inclusion and placement of each sub-factor). For example, if some aspects of training were implicitly included in the industry SAT but were explicitly included and supported in the academic literature, they could be added. The literature is added dynamically as we progress through the remaining steps of the methodology. Therefore, the literature review in Step 2 is not final, it is the starting point of an iterative process, and the identification of relevant literature continues to process through the remaining steps. It should be noted that the Nuclear Energy Institute issued Efficiency Bulletin: 17-15 'Standardization of the Systematic Approach to Training' (NEI, 2017), provides suggestions to the industry that are not fully incorporated into the training causal model shown in this paper.
- Step 3: Locating the selected organizational factor within the SoTeRiA framework (Figure 3.1): Training is a sub-factor of "human resource practices," which is a factor of "organizational structure and practices," i.e., Node 7 of SoTeRiA; Fig 1.
- Step 4: Identifying logical abstract-level phases evolving and leading to the quality of training: Based on evidence supporting independent causality and cross-level causality, high-level patterns depicting programs and processes associated with training follow the high-level

phases of Analysis, Design, Development, Implementation and Evaluation (ADDIE) (Molenda, 2003). The phases of SAT are consistent with those of ADDIE, with the differentiation of 'design and development' being considered as one phase in SAT. Therefore, for the SAT, the phases are; needs assessment, design and development, implementation, and evaluation (Kozlowski & Salas, 2009). In the causal model developed in this research, "implementation" and "evaluation" are considered as two types of activity factors in Level 1 of Fig 6, influencing the quality of "In-House Training." The other two phases including "design and development" and "need assessment" are covered through the causal factors affecting "Implementation." For example, "Program Design" and "Training Needs Analysis" are the causal factors in Levels 2 and 2.1 of Figure 3.6, respectively. This section only demonstrates the causal model associated with implementation quality, and the causal models supporting evaluation factors (e.g., internal evaluation and regulatory evaluation in Level 1 of Figure 3.6) are not covered.

- Step 5: Developing theoretical causal constructs for the organizational mechanisms leading to the quality of training: Using the semi-formal process modeling approach of SADT (Figure 3.5), any activity in Level 1 of Figure 3.6 is affected by its direct causes including the direct resource/tool, procedure, and personnel. These causal factors are placed in Level 1.1 of Figure 3.6. For example, the quality of implementation depends on the quality of "Training Procedures (procedure)/Facility (resource/tool)" and the "Instructor Performance" (personnel). In the SADT approach for the "implementation" activity node, procedure and resource/tool are lumped into one factor, i.e., "Training Procedures/Facility," because enough evidence to separately quantify them have not been found. The next level of causality, Level 1.1.1 in Figure 3.6, includes the sub-factors influencing the quality of resources, procedures, and instructors in Level 1.1. For example, "Instructor Performance" is influenced by "Instructor Training," "Instructor Time & Preparation," and "Instructor Knowledge." Level 2 of the causal model includes "Program Design," that is, the activity supporting the factors in Level 1.1.1 of the model. Again, based on SADT approach, Level 2.1 covers the direct resource/tool ("Training Records Documentation System" in Figure 3.6), procedure ("Training Needs Analysis" in Figure 3.6), and personnel ("Instructional Technologists" in Figure 3.6) that are needed for the activity in Level 2 (i.e., Program and Design). Level 2.1.1 of the causal model includes the sub-factors influencing the quality of the resource and procedures in Level 2.1. Every node and relationship between layers are supported by evidence from literature (academic articles, regulatory and industry documents) and standards to create a theoretical justification and validation of its placement and inter-relationships within the model. For example, Table 3.3 shows a partial list for the industry, regulatory and academic references that are used for the factor “Job/Task Analysis” in Level 2.1.2 of the causal model. The full implementation information for the ‘Training’ organizational causal input model in DT-BASE can be found in the supplementary dataset [dataset] (Pence & Mohaghegh, 2018).

It should be noted that the numbers associated with the Levels in Figure 3.6 are used to organize and communicate the causal model. However, there is theoretical support for the ordering and arrangement of these Levels in the model. The logical order of Levels 0, 1, and 2, is explained in Step 4 (above), and is supported by ADDIE (Molenda, 2003) and the SAT (DOE, 2014; NEI, 2017; Yoder, 1993). The logical order of levels 1.1, 1.1.1, 2.1, 2.1.1, and 2.1.2 is explained in Step 5 (above) and is structured by SADT (Heins, 1993; Marca & McGowan, 1987).

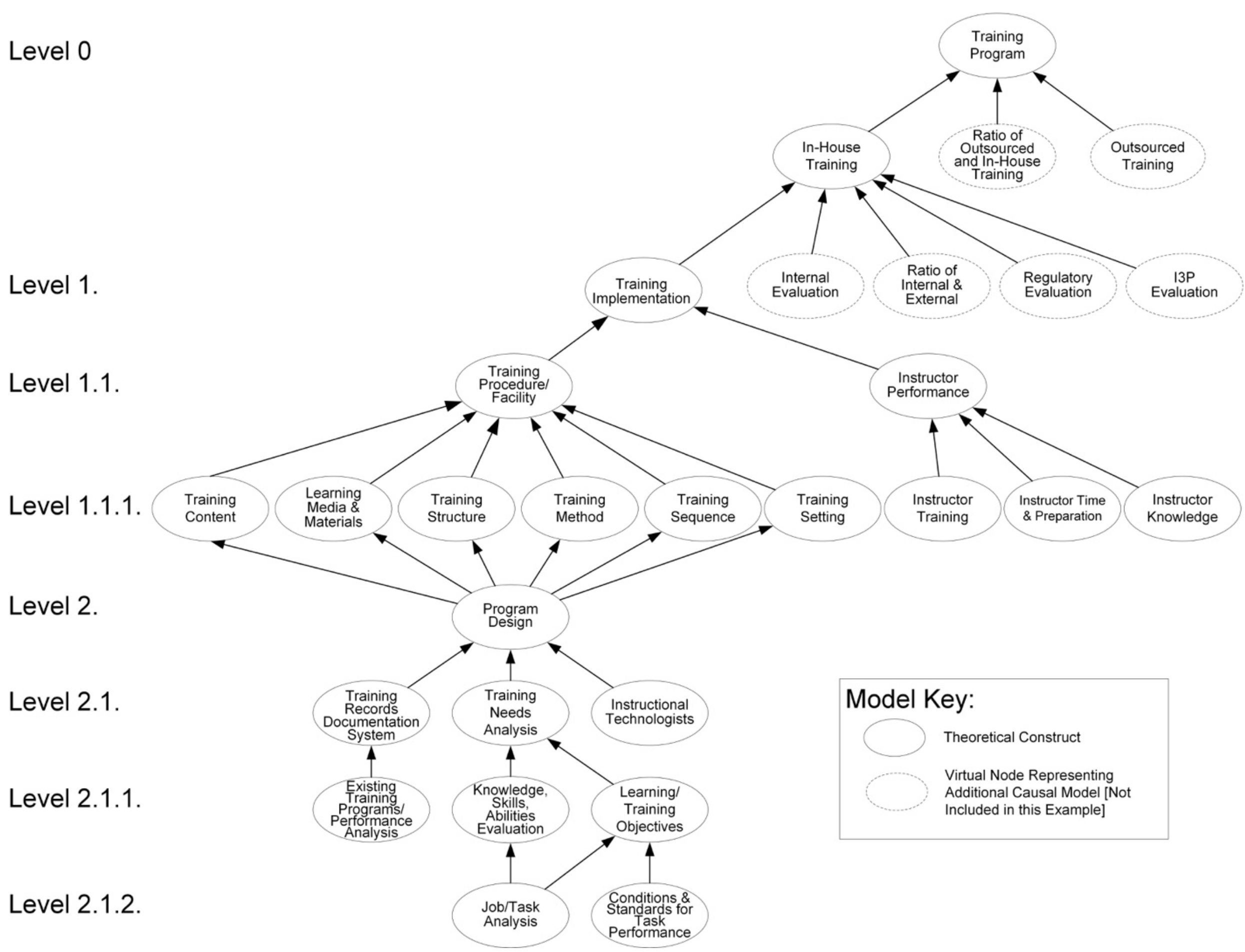

Figure 3.6: NPP Training Causal Model Developed based on Element #1.1 of DT-BASE

Table 3.3: Example for the Construct of Job/Task Analysis from [dataset] (Pence & Mohaghegh, 2018)

Perspective*	Node: Job/Task Analysis
Industry Perspective	"The systematic process of examining a task by collecting data from subject-matter experts and/or source documents to identify conditions standards references knowledge and skills associated with each task element." [dataset] (Pence & Mohaghegh, 2018)
Regulatory Perspective	"The result of the job analysis will be a set of typical tasks which represents the training content of the job. Skills and knowledge needed for the job can be derived from the typical tasks." (Ref. (Andersson et al., 1979))
Academic Perspective	"Abilities-oriented job analysis is concerned with identifying human attributes necessary to perform the job" (Ref. (Levine, 1983))

*This example is reduced to one reference for each perspective.

In element #1.2 of DT-BASE (Figure 3.2), the analyst enters the values for M_1, M_2, and M_3 based on his/her interpretation of each piece of evidence and using the probability categories listed in Table 3.2. The full M values used for the 'Training' organizational causal input model in DT-BASE can be found in the publicly available supplementary dataset [dataset] (Pence & Mohaghegh, 2018). As an example of one entry in the database, evidence to support the connection between 'Job/Task Analysis'(JTA) and 'Knowledge, Skills and Abilities (KSA) Evaluation' (i.e., pre-training evaluation of KSAs) is extracted from a reference with the following contextual statement; "entry-level requirements should be based on a familiarity with the general level of KSAs of the trainees and by a careful review of documents such as job descriptions, position descriptions or personnel qualification requirements" (DOE, 1994). Considering this piece of evidence, the analyst's interpretation based on probability language is shown in Table 3.4. Another piece of evidence for the same causal edge is shown in Table 3.5 to demonstrate the aggregation of conditional probabilities based on multiple evidence in element #1.3.

Table 3.4: Evidence Entry for the First Reference Supporting the Causality Between 'Job/Task Analysis' (JTA) and 'Knowledge, Skills and Abilities' (KSA) (Source: (DOE, 2014))

Parameter	Lower Bound	Upper Bound	Median	Memo
M_1	0.9	0.99	0.95	Official Government Document, Revised in 2014 (Very Likely Credible)

Table 3.4 (cont.)

Parameter	Lower Bound	Upper Bound	Median	Memo
M_2	0.66	0.9	0.78	Knowledge, Skills and Abilities are developed after careful review of job descriptions (DOE, 2014) (Likely)
M_3	0.66	0.9	0.78	Analyst is likely confident about the topic of Job Analysis and Knowledge, Skills and Abilities (Likely Confident)

Table 3.5: Evidence Entry for the Second Reference Supporting the Causality Between 'Job/Task Analysis' (JTA) and 'Knowledge, Skills and Abilities' (KSA) (Source: (Andersson et al., 1979))

Parameter	Lower Bound	Upper Bound	Median	Memo
M_1	0.66	0.9	0.78	International Government Document, Over 30 Years Old (Likely Credible)
M_2	0.66	0.9	0.78	“The result of the job analysis will be a set of typical tasks which represents the training content of the job. Skills and knowledge needed for the job can be derived from typical tasks” (Andersson et al., 1979) (Likely)
M_3	0.66	0.9	0.78	Analyst is likely confident about the topic of Job Analysis and KSA (Likely Confident)

The analyst interpretation process is repeated with multiple evidence entries, generating unique M_1, M_2, and M_3 values for each entry. For the training causal model, a minimum of three references were entered for each causal connection. Each piece of evidence can be seen in the Training model database [dataset] (Pence & Mohaghegh, 2018). Once all evidence is added to support causality, element# 1.3. of DT-BASE (Figure 3.2) is performed using either Arithmetic (Eq. 3.1) or Geometric (Eq. 3.2) aggregation methods. For example, considering two evidence entries in Tables 3.4 and 3.5, and adding a third evidence, where $M_1 = 0.945$, $M_2 = 0.995$, and M_3=0.78, the results of arithmetic and geometric aggregations for the conditional probability of good quality KSA, given a good quality JTA has been performed, are $Pr(KSA|JTA) = 0.86$ and $Pr(KSA|JTA) = 0.85$, respectively.

The resulting conditional probabilities for each causal relationship in the network are then extended in element #1.4 of DT-BASE to generate the CPT for the BBN (Element #1.5) using ICI modeling (explained in Section 3.2.2.1.4). In this example, the Noisy-OR method (Eq. 3.4) is used. Using the evidence entries in the Training causal model (Pence & Mohaghegh, 2018), the CPT for the target node Training Implementation is shown in Table 3.6. It should be noted that the conditional probabilities in Table 3.6 are not direct representations of the outcome (success or failure) of a training program, instead they are indicators of the quality of the elements comprising a training program; for example, the 50% probability shown in Table 3.6 is a conditional probability of having “poor training implementation” given “poor quality training procedure” and “poor quality instructor performance.” In this example, an LV is assigned to each layer based on probability language, considering it is ‘unlikely’ that the model is complete, with a lower bound of 0.1 and an upper bound of 0.33 to represent model uncertainty. Integration in a BBN computational platform (Element #1.5) is performed using the DT-BASE web application (Pence & Mohaghegh, 2017).

Table 3.6: Conditional Probability Table for Training Implementation Target Node

Training Procedure		Good Quality		Poor Quality	
Instructor Performance		Good Quality	Poor Quality	Good Quality	Poor Quality
Training Implementation	Good Quality	0.98	0.93	0.87	0.51
Training Implementation	Poor Quality	0.02	0.07	0.13	0.50

3.3.2. Applying DT-SITE Elements to Model and Quantify Training Quality in Nuclear Power Plants

This section explains the results of implementing DT-SITE elements (Figure 3.2) to quantify the training causal model utilizing plant-specific data. Since DT-SITE has not yet been integrated into the DT-BASE application, a preliminary text mining approach, in the form of a keyword search, was run in MATLAB Simulink software (Pence et al., 2015a). Using string search functions in MATLAB, each CAP entry was analyzed for the occurrence of keywords from the training causal model, and the results were mapped to a matrix resembling the conditional probability table of the training causal model. The approach was applied to one full year (2013-2014) of CAP data from one NPP, which initially included fifty thousand initial entries and follow-up entries. The algorithm, applied only to ‘initial’ CAP entries (i.e., not corrective actions or resolutions) totaling around fifteen thousand, searched for keywords associated with nodes in the causal model (Figure 3.6), finding the occurrence and co-occurrence of theoretical constructs within each entry of CAP. Using truth tables, the results are stored in a CPT, serving as the new frequency dataset. Frequencies were converted to probabilities by dividing the total number of entries during the data collection period of one year (see Section 3.2.2.2.2) (Pence et al., 2015a). The resulting conditional probabilities were used to calculate the probability of the target node probability of the Training BBN (Figure 3.6).

This simplified word search approach is applicable for CAP entries because of the format of the CAP entries, where ‘cause identification’ is explicitly separated from other text data. Therefore, using MATLAB Simulink string search functions, it was possible to analyze each entry for the occurrence of keywords and assign matches in a matrix which resembled the conditional probability tables of our causal models. In future work, a more rigorous text mining will be developed to expand DT-SITE applicability to more unstructured datasets (e.g., Licensee Event Reports (LERs), root cause analysis documents, and maintenance logs) which require preprocessing for cleaning text.

Because of the difficulty in obtaining CAP data, and the use of CAP data for only one year from one NPP in this example, the accuracy of estimated probabilities is dependent on the quantity of CAP entries, as well as the quality of CAP entries. To partially overcome the limitation of data quantity, as explained in Section 3.2.2, a two-step methodology is used in this research, where DT-BASE is used to generate the preliminary causal model and quantification based on generic information from literature and analyst interpretation, and DT-SITE then analyzes the plant-specific data (i.e., CAP data in this case study) to update the causal model using a Bayesian approach. With this approach, the lack of plant-specific data is partially addressed by combining it with generic information from the literature. The authors also plan to improve these estimates in future work by increasing the CAP dataset size and considering the quality of CAP data entries (as also mentioned in Section 3.3.3). Also, ongoing research by the authors focuses on developing a methodology to quantify the degree of confidence in the probability estimates by characterizing the epistemic uncertainty associated with limited data size, the relevancy of the data, and subjective interpretation of information.

Since DT-SITE has not yet been integrated into the DT-BASE application, it is not feasible at this stage of the research to integrate each conditional probability of SITE and BASE in element #2.4 of DT-SITE in order to develop an updated organizational causal input model (Element #2.5 in Figure 3.2). Therefore, for this example, only the “target node” probability from DT-BASE and DT-SITE are integrated using the Bayesian method explained in Section 3.2.2.2.4. Bayesian updating is performed using the open source program OpenBUGS (Spiegelhalter et al., 2007) to integrate the target node probability resulted from DT-BASE (Section 3.3.1) [dataset] (Pence & Mohaghegh, 2018) and the target node probability resulting from a simplified demonstration of DT-SITE using a sample dataset (Pence et al., 2015a).

In this Bayesian updating, the unknown of interest is Pr (Training Quality = Poor), denoted as P_{TQ}. A non-homogeneous population is assumed over P_{TQ}, as the evidence extracted from literature in the DT-BASE (Section 3.3.1) can include information from multiple sources and contexts. The population variability over P_{TQ} is represented by the beta distribution with two hyperparameters, α, and β. 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. For two hyperparameters, α and β, independent flat hyper-prior distributions spread over all positive values are developed (Atwood, 1996; Smith et al., 2009). Under this setting, the Bayes' theorem is formulated as follows:

$$\pi\left(\alpha,\beta|\underline{D}\right) \propto \int_{P_{TQ}} L\left(\underline{D}|P_{TQ}\right)\varphi\left(P_{TQ}|\alpha,\beta\right)dP_{TQ}\cdot\pi_0(\alpha,\beta) \qquad (3.16)$$

where

$\pi\left(\alpha,\beta|\underline{D}\right)$: Posterior distribution of the hyper parameters α and β

$L\left(\underline{D}|P_{TQ}\right)$: Likelihood function for the evidence $\underline{D}$, given the true value P_{TQ}

$\varphi\left(P_{TQ}|\alpha,\beta\right)$: Probability distribution for the hyper parameters α and β (beta distribution)

$\pi_0(\alpha,\beta)$: Prior distribution of the hyper parameters α and β

After computing the posterior distribution for α and β based on Eq. 3.16, the updated probability distribution for P_{TQ} is obtained using the law of total probability.

As mentioned in Section 3.2.2.2.4, the likelihood function should be chosen based on the types of evidence available for informing the estimation of the unknown of interest. In this case study, the available evidence consists of the P_{TQ} estimates generated by DT-BASE and DT-SITE, $\underline{D} = \left\{\hat{P}_{TQ,BASE},\hat{P}_{TQ,SITE}\right\}$. As shown in Eq. 3.16, if we assume that the P_{TQ} estimates from DT-BASE and DT-SITE are independent, the likelihood function is written as follows:

$$L\left(\underline{D}|P_{TQ}\right) = L\left(\hat{P}_{TQ,BASE}|P_{TQ}\right) * L\left(\hat{P}_{TQ,SITE}|P_{TQ}\right) \quad (3.17)$$

In Eq. 3.17, both pieces of evidence, $\hat{P}_{TQ,BASE}$ and $\hat{P}_{TQ,SITE}$, are outputs from the BBN model; thus, an additive or multiplicative model would be a reasonable choice for the likelihood function that represents the degree of model error (Droguett & Mosleh, 2000; Droguett & Mosleh, 2008). The selection between additive and multiplicative models depend on the nature of the problem and available evidence. At this stage of research, for demonstration of the methodology, the multiplicative error model is selected as the likelihood function. Based on this model, $\hat{P}_{TQ,i}; i \in \{BASE, SITE\}$, is represented by the product of the true value of the unknown quantity and the error term: $\hat{P}_{TQ,i} = P_{TQ}\cdot E_i$. The likelihood function for each piece of evidence is given as the lognormal distribution shown in Eq. 3.18:

$$L\left(\hat{P}_{TQ,i}|P_{TQ}\right) = \frac{1}{\sqrt{2\pi}\sigma_i\hat{P}_{TQ,i}} exp\left[-\frac{1}{2}\left(\frac{ln\,\hat{P}_{TQ,i}-\left(ln\,P_{TQ}+ln\,b_i\right)}{\sigma_i}\right)^2\right]; i \in \{BASE, SITE\}, \quad (3.18)$$

where b_i and σ_i stand for the bias factor and the logarithmic standard deviation of the error term E_i, respectively. For example, the analyst can assume that the causal models developed for DT-BASE and DT-SITE have no systematic bias concerning the true value ($b_{BASE} = b_{SITE} = 1$). Meanwhile, σ_i for each model can be estimated by considering upper and lower bounds for $\hat{P}_{TQ,i}$, which need to be entered by the analyst or estimated by performing uncertainty propagation in the DT-BASE and DT-SITE models. When the upper and lower bounds of $\hat{P}_{TQ,i}$ are entered as $P_{TQ,i;upp}$ and $P_{TQ,i;low}$, then σ_i can be estimated from Eq. 3.19 by considering the 95th and 5th percentiles of the lognormal likelihood equal to the upper and lower bounds:

$$\sigma_i = \frac{1}{\Phi^{-1}(0.95)} ln \sqrt{\frac{P_{TQ,i;upp}}{P_{TQ,i;low}}}\,, \qquad (3.19)$$

where Φ^{-1} is the inverse cumulative distribution function of the standard normal distribution. The implementation of Bayesian updating and the multiplicative error model is further explained in Section 3.3.2 in the context of the NPP case study. As the conversation-text cycle progresses in an organization, a new piece of evidence can be generated. Using BBN inference techniques, the new piece of evidence can be conditioned in the BBN engine to provide real-time updating for the target node probability of the BBN model.

The results from BASE and SITE are treated as two independent pieces of evidence: $\hat{P}_{TQ,BASE} = 0.0296$ and $\hat{P}_{TQ,SITE} = 0.00023$. σ_i is estimated using Eq. 3.19, assuming: (i) the upper bound and lower bounds of the target node probability estimates are 0.1 and 0.005, respectively, and (ii) 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. Using OpenBUGS, the posterior distributions for hyperparameters α and β are computed, and the expected beta distribution for the integrated probability of the poor quality of training target node is obtained by calculating the mean of the family of beta distributions over the posterior distributions of hyperparameters. The Bayesian integration of DT-BASE and DT-SITE results in the expected beta distribution shown in Figure 3.7, with a median of 0.0039.

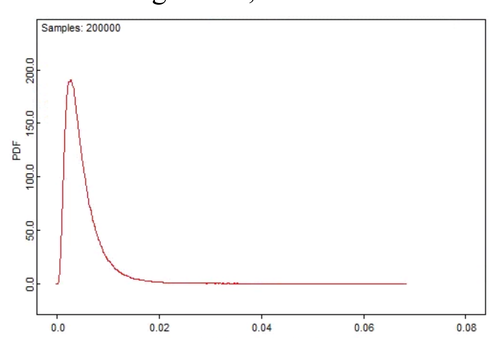

Figure 3.7: DT-BASE and DT-SITE Bayesian Integration for Poor Training Quality Distribution: OpenBUGS Output

3.3.3. Sensitivity Analysis & Extended Discussion

One of the advantages of the I-PRA framework is that sensitivity and importance measure analyses can be used to obtain the ranking of organizational risk-contributing factors based on their contribution to human errors and system risk. To illustrate this advantage, sensitivity analysis is conducted to rank factors based on their influence on the target node probability, i.e., Pr (Training Quality = Poor). This study uses the Fussell-Vesely Importance Measure (FV-IM) method, developed in classical PRA (Van der Borst & Schoonakker, 2001; Vesely et al., 1983) and extended to BBN by Groth et al. (Groth et al., 2010). The FV-IM method measures the sensitivity of the model output (i.e., target node probability, P_{TQ}) to individual factors by:

$$I_{B_i}^{FV} = \frac{P_{TQ} - P_{TQ|B_i=Good\ Quality}}{P_{TQ}}, \quad (3.20)$$

where $I_{B_i}^{FV}$ is the FV-IM computed for the factor B_i, P_{TQ} is the nominal output of the target node probability, where each causal node has its nominal/realistic state, and $P_{TQ|B_i=Good\ Quality}$ is the target node probability computed by conditioning that the node B_i has a 'Good Quality' with certainty. Conceptually, Eq. 3.20 assesses how much the target node probability decreases (i.e., the probability of Poor Quality of Training decreases) when each child node has a perfectly 'Good Quality'; hence, $I_{B_i}^{FV}$ indicates the importance of each factor in terms of improving the training quality. In the commercial BBN software GeNIe Modeler, the set evidence function is used to compute Eq. 3.20 for each factor by setting the occurrence of 'Poor Quality' to 0 for each node in the model to see the changed probability of the training implementation target node, Pr (Training Quality = Poor), which is logged in Table 3.7.

Table 3.7: DT-BASE Fussell-Vesely Importance Measure Results ('Node' Set Evidence_Poor = 0)

Level of Causality in Figure 3.6	Node (Poor Quality = 0)	FV-IM	Ranking
2.	Training Program Design	26.8%	1
1.1.	Training Procedure	25.7%	2
1.1.	Instructor Performance	21.5%	3
1.1.1.	Training Sequence	12.0%	4
1.1.1.	Training Method	12.0%	5
1.1.1.	Training Setting	12.0%	6
1.1.1.	Training Content	12.0%	7
1.1.1.	Training Structure	11.8%	8
1.1.1.	Training Media	11.8%	9
1.1.1.	Instructor Training	11.8%	10

Table 3.7 (cont.)

Level of Causality in Figure 3.6	Node (Poor Quality = 0)	FV-IM	Ranking
1.1.1.	Instructor Knowledge	11.7%	11
1.1.1.	Instructor Time Preparation	11.7%	12
2.1.	Training Records Documentation System	10.3%	13
2.1.	Training Needs Analysis	9.9%	14
2.1.	Instructional Technologist	6.2%	15
2.1.1.	Performance Analysis	4.3%	16
2.1.1.	Training Objectives	2.9%	17
2.1.1.	Knowledge, Skills, and Abilities Evaluation	2.2%	18
2.1.2.	Job/Task Analysis	1.9%	19
2.1.2.	Conditions & Standards	1.8%	20

It should be noted that due to the limited data set used in this analysis, the FV-IM differences identified below 1% are not interpreted as significant. As additional data is included in future work for this type of analysis, these small differences can be evaluated in a more meaningful way for risk management. The FV-IM results (Table 3.7) for the DT-BASE model reveal the following:

- Among all the causal factors, "Program Design," "Training Procedures/Facility," and "Instructor Performance" are identified as the first, second, and third most important factors, respectively.
- From Level 1.1. of the causal model (Figure 3.6), "Training Procedures/Facility" is ranked more important than "Instructor Performance," with a 4% difference.
- In Level 1.1.1 of the causal model (Figure 3.6), there are small differences among the estimated FV-IMs, and so the factors are considered at the same level of significance.
- In Level 2.1 of the causal model (Figure 3.6), among the sub-factors influencing the quality of "Program Design," "Training Records Documentation System" and "Training Needs Analysis" are identified as more important than "Instructional Technologists." These two factors may require more attention for the improvement of the training program. For example, Training Records and Documentation Systems manage information to help maintain employee licenses, qualifications, and certifications by scheduling training and continuing training. Training Records and Documentation Systems may also keep track of attendance/completion for crediting, and of performance evaluation results to inform the next cycle of training scheduling.

The importance ranking results provide insights for decision-makers responsible for resource allocation in order to develop effective strategies for improving operator training and decreasing human errors. It also gives the analyst the important factors that require more accurate data extraction and interpretation in order to generate more accurate practical recommendations for improvement policy.

Future work will address methodological advancements in sensitivity analysis for the Data-Theoretic Module in the I-PRA (Figure 3.2): (i) conducting multi-way (Sakurahara, T et al., 2014) and global sensitivity methods (Cheng et al., 2017; Sakurahara, T. et al., 2017; Sakurahara, T. et al., 2018; Sakurahara, T. et al., 2014) to account for the influences of non-linearity and interactions among multiple input parameters; and (ii) integration of DT-BASE and DT-SITE into one computational platform to run the sensitivity analysis on a single causal model. The ongoing research by the authors is focusing on the integration of the DT-BASE and DT-SITE into one computational platform so that the Bayesian updating of DT-BASE and DT-SITE (explained in Section 3.2.2.2.4) can be conducted at the level of conditional probabilities (rather than at the level of target node that is the case in Section 3.3.2) to develop one updated training causal model to be used for the SA.

As mentioned in Section 3.2.2.2.2, the estimated marginal probabilities are biased by the number (and quality) of CAP entries; therefore, Pr (Training Quality = Poor) = P_{TQ} is also biased by CAP entries. Future research should focus on resolving this bias; for example, by the following conceptualization. The ideal goal is to find the unbiased probability of "Poor Training Quality" (P), which can be defined as of A'/N_{Demand} where (A') stands for the real number of incidents involving operator training as a contributor, during the data collection period and, (N_{Demand}) represents the total number of operator demands during the data collection period. With this definition, (P) takes on values between 1.0 (every demanded action involves training issues) and 0.0 (training is never a contributor). Eq. 3.21 shows the relationship between (P), which is the unbiased probability of poor training quality, and the output of the Data-Theoretic (P_{TQ}) (i.e., the biased probability of poor training) which is associated to 'A/N_{CAP}' (i.e., the ratio of all training issues (A) to all reported incidents during the data collection period (N_{CAP})). In Eq. 3.21, A'/A stands for the quality of the CAP program in terms of accurately identifying training contributions. If all incidents involving training are correctly identified (A'/A) = 1; if there is any under-reporting, A'/A > 1 and (P) is correspondingly increased. To calculate (P), future research will focus on the application of a qualitative/qualitative strategy to assign a value to the quality of NPP CAP programs. Another required term to estimate (P) is the value of (N_{Demand}) in Eq. 3.21, and its estimation also needs further empirical research.

$$P = \frac{A\prime}{N_{Demand}} = \frac{A}{N_{CAP}} \times \frac{N_{CAP}}{N_{Demand}} \times \frac{A'}{A} \qquad (3.21)$$

As stated in Section 3.2.1, to operationalize the entire I-PRA framework (Figure 3.2), the key performance measures (e.g., Ka_1, Ka_2, Ka_3 in Figure 3.2), indicating the measured performance outputs of the organizational model, need to be generated to help define the states of PSFs in HRA. For instance, in the training case study, a key performance measure associated with the training/experience PSF in I-PRA needs to be generated. Ongoing research by the authors is on developing a methodology for using the estimated training quality distribution (Figure 3.7) from the Data-Theoretic Module, along with the analysis in Eq. 3.21, to develop a plant-specific training indicator that can be used as a key performance measure in I-PRA. By developing threshold values that can be associated with the low, nominal, and high training/experience PSFs in the Standardized Plant Analysis of Risk-Human Reliability Analysis (SPAR-H) HRA method (Gertman et al., 2005), the authors plan to develop a technique for calibrating the model outputs and mapping them to the states of PSFs for the same plant's risk scenarios. It should be noted, however, that the scope of the training causal model in this paper is not specific to one procedural action, and therefore, additional research is needed to develop causal factors associated with task-specific training quality that creates an interface to the PSFs of HRA. The authors envision that updating the states of PSFs (#5 in Figure 3.2) in the interface module of I-PRA would not only help develop site-specific human error probabilities but would also help address issues of HRA dependencies (Blackman & Boring, 2017; Gertman et al., 2005) as well as dependency among human actions.

Because it is not practical to connect all organizational factors to all PSFs in HRA, future research will focus on developing a structured approach to analyze the following items: **(a)** which HEPs need to be connected to the underlying organizational mechanisms, **(b)** which PSFs need to be connected to the underlying organizational mechanisms, **(c)** what organizational factors should be explicitly and causally modeled, and **(d)** the depth of causality and level of details that selected organizational factors should be expanded to. With respect to items (a) and (b), because the Data-Theoretic approach is developed for integration with PRA, importance measure analysis (e.g., Fussell-Vesely importance measure, Risk Achievement Worth, and Birnbaum importance measure (Cheok et al., 1998)) can be used to identify human failure events that significantly contribute to risk. Within each of these events, the dominant PSFs could be identified based on (i) existing guidance, task type, operating context, and/or (ii) a quantitative sensitivity analysis which aims to assess the sensitivity of the system risk estimate to each PSF. At this point, the Data-Theoretic approach can be applied for developing detailed causal models for those important HEPs and their dominant PSFs. Item (c) relates to the first step of the theory building process in Element #1.1 of DT-BASE and, as it is mentioned in Section 3.2.2.1.1, this step is associated with Principle I.A (i.e., identifying unknown of interest) in Table 3.1. The selection of dominant organizational factors associated with a specific PSF can be conducted using data (if available) and/or organizational science literature. Item (d) relates to Step 5 of theory building in Element #1.1 of DT-BASE as well as Principle II.E in Table 3.1. The depth of causality and level of detail in this context need to be determined by the analyst, considering several aspects, such as (i) risk importance of each causal factor, (ii) availability of data at each level of causality, and (iii) usefulness in accident prevention (e.g., the level of causal factors that are more effective for risk management). It should be noted that the process of model development and data analytics for Data-Theoretic approach is iterative. In other words, the analyst needs to start with a certain level of causality, by conducting risk importance measure and sensitivity analyses, to identify the causal factors where extension and quantification is needed

To produce a more accurate distribution of training quality (Figure 3.7), the authors are executing uncertainty analysis with respect to the analysts' manual extraction and interpretation of generic information in DT-BASE (Section 3.2.2.1). In the current training case study, the point values of the evidence weighting variables M_1, M_2, and M_3 are used. However, there are potential issues associated with different meanings by different analysts and with different contextual interpretations (Bjerga et al., 2016; Morgan, 2014). In this paper, the authors make the assumption that subjectivity and between-analyst variability is allowable for theory-building if the associated uncertainty is explicitly identified and characterized. The authors have ongoing research to incorporate uncertainty analysis techniques in the DT-BASE code to consider the entire range of probability values for M_1, M_2, and M_3.

The boundary between 'good' and 'poor' in the performance outcome nodes (e.g., safety critical tasks) in the SoTeRiA framework is reasonably clear; however, as the analyst gets further from the performance outcome nodes, the boundary between good and poor in the causal factors involves expert or analyst subjective judgment and uncertainty. The current stage of this research does not focus on analyzing the uncertainty involved in the measurement of good versus poor in each single factor; instead, the goal of this paper is to the develop a unified platform to quantitatively connect underlying organizational causal factors (as well as their associated variability and uncertainty) to the safety performance outcome (e.g., estimated risk). The next stage of the research will focus on running sensitivity analysis with respect to these variabilities and uncertainties to prioritize the critical areas that need more in-depth studies. Future research will also consider running sensitivity analysis with respect to underlying assumptions (e.g., unbiased estimates, lognormally distributed uncertainties, etc.) in the methodology and application to provide additional justification for the identified critical assumptions.

3.4. CONCLUDING REMARKS

Organizational factors have an ever-present underlying influence on socio-technical systems and have been identified as important contributors to incidents and accidents in diverse industries. Due to the complexity of organizational performance modeling, the integration of organizational mechanisms into Probabilistic Risk Assessment (PRA) has been a challenge. This paper is a product of a line of research to incorporate organizational factors into Human Reliability Analysis (HRA) and PRA to (a) explicitly assess the risk due to specific organizational weaknesses, (b) find and rank the critical organizational root causes of failure, which enhances risk management, and (c) avoid the possibility of under-or-over estimating the risk associated with human error.

Two requirements for incorporating emergent organizational safety behavior into PRA include: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links; (ii) the 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.

To meet the first requirement in this research, the Socio-Technical Risk Analysis (SoTeRiA) (Figure 3.1), a multi-level theoretical framework that connects the structural and behavioral aspects of an organization with PRA, is used (Mohaghegh, 2007). Regarding the "modeling" techniques, this research introduces the Integrated PRA (I-PRA) methodological framework (Figure 3.2) to operationalize SoTeRiA and to improve the realism of risk estimations by quantifying the incorporation of human and organizational performance into PRA. I-PRA preserves plant-specific PRA models while generating a probabilistic interface to connect the model of underlying failure mechanisms to PRA. This makes I-PRA economically efficient and practical for adoption by the nuclear industry. Regarding "measurement" techniques, this research develops the Data-Theoretic approach, the focus of this paper, which is executed in the data input module of I-PRA (Figure 3.2). The Data-Theoretic is an approach where "data analytics" are guided by "theory" to enhance the accuracy and completeness of "causality" being analyzed from data. The Data-Theoretic approach not only contributes to the development of a new "measurement" technique for organizational factors, but also makes theoretical contributions by expanding the theoretical causal details of SoTeRiA.

The Data-Theoretic module of I-PRA (Figure 3.2) has two sub-modules including DT-BASE and DT-SITE, and their elements are explained in detail in Sections 3.2.2.1 and 3.2.2.2. The Data-Theoretic approach is advancing the measurement of organizational factors in the following ways: **(1)** it combines different sources and types of information: (a) articles from academic literature, practical industry procedures and regulatory standards from industry are integrated through DT-BASE elements, (b) analysts' "subjective" interpretation of information in DT-BASE is combined with "objective" event data extracted in DT-SITE, and (c) "generic" information obtained in DT-BASE is integrated with "plant-specific" information extracted in DT-SITE; **(2)** it guides "data analytics" with "theory." The theoretical causal structure of the SoTeRiA framework and the contextual keywords of each node in SoTeRiA guide data analytics; therefore, the underlying theory supports the completeness of causal factors, the accuracy of their causal relationships, and helps avoid the potentially misleading results of a solely data-oriented approach; **(3)** it uses text mining (in DT-SITE), in addition to expert opinion (in DT-BASE), as a measurement technique. Although lack of data has been suggested as one of the key reasons for making slow progress in the incorporation of organizational factors into PRA, this research provides a new perspective by highlighting that data is available for organizational factors; however, this data is different from tabular equipment reliability data. Organizational data are a compilation of textual operational experience documents such as Corrective Action Program (CAP) entries, Licensee Event Reports (LERs), root cause analysis documents, and maintenance logs that are unstructured and heterogeneous; therefore, it is necessary to use text mining as a data analytics technique for socio-technical risk analysis.

A case study in this paper demonstrates the implementation of DT-BASE elements for the development of the theoretical causal model for organizational "training" (Figure 3.6) and for its generic quantification. The case study also explains the application of DT-SITE elements to quantify the causal model for training, utilizing plant-specific CAP data. The Bayesian integration of DT-BASE and DT-SITE results has generated the distribution of poor training quality (Figure 3.7) with a median of 0.0039. An importance measure analysis is performed on the causal model for training, and as a result, "Program Design," which is highly influenced by the quality of "Training Records Documentation System," is identified as the most important factor. More detailed results of the ranking of the factors are included in Table 3.7. This type of ranking contributes to more scientific and in-depth root cause analysis and more effective prevention of system failures caused by human errors or organizational factors. The causal model for training is not only theoretically validated but is also verified on its structure and contents by training experts at a Nuclear Power Plant (NPP). However, it should be noted that there are several assumptions and simplifications that were made in this analysis, and these are highlighted throughout the paper; hence, the numerical outputs of the case study, presented in this paper, are only for demonstration and should not be used directly in the context of specific practical applications. In ongoing research, the authors are conducting a Probabilistic Validation (Sakurahara, Tatsuya et al., 2018a) methodology to evaluate and measure the epistemic uncertainty (or the degree of confidence) associated with the estimated probability from the model as a measure of validation.

The computational platform of DT-BASE is an open-source web application (Pence & Mohaghegh, 2017) to enable a scientific network for collaborative model building. Using a client-server architecture, multiple analysts can work in parallel on a single causal model. Ongoing research by the authors focuses on advancing several modules of I-PRA (Figure 3.2), as follows: (a) developing advanced safety-oriented text mining that can be applicable for a wide range of unstructured organizational communications such as root cause analysis documents, work packages, training records, management systems, maintenance reports, and policy documents for DT-SITE; (b) integrating DT-SITE and DT-BASE into one computational platform to improve the Bayesian updating (See discussion in Section 3.3.3); (c) adding uncertainty analysis into the DT-BASE code (See discussion in Section 3.3.3); (d) advancing spatio-temporal methodologies (Bui et al., 2016; Bui et al., 2017; Pence & Mohaghegh, 2015; Pence et al., 2015b) for the simulation module (#3 in Figure 3.2) of I-PRA and facilitating the interface of the Data-Theoretic module and the simulation module; (e) developing methodologies for updating PSFs (# 5 in Figure 3.2) of existing HRA techniques based on the results of organizational causal modeling (See discussion in Section 3.3.3); (f) applying Data-Theoretic approach to other factors of SoTeRiA, such as the quality of organizational safety procedures and safety culture; and (g) developing global sensitivity analysis and importance measure analyses (Sakurahara, T. et al., 2017; Sakurahara, T et al., 2014) for the Data-Theoretic approach to increase the validity of the ranking of factors in the training causal model (See discussion in Section 3.3.3).

The topic of analyzing organizational influence on the risk of technological systems is a complex multidisciplinary research area. Although this paper provides a scientific contribution from the perspectives of modeling and measuring of organizational factors in PRA, many critical challenges remain, requiring future research. Some of these challenges may include: (i) the need for comprehensive calibration and integration of organizational mechanisms into HRA and PRA across the lifecycle (i.e., design, construction, operation, decommissioning), (ii) the need to include inter-organizational and broader factors in organizational performance models, (iii) dealing with a wider variety and larger volume of unstructured data sources (e.g., Licensee Event Reports, Root Cause Analysis reports, etc.), and calibrating those data sources to explicitly consider data quality and bias, (iv) dealing with dependencies among diverse data sources and amongst underlying performance shaping factor models, (v) implementing quantitative techniques for handling complex interactions in a causal model growing exponentially, (vi) considering the role of automated data analytics and data mining techniques in the building of theoretical causal models, (vii) methodological advancement of sensitivity analysis and importance measure analysis in the I-PRA framework, and (ix) Probabilistic Validation to characterize and propagate sources of epistemic uncertainty. Forthcoming publications by the authors will provide more thorough reviews of studies associated with theorizing, modeling, and measuring organizational factors, considering their impact on technological system risk to comprehensively adopt knowledge from diverse disciplines for the advancement of PRA.

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CHAPTER 4: DATA-THEORETIC APPROACH FOR SOCIO-TECHNICAL RISK ANALYSIS: TEXT MINING LICENSEE EVENT REPORTS OF U.S. NUCLEAR POWER PLANTS[1]

ABSTRACT

This paper is a product of a line of research that uses the Socio-Technical Risk Analysis (SoTeRiA) theoretical framework and Integrated PRA (I-PRA) methodological framework to theorize and quantify underlying organizational mechanisms contributing to socio-technical system risk scenarios. I-PRA has an input module that executes the Data-Theoretic (DT) approach, where "data analytics" can be guided by "theory." The DT input module of I-PRA has two sub-modules: (1) DT-BASE, for developing detailed grounded theory-based causal relationships in SoTeRiA, equipped with a software-supported BASEline quantification utilizing information extracted from academic articles, industry procedures, and regulatory standards, and (2) DT-SITE, using data analytics to refine and measure the causal factors of SoTeRiA based on industry event databases and using Bayesian analysis to update the baseline quantification. This paper focuses on the advancement of DT-SITE, contributing to the integration of text mining with the measurement of organizational factors for PRA, and demonstrating the following methodological elements and steps in DT-SITE: **(Element 2.1)** Text mining: (Step i) collect and pre-process unstructured text data, (Step ii) identify theory-based seed terms based on DT-BASE causal model, (Step iii) generate features, and (Step iv) build and evaluate classifiers (e.g., by using Support Vector Machine [SVM]); and **(Element 2.2)** Estimating probabilities and their associated uncertainties. The DT-SITE methodology is applied in a case study targeting the "training system" in Nuclear Power Plants (NPPs) and using Licensee Event Reports (LERs) from the U.S. nuclear power industry, where LER-specific data extraction and pre-processing tools are developed.

4.1. INTRODUCTION AND STATEMENT OF OBJECTIVES

Organizational factors remain elusive and latent contributors to incidents and accidents in high-consequence industries, such as nuclear power, aviation, oil and gas, and healthcare. Probabilistic Risk Assessment (PRA)/Probabilistic Safety Assessment (PSA) (NRC, 1975) is a formal methodology for estimating risk emerging from the interactions of equipment failure and human error, where Human Reliability Analysis (HRA) (Mosleh & Chang, 2004; Swain & Guttmann, 1983) is used for modeling and quantifying human error in risk scenarios. This paper is the product of a line of research on the advancement of 'socio-technical' risk analysis to explicitly incorporate organizational factors into PRA/HRA. In this

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research, the explicit incorporation of organizational factors refers to the model-based or mechanistic integration (e.g., (Rios, 2004)) of organizational performance with PRA elements, allowing for more accurate analysis of the contribution of organizational factors to human error (i.e., through HRA), equipment failure, and Common Cause Failures (CCFs). For example, organizational factors, such as the training quality of a maintenance crew, may influence labor-centric maintenance performance, which in turn can affect physical failure mechanisms (e.g., stress corrosion) of equipment.

Mohaghegh et al., (2007, 2009, 2010) reviewed existing theoretical frameworks and quantitative techniques related to the explicit incorporation of organizational factors into risk models (Mohaghegh, 2007; Mohaghegh, 2009; Mohaghegh, 2010a, 2010b; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2007, 2009a, 2009b) and highlighted two requirements for incorporating emergent organizational safety behavior into PRA: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links, and (ii) the 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.

For the first requirement, a theoretical framework, called Socio-Technical Risk Analysis (SoTeRiA) (Figure 4.1) (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a), was developed based on a multi-level organizational performance model developed by Ostroff (Ostroff et al., 2003). SoTeRiA is a theoretical causal framework for explicitly integrating both the social aspects (e.g., safety culture) and the structural features (e.g., safety practices) of an organization with a technical system PRA. SoTeRiA theorizes multiple levels of internal mechanisms, including individual, unit, group, and organization (Nodes 2 to 9 in Figure 4.1), and their interactions with the external environment, including physical, regulatory, business, and sociopolitical climate (Node 10 and Nodes 12 to 16 in Figure 4.1). Pence et al., (2019) expanded the SoTeRiA framework to include the performance of an organization's "training system" (i.e., within Node 7, Organizational Structure & Practices in Figure 4.1), which is applied in Section 4.4 of this paper.

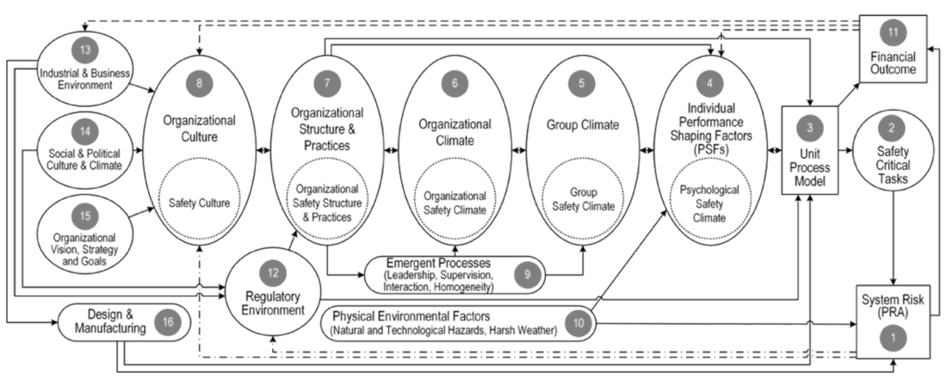

Figure 4.1: Socio-Technical Risk Analysis (SoTeRiA) theoretical framework (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a)

Operationalizing and quantifying SoTeRiA requires the development of appropriate "modeling" and "measurement" techniques. With respect to modeling techniques, Mohaghegh et al. (2007, 2009, 2010) developed a hybrid technique that combines the probabilistic method of Bayesian Belief Network (BBN) and a dynamic simulation-based technique (i.e., system dynamics) (Mohaghegh, 2007, 2010a; Mohaghegh et al., 2009) with the classical PRA methods to quantify SoTeRiA causal factors (Mohaghegh, 2007, 2010a). The previous publication (Pence et al., 2019b) by some of the authors of this paper introduced the Integrated PRA (I-PRA) methodological framework (briefly explained in Section 4.3 and instantiated in Figure 4.2) that is an advancement of the original work by Mohaghegh et al., (Mohaghegh et al., 2009) and is based on an adaptation of the I-PRA approach which has been already applied for incorporating physical failure mechanisms into PRA for the risk-informed resolution of Generic Safety Issue 191 (Bui et al., 2019; Mohaghegh et al., 2013) and fire PRA (Sakurahara et al., 2017; Sakurahara et al., 2018a; Sakurahara et al., 2018b; Sakurahara et al., 2015).

Pence et al., (2019) created the input module of the I-PRA framework by developing the Data-Theoretic (DT) approach, where "data analytics" can be guided by "theory." (Pence et al., 2019b) The Data-Theoretic input module of I-PRA has two sub-modules: (i) DT-BASE, for developing detailed grounded theory-based causal relationships in SoTeRiA, equipped with a software-supported BASEline quantification utilizing information extracted from academic articles, industry procedures, and regulatory standards, and (ii) DT-SITE, using data analytics to refine and measure the causal factors of SoTeRiA based on industry event databases and using Bayesian updating to modify the baseline quantification. Pence et al., (2019) covered the methodological elements of DT-BASE in detail, and briefly highlighted the methodological elements of DT-SITE. (Pence et al., 2019b). This paper focuses on the advancement of the DT-SITE methodological steps (see Section 4.3), contributing to the integration of text mining with the measurement of organizational factors for PRA.

To clarify how the approach proposed in this paper fills the gaps in the existing studies, Section 4.2 provides a thorough review of related studies. Section 4.3 covers the methodological and computational development of the Data-Theoretic input module, focusing on DT-SITE. In Section 4.4, the DT-SITE methodology is applied in a case study using Licensee Event Reports (LERs) from the U.S. nuclear power industry. LERs are submitted to the Nuclear Regulatory Commission (NRC) when "reportable events" occur at Nuclear Power Plants (NPPs), such as technical specification-required shutdown, or other events affecting plant safety barriers/functions. NPPs are required to submit LERs under Title 10 of the Code of Federal Regulations (10 CFR) Part 50.73, and guidelines for LER reporting are provided in NUREG 1022, rev. 3 (NRC, 2013a). LERs are standardized, semi-structured forms with header information, data entry fields, checkboxes, and free text fields. The free text fields of LERs are the source of unstructured data used in this paper. LERs are available in a public, searchable database containing LERs from 1980 to the present.[2] The LER database is a key source of event data (e.g., initiating events, equipment failure, human errors) and provides insights on plant operational experience, which can support industry and regulatory decision-making. In the case study of this paper (Section 4.4), LER-specific data extraction and pre-processing tools are developed and conducted, theory-based seed terms from a pre-existing DT-BASE model are leveraged for feature selection, Support Vector Machine (SVM)-based classifiers are built and evaluated, the probability of having "training deficiency" as one of the causes of reported events are estimated, and preliminary uncertainty analysis is conducted using multiple runs of k-fold cross-validation.

4.2. REVIEW OF RELATED STUDIES

Section 4.2.1 covers the review of the studies (from 2000 to 2018) that utilize machine learning-related techniques for the measurement of organizational factors in safety/risk analysis. Although the review of studies in Section 4.2.1 has generated some lessons learned to support the proposed method in Section 4.3, none of the existing studies were found to be associated with PRA. Therefore, Section 4.2.2 has broadened the review to include all existing machine learning studies (not specifically for organizational factors) that have been conducted from 2000 to 2019 under the field of PRA. The review in Section 4.2.2 generates additional information to compare different techniques and justify the selection of the methodology in Section 4.3. Lastly, because this paper specifically uses the U.S. nuclear industry LER dataset, the authors have conducted a review of data analysis studies from 2000 to 2018 that have analyzed LERs. Some of the LER studies included PRA-related machine learning analysis and are therefore covered in Section 4.2.2. The rest of the LER studies are related to PRA but did not use machine learning analysis, and they are reviewed in Section 4.2.3. The review in Section 4.2.3 helps identify what measurement techniques have been applied previously and identifies the challenges of analyzing LERs.

4.2.1. Review of Studies that Developed and/or Applied Machine Learning-Related Techniques for Organizational Factors in Safety/Risk Analysis

Table 4.1 reviews the existing studies (from 2008 to 2018) that develop and/or apply machine learning-related techniques for measuring organizational factors in safety/risk analysis. The following list covers the definitions of columns in Table 4.1 that are the same for the columns in Table 4.2 and 4.3 in Sections 4.2.2 and 4.2.3, respectively:

a. Data Source refers to the source of raw or pre-processed/aggregated data (e.g., LERs) that are used in the study.

[2] https://lersearch.inl.gov/LERSearchCriteria.aspx

b. Data Type can be unstructured (e.g., non-tabular or free text data) or structured (e.g., tabular or numerical data).

c. Data Format refers to the formatting, representation, or coding of the data (e.g., binary classification, binned/categorical, numerical variable, free text).

d. Type of Process refers to the primary knowledge discovery process being applied to the data. In this paper, the process of "text mining" refers to the entire Knowledge Discovery from Databases (KDD) process that includes selection, pre-processing, transformation, machine learning, interpretation, and evaluation (Fayyad et al., 1996). Machine learning processes are further divided into (i) "supervised," where labeled/classified data is provided, (ii) "semi-supervised," where labeled and unlabeled data are provided, and (iii) "unsupervised" where no labeling is provided (Han et al., 2011). Labels indicate the target category that a piece of data belongs to (e.g., if an email should be labeled in the category of "spam" or "non-spam") and are often generated by annotators' judgment. In addition to machine-learning processes, the review in this paper includes a Natural Language Processing (NLP)-related study in Table 4.2. NLP is used to analyze linguistic concepts of text, including part-of-speech (e.g., noun, verb) and grammatical structure (e.g., phrase, noun phrase) (Kao & Poteet, 2007). Another non-machine learning type of process is the parametric process that uses traditional statistical analyses such as regression that assumes an a priori statistical model (Han et al., 2011). Table 4.1 and Table 4.2 (in Section 4.2) do not cover parametric processes and focus only on studies using machine learning or NLP approaches but Table 4.3 (in Section 4.2.3) covers studies that use parametric processes for LERs.

e. Sub-type of Process refers to the different approaches available within each type of process. For example, for unsupervised machine learning algorithms, clustering is a common approach, while in supervised machine learning, classification is a common approach. The difference between clustering and classification is that classification uses labeling as an input to the machine learning process to differentiate between targeted categories, while clustering does not use labeling, but divides data into groups based on similarities in data attributes (Ethem, 2014). Additional sub-types of processes are included in Tables 4.1 and 4.2.

f. Type of Technique refers to the specific toolkit or algorithm that is utilized to operationalize the type of process, which varies in Tables 4.1 and 4.2.

Table 4.1: Review of studies (from 2000 to 2018) that developed and/or applied machine learning-related techniques for organizational factors in safety/risk analysis

Citation	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process	(e) Sub-type of Process	(f) Type of Technique
(Tirunagari et al., 2012)	Marine Accident Reports	Unstructured	Free Text	Unsupervised Machine Learning	Clustering	Self-Organizing Map (SOM)
(Moura et al., 2017)	Multi-attribute Technological Accidents Dataset (MATA-D) (from (Moura et al., 2016))	Structured	Binary Classification (presence or absence)	Unsupervised Machine Learning	Clustering	SOM
(Yu et al., 2018)	Multi-attribute Railway Accidents Dataset (MARA-D)	Structured	Binary Classification	Unsupervised Machine Learning	Clustering	SOM
(Doell et al., 2015)	MATA-D	Structured	Binary Classification	Unsupervised Machine Learning	Association Rule	Market Basket Analysis
(Feng et al., 2014)	Historical Data	Structured	Binned/Categorical	Semi-Supervised Machine Learning	Bayesian Network Structure	Ant Colony Optimization (ACO)

The literature review in this section (summarized in Table 4.1) highlights the following results:

(i) There are a limited number of studies that leveraged machine learning for measuring organizational factors in safety/risk analysis. One reason is that unlike the well-established and standardized practices for collecting data on equipment, there are no safety-oriented data collection schemas for measuring organizational factors in risk analysis. Without a granular data collection system, organizational factors are measured as high-level abstractions, labeled in the aggregate, and do not include the underlying root cause contributors to organizational weaknesses. Data collection practices are also different in industries that have more frequent accidents/incidents with lower consequences (e.g., rail accident/incident data (Yu et al., 2018)), which create differences in the availability and quality of data. Machine learning techniques can face practical difficulties when the number of observations limits datasets, or when there are deficiencies in an organization's recording and reporting practices. In the nuclear industry, for example, there are no formalized data collection standards for organizational factors. For analyzing organizational factors, methods and concepts from diverse disciplines should be adopted in an interdisciplinary framework (e.g., SoTeRiA in Figure 4.1), allowing for more comprehensive coverage of the path of influence on safety performance (Mohaghegh, 2007). Therefore, for the measurement of organizational factors, methodologies should be capable of dealing with limited or unstructured data, as well as differentiate between a wide array of theoretical constructs.

(ii) Among the studies that use machine learning to quantify organizational factors for safety/risk analysis, none of them were connected to, or performed analysis for PRA frameworks. This paper is a first-of-its-kind PRA-related study that develops a machine learning method for the quantification of organizational factors.

(iii) Among the studies that used machine learning to quantify organizational factors for safety/risk analysis, none of them used LER as their data source. The proposed method in this paper uses LER database.

(iv) All existing studies, except Tirunagari et al. (2012), that leveraged machine learning for measuring organizational factors in safety/risk analysis, were conducted on structured data. The method in Section 4.3 of this paper is developed for unstructured free-text data. The data format in Tirunagari et al. (2012) is also similar to the data format in this paper, i.e., free text data; however, the type of process and the type of technique proposed in Section 4.3 are different from the ones used by Tirunagari et al. (2012). The main reason for using a supervised machine learning approach in this study, rather than unsupervised processes, is the goal of the Data Theoretic approach; to guide data analytics with the theory (i.e., the theoretical causal model developed under the DT-BASE). This will be further explained in Section 4.3.

4.2.2. Review of Studies that Conceptualized or Applied Big Data Analytics and Machine Learning for PRA

Section 4.2.2.1 reviews the literature that conceptualized big data analytics and machine learning for PRA (primarily in NPP-related studies) but did not reach the stages of methodological development or application. Section 4.2.2.2 reviews existing studies (from 2000 to 2019) that developed and/or applied machine learning approaches for PRA, primarily for NPPs.

4.2.2.1. Studies that Conceptualized Big Data Analytics and Machine Learning for PRA

Smith et al., (2012) discussed the potential values of machine learning for advanced PRAs to support small modular reactors (Smith et al., 2012). Siu et al., (2013) discussed the role that content analytics and text analytics plays in supporting regulatory decision-making, and the Nuclear Regulatory Commission's (NRC's) plan to initiate scoping studies to explore the application of advanced data analytics techniques to support PRA activities (Siu, N et al., 2013). Pence et al., (2014) initiated a discussion on the potential role of big data analytics and the internet of things in measuring and performing real-time monitoring of safety performance in the changing landscape of risk. Pence et al., (2014) considered topics of big data for measuring organizational factors for PRA (Pence et al., 2014), identifying potential uses for "dark data" (i.e., data not generally used for other purposes (Heidorn, 2008)), and a discussion on how to leverage the information that organizations collect, process, and store for regular business activities for risk analysis. Wishart et al., (2015) discussed the challenges of data storage for PRA, where traditionally, Microsoft Excel and Access were used to manage some PRA datasets. When a large volume of data is collected, the memory limits of these tools can be reached, which might affect the processing power of computational resources (Wishart et al., 2015). Wishart et al., (2015) also discussed the collection and use of plant walkdown data (e.g., structured forms, unstructured field notes or images for fire and flooding PRA) and equipment condition data as potential datasets (Wishart et al., 2015). Cha et al., (2015) discussed the role of big data in Operations and Maintenance (O&M) for NPPs (Cha et al., 2015). Some studies discussed big data for analyzing equipment reliability (e.g., (Yeliseyeva & Malovik, 2017)), software reliability (e.g., (Liu et al., 2017)), and big data in virtual plant/physics models (e.g., (Wu, 2019)). In 2017 and 2018, workshops were held to discuss the uses of big data for NPPs, with several presentations on big data analytics in PRA (Smidts et al., 2019). Farley et al., (2018) discussed the potential for machine learning to support the front-end and back-end of dynamic PRA analysis, for example by analyzing the action possibility space of human operators using NLP tools to identify the most relevant procedures and maintenance records (Farley et al., 2018). Szilard et al., (2018) discussed the potential uses of computational algorithms, such as machine learning and Artificial Intelligence (AI), to be used in the nuclear industry for automated risk-informed plant processes. For example, the automatic analysis of failure data can be used for maintenance rule monitoring by evaluating plant event reports to screen functional failures and maintenance preventable actions (Szilard et al., 2018). Al Rashdan et al., (2018) discussed the potential uses of data analytics for online monitoring of equipment and systems in support of risk management, but specific methods were not clarified (Al Rashdan et al., 2018). Groth and Bensib (2018) discussed potential sources of big data from the main control room, sensor arrays, industry operational experience, and plant operational data, that could provide trend analytics and diagnostics, resulting in online status visualizations and decision support tools (Groth, Katrina & Bensi, 2018). Keusseyan (2018) stated that big data can be used to leverage resources for engineering, operations, maintenance, management, and regulatory oversight (Keusseyan, 2018). Several papers discussed the potential use of text mining for analyzing procedures for HRA (Boring et al., 2018; Rasmussen et al., 2018). Leveraging relevant literature on severe accidents of NPPs from the Google Scholar database, Zhao and Smidts (2019) discussed the use of machine learning approaches for content analysis in the development of knowledge base, which could be used to support HRA and PRA (Zhao & Smidts, 2019).

4.2.2.2. Studies that Developed and/or Applied Machine Learning Approaches for PRA

Table 4.2 covers the review of existing studies that developed and/or applied machine learning approaches for PRA, primarily for NPPs. The definitions of the columns of Table 4.2 ("a" to "f") are consistent with the definitions of columns in Table 4.1, listed at the beginning of Section 4.2.1.

Table 4.2: Review of studies that developed and/or applied machine learning approaches for PRA

Citation	**(a) Data Source(s)**	**(b) Data Type**	**(c) Data Format**	**(d) Type of Process**	**(e) Sub-Type of Process**	**(f) Type of Technique**
(Di Maio et al., 2015, 2016b)	Simulink, Dynamic Event Tree (DET)	Structured	Multiple-Valued Logic (MVL)	Unsupervised Machine Learning	Clustering	Modified Binary Differential Evolution (MBDE), K-Means Clustering Algorithm
(Osborn et al., 2013)	Analysis of Dynamic Accident Progression Trees (ADAPT)/MELCOR/MELCOR Accident Consequence Code System (MACCS) Codes	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	Mean Shift

Table 4.2 (cont.)

Citation	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process	(e) Sub-Type of Process	(f) Type of Technique
(Mandelli et al., 2013)	Adaptive Sampling of ADAPT/ Reactor Excursion and Leak Analysis Program (RELAP)-5/ Risk Analysis and Virtual Environment (RAVEN) Outputs	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	Symbolic Aggregate approXimation (SAX), Time Series Knowledge Representation (TSKR)
(Sen et al., 2015)	BISON/RAVEN	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	(Various) SciKit-Learn[3] Library Algorithms
(Maljovec et al., 2016)	Nuclear Simulation Datasets	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	Hierarchical Clustering, Topological Clustering
(Al-Dahidi et al., 2015)	NPP Multidimensional Transient Events	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	Cluster-based Similarity Partitioning and Serial Graph Partitioning and Fill-reducing

[3] https://scikit-learn.org

Table 4.2 (cont.)

Citation	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process	(e) Sub-Type of Process	(f) Type of Technique
						Matrix Ordering Algorithms (CSPA-METIS)
(Mandelli, D. et al., 2018)	RAVEN, Monte-Carlo	Structured	Numerical Values	Unsupervised Machine Learning	Clustering	Hierarchical clustering, K-means Algorithm, Mean-Shift Algorithm
(Cogliati et al., 2016)	RAVEN	Structured (Time Dependent Data)	Numerical Values	Unsupervised & Supervised Machine Learning	Clustering, Dimensionality Reduction	(Various) SciKit-Learn[1] Library Algorithms
(Tian et al., 2018)	Transient Datasets, Linear Interpolation Dataset	Structured	Numerical Values	Unsupervised Machine Learning	Neural Network (NN)	Multilayer Perceptron (MLP)
(Worrell et al., 2019)	Consolidated Fire and Smoke Transport (CFAST) simulations	Structured	Numerical Values	Unsupervised Machine Learning	Metamodel	Regression Tree, l-Nearest Neighbor (kNN) Regression, Support Vector Machine (SVM)

Table 4.2 (cont.)

Citation	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process	(e) Sub-Type of Process	(f) Type of Technique
(Wang, Z. et al., 2018)	Seismic Fragility Curve Simulations	Structured	Numerical Values	Unsupervised Machine Learning	Artificial Neural Network (ANN)	ANN python package Neurolab[4]
(Zou et al., 2018)	National Nuclear Safety Administration (NNSA) Experience Feedback Platform	Structured	Binned/ Categorical	Unsupervised Machine Learning	Clustering, Association Rule Mining	Group Average Clustering Method
(Di Maio et al., 2016a; Di Maio et al., 2017a, 2017b)	Event Scenario Data	Structured	Binned/ Categorical	Semi-Supervised Machine Learning	Clustering	Semi-Supervised Self-Organizing Maps (SSSOMs)
(Ham & Park, 2018; Park et al., 2018)	Korean Nuclear Event Evaluation Database (NEED) Incident Reporting System	Structured	Binned/ Categorical	Supervised Machine Learning	Classification	Classification And Regression Tree (CART)
(Lee et al., 2018)	ADAPT/MELCOR/Radiological Assessment System for Consequence Analysis (RASCAL)	Structured	Binned/ Categorical	Supervised Machine Learning	Classification	Convolutional Neural Network (CNN)
(Mandelli, Diego et al., 2018)	Spambase Data Set[5]	Unstructured	Free Text	Supervised Machine Learning	Classification	Logistic Regression

[4] https://code.google.com/archive/p/neurolab/
[5] https://archive.ics.uci.edu/ml/datasets/Spambase

Table 4.2 (cont.)

Citation	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process	(e) Sub-Type of Process	(f) Type of Technique
(Young et al., 2004)	LER	Unstructured	Free Text	Unsupervised Machine Learning	Clustering	IN-SPIRE[6]
(Siu, Nathan & Coyne, 2018; Siu, N et al., 2016)	LER	Unstructured	Free Text	Supervised Machine Learning	Classification	IBM Watson Content Analytics (ICA) Version 2.2
(Zhao et al., 2018)	LER	Unstructured	Free Text	Natural Language Processing (NLP)	Part of Speech Tagging, Dependency Parser	Stanford CoreNLP API[7]

The literature review in this section (summarized in Table 4.2) highlights the following results:

i. There are a limited number of studies using machine learning to quantify PRA model elements, and none of the studies included organizational factors, as highlighted in Section 4.2.1 as well. The application of machine learning approaches for PRA primarily analyzed physical phenomena (e.g., using data sources resulted from MELCOR [severe nuclear accident progression code], BISON [nuclear fuel performance code], Consolidated Fire and Smoke Transport (CFAST) [zone-based fire model]), where machine learning was used to cluster the simulation outcomes. In these studies, the data are not historical events and instead are the results of simulation codes; therefore, the main challenge is dealing with large volume of data rather than processing heterogeneous data.

ii. Several studies leveraged the Risk Analysis and Virtual Environment (RAVEN) computational platform to operationalize machine learning for time-dependent data resulted from simulations that were equipped with sampling and uncertainty analysis (e.g., ADAPT/RELAP/RAVEN; (Mandelli et al., 2013).

iii. Among the PRA-oriented machine learning/NLP studies, nine (i.e., (Al-Dahidi et al., 2015; Ham & Park, 2018; Mandelli, Diego et al., 2018; Park et al., 2018; Siu, Nathan & Coyne, 2018; Siu, N et al.,

[6] https://in-spire.pnnl.gov/
[7] https://stanfordnlp.github.io/CoreNLP/api.html

2016; Young et al., 2004; Zhao et al., 2018; Zou et al., 2018))[8] used historical event data rather than results of simulation codes. Among these nine studies, four used unstructured free text data, three of which used LERs, and among these three, one used NLP instead of machine learning (i.e., (Zhao et al., 2018)). This indicates that there are limited studies using text mining approaches for PRA. The Data-Theoretic methodology in this paper offers a text mining approach for PRA, where the supervised machine learning process is conducted on unstructured free text data from LERs to perform classification using the SVM technique. SVM, compared to Logistic Regression (e.g., used by (Mandelli, Diego et al., 2018)) has been shown to perform better for highly imbalanced/skewed datasets (Musa, 2013). A dataset is considered imbalanced/skewed when classification (i.e., labeled) categories are disproportionately represented in a dataset (Chawla, 2009). In the case of the LER dataset used in the case study of this paper, data is highly imbalanced/skewed (i.e., the classified categories are relatively rare/unusual occurrences, composing a "minority" category), making it difficult for machine learning to detect the minority category from the regular/"majority" category (Köknar-Tezel & Latecki, 2009; Wang, B.X. & Japkowicz, 2010)). Modifying the classifier is one approach for improving classifier accuracy for imbalanced/skewed data (Wang, B.X. & Japkowicz, 2010). This paper modifies the classifier to address the imbalanced/skewed data issue of LERs and is discussed in Section 4.4. Compared to the well-known/open source machine learning algorithms for SVM and Logistic Regression, the performance evaluations of commercial software packages (e.g., IN-SPIRE, IBM Watson Content Analytics [ICA]), used by (Young et al., 2004) and (Siu, Nathan & Coyne, 2018; Siu, N et al., 2016), are limited due to a lack of open source, repeatable, and reproducible evaluations. Additional research is needed to compare the performance evaluation of machine learning techniques for unstructured data to justify the best selection for PRA.

4.2.3. Review of Parametric Data Analysis Conducted on the U.S. Nuclear Industry Licensee Event Reports

Three LER studies used machine learning methods (or NLP) and are covered in Section 4.2.2.2. The rest of existing LER studies used parametric data analysis and are covered in Table 4.3. The definitions of the columns of Table 4.3 ("a" to "d") are consistent with the definitions of columns in Table 4.1 that are listed at the beginning of Section 4.2.1, with the addition of "Application Area," which indicates the focus of the analysis for NPP-related studies.

[8] It should be noted that in the study by Zhao et al., (2018), the NLP toolkit was used for entity recognition, coreference, and basic dependencies but was not implemented as part of a machine learning process. This study is included in Table 4.2 (rather than Table 4.3) since it had some level of sophistication, similar to the LER studies in Table 4.2, compared to the LER studies in Table 4.3 that used parametric approaches.

Table 4.3: Review of non-machine learning studies that analyzed U.S. nuclear industry LERs

Citation(s)	Application Area	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process
(Braverman et al., 2000)	Age-related degradation of structures and passive components	Coded LERs, NRC Correspondences, NUREGS, Industry Reports	Structured	Binned/Categorical	Parametric
(Gertman et al., 2002)	Human Performance	Coded LERs, Augmented Inspection Team (AIT) Reports	Structured	Binned/Categorical	Parametric
(Hallbert et al., 2006)	Human Performance	Coded LERs, AIT Reports, other reports	Structured	Binned/Categorical	Parametric
(USNRC, 2018)	Accident Sequence Precursor (ASP) Program	Coded LERs	Structured	Binned/Categorical	Parametric
(Schroer & Modarres, 2013)	Multi-Unit Dependencies	Coded LERs	Structured	Binned/Categorical	Parametric
(Modarres et al., 2017)	Multi-Unit Dependencies	Coded LERs	Structured	Binned/Categorical	Parametric
(Zhou & Modarres, 2017)	Multi-Unit Dependencies	Coded LERs	Structured	Binned/Categorical	Parametric
(Germain, S.W.S., 2014)	Industry Trends Program, Standardized Plant Analysis	Coded LERs	Structured	Binned/Categorical	Parametric

Table 4.3 (cont.)

Citation(s)	Application Area	(a) Data Source(s)	(b) Data Type	(c) Data Format	(d) Type of Process
	Risk (SPAR) Models				
(Nie et al., 2008; Nie et al., 2009)	Aging Degradation of Passive Components, Seismic Capability Evaluation	Coded LERs	Structured	Binned/Categorical	Parametric
(Šimić et al., 2015)	Event Group Ranking	Coded LERs	Structured	Binned/Categorical	Parametric
(Germain, S.S. et al., 2017)	Outage Risk Management	Coded LERs	Structured	Binned/Categorical	Parametric
(Groth, K.M. & Mosleh, 2012) (Groth, KM & Mosleh, 2009)	Human Performance	Coded LERs, Human Events Repository Analysis (HERA) and Human Factors Information System (HFIS)	Structured	Binned/Categorical	Parametric
(Fleming & Lydell, 2004)	Pipe Failure Rates and Rupture Frequencies	Coded LERs, PIPExp	Structured	Binned/Categorical	Parametric

The literature review in this section (summarized in Table 4.3) highlights the following results:

i. The majority of studies that conducted data analysis on LERs used (a) coded LERs (structured data) and (b) a parametric type of process.

a. All the studies listed in Table 4.3 used "coded" LERs for their analysis. The coding of text data is a manual process of assessing each document/data entry to interpret if specific themes or theoretical concepts emerge (Saldaña, 2015). For example, Hallbert et al., (2006) used a worksheet of predefined subevent codes (e.g., for identifying attributes associated with work type, personnel, human action type) for qualitatively analyzing LER events, where detailed codes for 'personnel' were used to identify the involvement of operations (e.g., operations supervisors (O-S), control room operators (CR)) and maintenance and testing (e.g., maintenance supervision/planning (M-S)) personnel in LER events (Hallbert et al., 2006). The qualitative coding results in a new "structured" set of binned/categorical data, summarizing the statistics of the LERs, and the resulting categories are then quantitatively analyzed. The reliability of human coders contributes to the overall quality of coded LERs; however, the existing studies listed in Table 4.3 did not consider the quality of human coders in their analysis. One potential reason for this lack of consideration of coder quality is that without standardized terminology or guidance on interpreting the language representing specific categories in LERs, it would be difficult for coders to reach consensus and identify targeted concepts and categories. For example, considering synonyms (i.e., variations in industry vocabulary) and polysemy (i.e., words with multiple meanings) in LER texts, diverse interpretations may emerge. In the case study (Section 4.4) of this paper, LERs are "annotated" (rather than coded). Annotation is the manual process of labeling qualitative concepts in text, which can be conducted at multiple levels of analysis (i.e., word, sentence, paragraph, section, document/data entry) (Weiss et al., 2010). Annotated labels provide targeted areas for machine learning algorithms to leverage semantic and NLP techniques in text mining. While coding is conducted on the entire dataset and the quantitative results (i.e., coded LERs) are statistically analyzed, annotations can be performed on a subset of data, and the results provide guidance for machine learning algorithms being conducted on the entire dataset (or larger dataset). In text mining, annotations are also used as a benchmark for evaluating the performance of machine learning algorithms, and therefore, the reliability of human annotators must be explicitly measured. In this paper, a theoretical causal model (developed in DT-BASE) is used to standardize terminologies of organizational factors and provide guides for annotators. In addition, the kappa statistic (Landis & Koch, 1977) is used to measure the inter-rater reliability of annotators. Further explanations are provided in Sections 4.3 and 4.4. This paper is the first study to conduct annotation and measure inter-rater reliability of annotations on LERs.

b. Compared with parametric processes, machine learning methods are able to scale-up human annotation efforts so that skewed and rarely occurring information is not overlooked, better compensate for the ordinality of LER data, analyze larger volumes of data, and corroborate manual coding/annotations with automated approaches. Among all the studies that conducted data analysis on LERs, three of them used machine learning approaches (Siu, Nathan & Coyne, 2018; Siu, N et al., 2016; Young et al., 2004)) as highlighted by Table 4.2. Among these studies, two applied the supervised machine learning process of classification for analyzing LERs (Siu, Nathan & Coyne, 2018; Siu, N et al., 2016); however, their process was not guided by a theoretical framework. The Data-Theoretic methodology introduced in Section 4.3 makes unique contributions to studies of LERs by offering a supervised machine learning process that is guided by a theoretical causal framework. Further explanations are provided in Sections 4.3 and 4.4.

ii. With respect to application areas, most studies in Table 4.3 that analyzed coded and structured LER data were focused on analyzing equipment failure and human error. The application areas of the LER studies in Table 4.2 that conducted machine learning included (i) high-level exploration of LER language (Young et al., 2004) and (ii) exploratory analysis on initiating events (Siu, Nathan & Coyne, 2018; Siu, N et al., 2016), while the one study, using NLP, had the application area of (iii) exploratory analysis on LER causal language (Zhao et al., 2018). In 2007, Galán et al., conceptualized the use of LERs for measuring the occurrence of component failures due to organizational factors; however, the study did not implement any approach, nor did it propose a quantitative method for classifying data in LER entries (Galán et al., 2007), and therefore, was not included in Table 4.3. Section 4.3 of this paper proposes the first-of-its-kind machine learning method to quantitatively analyze LERs for the application area of organizational factors.

4.3. METHODOLOGICAL AND COMPUTATIONAL DEVELOPMENTS FOR THE DATA-THEORETIC INPUT MODULE OF INTEGRATED PRA (I-PRA): ADVANCEMENT OF DT-SITE

Pence et al., (2019) introduced the Integrated PRA (I-PRA) methodological framework (Figure 4.2) to quantify the SoTeRiA theoretical causal framework (Figure 4.1) (Pence et al., 2019b). As Figure 4.2 shows, I-PRA is a multi-level risk assessment framework that begins with the Data-Theoretic module extracting and formalizing the organizational data required for the simulation of underlying organizational mechanisms (Element 3 in Figure 4.2) that affect the states of Performance Shaping Factor (PSF) (e.g., a_1, a_2, and a_3) and that, therefore, influence the probability of human errors (e.g., event "a" in the FT) in the site-specific PRA module. Through the interface module, the "Spatiotemporal Simulation of Organizational Failure Mechanisms" (Element 3 in Figure 4.2) is connected to the associated PSFs in the site-specific PRA module. In the interface module, the uncertainties associated with input data are characterized and propagated by the uncertainty analyzer (Element 4 in Figure 4.2) to make the simulation module probabilistic and ready to be connected to the site-specific PRA model.

Pence et al., (2019) created the input module of the I-PRA framework by developing the Data-Theoretic (DT) approach, where "data analytics" can be guided by "theory" (Pence et al., 2019b). The Data-Theoretic input module of I-PRA has two sub-modules: (i) DT-BASE (Element 1 in Figure 4.2; the white boxes on the left in the Data-Theoretic input module) that focuses on the development of detailed causal relationships in SoTeRiA, based on a theory-building process and equipped with a software-supported BASEline quantification utilizing analyst interpretation of generic information extracted from articles and standards; and (ii) DT-SITE (Element 2 in Figure 4.2; the light blue boxes on the right in the Data-Theoretic input module) that relates to conducting data analytics (text mining) to quantify SoTeRiA causal elements based on industry event databases and by Bayesian updating of the baseline quantification established by DT-BASE.

The Data-Theoretic module uses the high-level causal relationship of SoTeRiA (Figure 4.1) as a preliminary causal structural shell in Element 1.5 (Figure 4.2) to guide the analyst when adding more detailed causal constructs. Elements 1.1 to 1.4 of DT-BASE are the steps for adding more detailed causal constructs and quantifying the targeted causal model in Element 1.5. The scope of the targeted causal model in Element 1.5 can include adding details to one node of Figure 4.1 or adding details to multiple nodes of Figure 4.1 while preserving the high-level interconnections among those nodes (based on the causal connection of SoTeRiA in Figure 4.1). In this paper, the scope of the targeted causal model is the "training system" (i.e., Systematic Approach to Training (NEI, 2017)) of NPPs, which is related to Node 7 in Figure 4.1. The targeted causal model that is gradually built and quantified through Elements 1.1 to 1.4 of DT-BASE forms the Organizational Causal Input Model in Element 1.5 as the input to DT-SITE. The quantification of the Organizational Causal Input Model is updated through DT-SITE Elements 2.1 to 2.4 to generate an updated version of the same causal model in Element 2.5, ready to provide input for the simulation module. In other words, the Organizational Causal Input Model in Element 2.5, a targeted-scope model of SoTeRiA (Figure 4.1) with more detailed levels of causality, gives the input information (i.e., the causal structures and their associated measures) for the spatio-temporal simulation module (Element 3 in Figure 4.2), where the analyst can add temporal and/or spatial dimensions. The key performance measures (e.g., Ka_1, Ka_2, Ka_3 in Figure 4.2) refer to the measured performance outputs of the organizational model that help define the states of PSFs. For example, the quality of organizational training affects the state of training/experience PSF in HRA. Thus, the estimated quality of training from the organizational model is a key performance measure associated with the training/experience PSF in I-PRA. In the interface module, by having the probability distributions of the key performance measures resulting from the uncertainty analysis, the probability of each state of PSFs (e.g., low, nominal, high) is generated (Element 5 in Figure 4.2) by estimating the probability that the associated key performance measure exceeds threshold values.

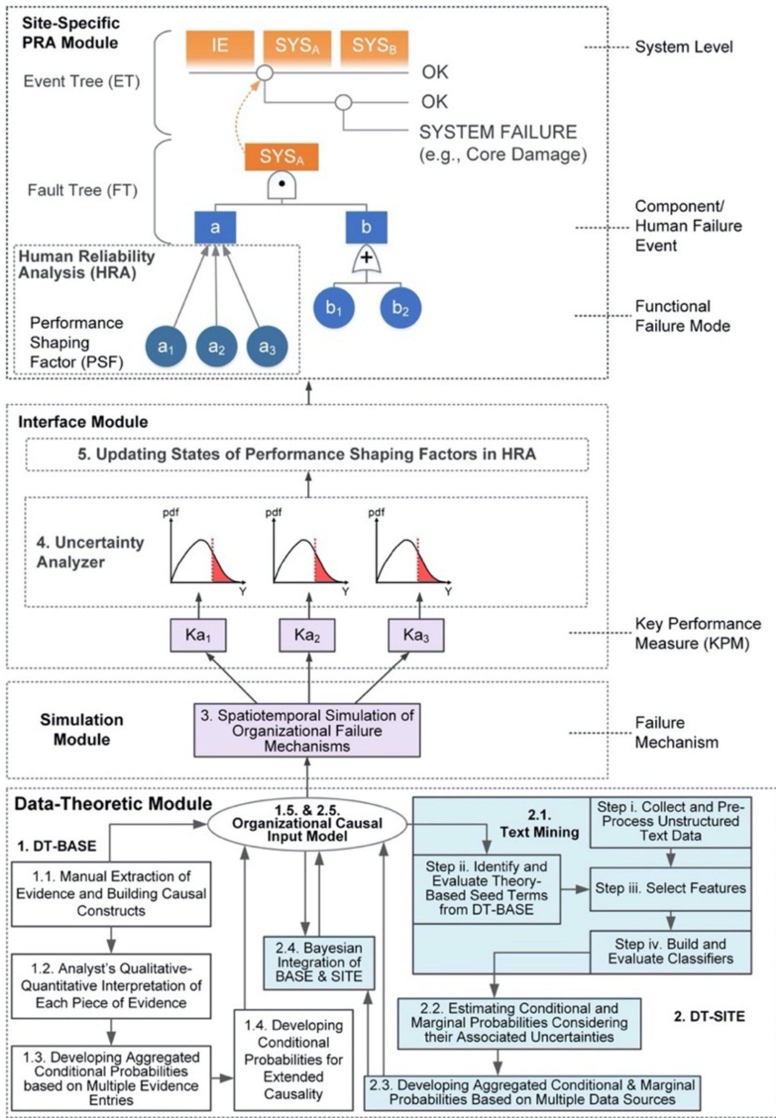

Figure 4.2: Integrated PRA (I-PRA) methodological framework for quantifying SoTeRiA

Pence et al., (2019) covered the methodological elements of DT-BASE in detail, and briefly highlighted the methodological elements of DT-SITE. (Pence et al., 2019b). This paper focuses on the advancement of the DT-SITE methodological steps (see Section 4.3.1) and their applications for NPPs (Section 4.4). The Data-Theoretic approach advances measurement techniques for organizational factors in the following ways:

1. It guides "data analytics" with "theory." Theory enhances the accuracy and completeness of causality being analyzed from data and helps avoid potentially misleading results from solely data-oriented

approaches. In the Data-Theoretic approach, the theoretical causal structure of the SoTeRiA framework (Figure 4.1) and the contextual keywords of each node in SoTeRiA provide the categories for labeling data, which can be used to train the classifier in supervised machine learning, so that the underlying theory supports the completeness of causal factors and their causal relationships in text mining results.

2. It combines different sources and types of information from academic literature, practical industry procedures, and regulatory standards in DT-BASE elements, considering the analysts' "subjective" interpretation of the information. The "generic" information obtained in DT-BASE is then integrated with industry-specific information extracted from industry event databases in DT-SITE.
3. It uses text mining (in DT-SITE), in addition to expert opinion (DT-BASE), as a measurement technique. This research leverages available data for organizational factors, even though the data has a different nature than tabular numerical formatting. Archival data, documents, and texts serve as primary organization-level data. The Communicative Constitution of Organization (CCO) is a widely-accepted multidisciplinary perspective of organizational communication theory, which asserts that "organizations are constituted (and maintained) through human communication" (Cooren et al., 2011). For example, organizational documents in circulation at NPPs are stable data that move forward through space and time, and these documents are what constitute the organization (Ashcraft et al., 2009; Güney & Cresswell, 2012; Taylor et al., 1996).

4.3.1. DT-SITE Elements of the Data-Theoretic Input Module in I-PRA

As the I-PRA framework (Figure 4.2) shows, the output of Element 1.5 of DT-BASE (i.e., the Organizational Causal Input Model) provides the causal factors, their related keywords (i.e., synonyms, categories, labels), and causal relationships as inputs for the elements of DT-SITE. Pence et al., (2019) proposed the following five methodological elements for DT-SITE:

- Text Mining (Element 2.1 in Figure 4.2)
- Estimating Conditional and Marginal Probabilities Considering their Associated Uncertainties (Element 2.2 in Figure 4.2)
- Developing Aggregated Conditional and Marginal Probabilities based on Multiple Data Sources (Element 2.3 in Figure 4.2)
- Bayesian Integration of SITE and BASE Probabilities (Element 2.4 in Figure 4.2)
- Integration in the Organizational Causal Input Model/BBN Computational Platform (Element 2.5 in Figure 4.2)

In the previous research by some of the authors of this paper, a simplified keyword search was implemented to fulfill Element 2.1 in DT-SITE (Pence et al., 2019b; Pence, J et al., 2017). Pence et al.,

(2019) also developed general methodologies for Elements 2.2, 2.3, 2.4, and 2.5, focusing on updating conditional and marginal probabilities of a BBN that was developed and quantified from the DT-BASE for the Organizational Casual Input Model (Pence et al., 2019b). Section 4.3.1.1 advances the methodological steps of text mining (Element 2.1) in DT-SITE. Section 4.3.1.2 elaborates on Element 2.2 and provides explanations on how to use the results of text mining (Element 2.1) to estimate the target node probability (and its associated uncertainty) of the Organizational Causal Input Model. Future research will further advance Elements 2.2, 2.3 and 2.4 to use the results of text mining for the update of the conditional probabilities of the BBN developed in DT-BASE.

4.3.1.1. Text Mining (Element 2.1 in Figure 4.2)

Element 2.1 of DT-SITE establishes a bridge between the different nomenclatures used in industry, regulatory, and academic settings (i.e., the casual factors and relationships built in DT-BASE) to the language used in textual artifacts from industry-wide event reporting systems. This paper proposes four methodological steps for Element 2.1 in DT-SITE:

- Collect and pre-process unstructured free text data (Step i of Element 2.1 in Figure 4.2),
- Identify and evaluate theory-based seed terms from DT-BASE (Step ii of Element 2.1 in Figure 4.2),
- Select features (Step iii of Element 2.1 in Figure 4.2), and
- Build and evaluate classifiers (Step iv of Element 2.1 in Figure 4.2).

The flowchart in Figure 4.3 demonstrates the computational implementation of the four steps of Element 2.1 (text mining) and Element 2.2 of DT-SITE. The following sub-sections explain in detail the four steps of Element 2.1 and the computational flowchart. Section 4.3.1.2 covers the explanation of Element 2.2.

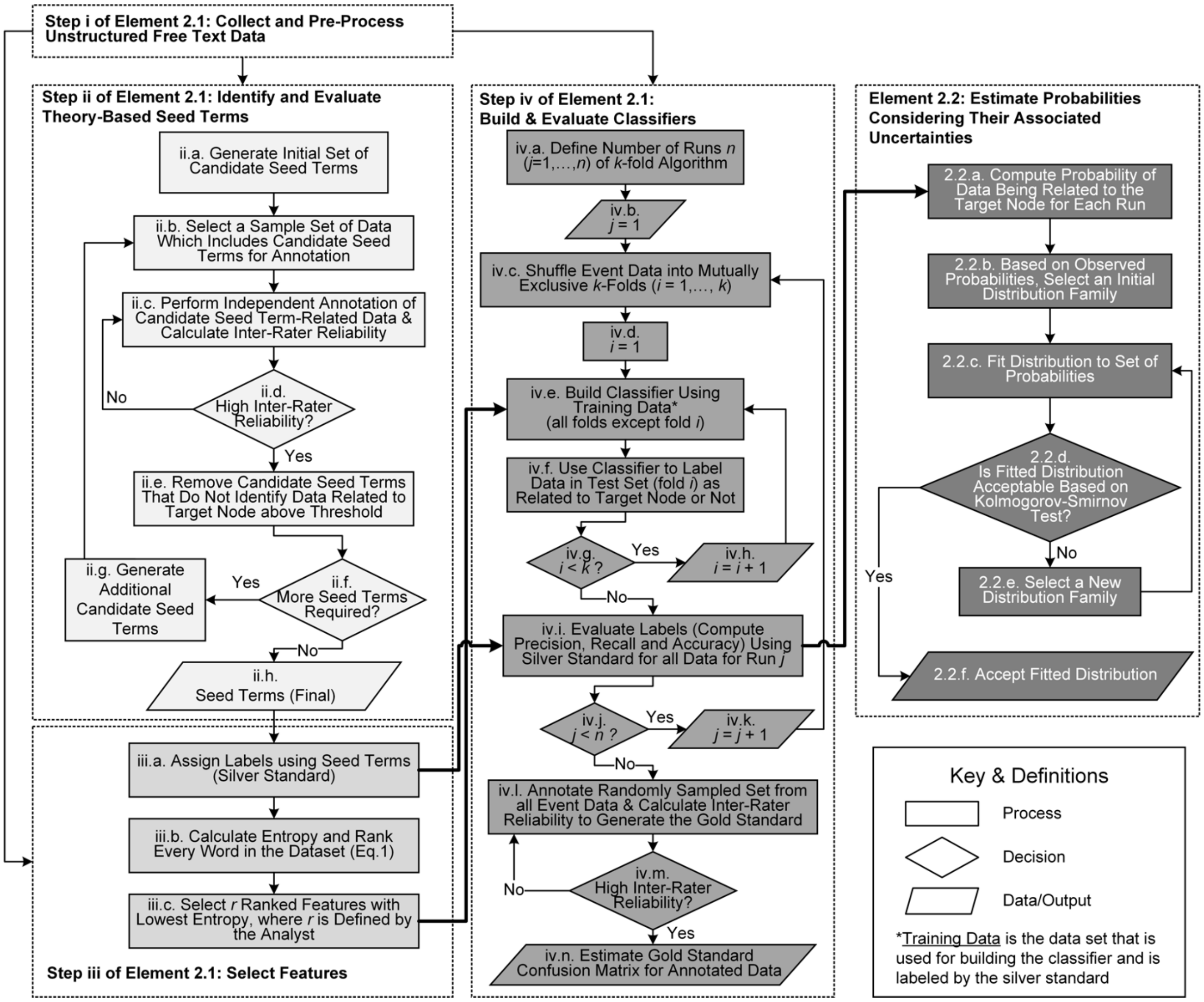

Figure 4.3: Computational flowchart of DT-SITE Element 2.1 (Steps i-iv) and Element 2.2

4.3.1.1.1. Collect and pre-process unstructured free text data (Step i of DT-SITE Element 2.1 in Figure 4.3)

Textual data requires pre-processing, including data cleaning (e.g., removing non-ASCII characters), data formatting (e.g., usable text files), and data management (e.g., file labeling). Once the dataset has been collected in a usable format, text data is pre-processed to identify sentences and terms (e.g., using the Stanford CoreNLP toolkit (Manning et al., 2014)). It should be noted that due to the variety of data in industry reporting systems, specific computational processes are not provided for Step i, however, a detailed case study implementing Step i can be seen in Section 4.4.1.1.

4.3.1.1.2. Identify and evaluate theory-based seed terms in DT-BASE (Step ii of DT-SITE Element 2.1 in Figure 4.3)

Supervised algorithms require labeled text. Labels are aligned with text opportunistically from other datasets or by manual annotation. The advantage of using the DT-BASE theoretical causal model to drive text mining efforts is that candidate seed terms (i.e., terminology and vocabulary for specific causal factors), drawn from the theoretical constructs (i.e. with context, definitions, synonyms, and industry-specific language of causal factors) within the Organizational Causal Input Model (Element 1.5 in Figure 4.2), can be used to scale up human annotation efforts that are then used by the supervised algorithm. Identifying the final set of seed terms is an iterative process, where an initial set of seed terms are identified (ii.a in Figure 4.3) using the Organizational Causal Input Model (Element 1.5 in Figure 4.2) that is developed through the DT-BASE process (Elements 1.1. to 1.4 in Figure 4.2). A sample set of data that include the selected seed terms are randomly obtained for annotation (ii.b in Figure 4.3). Next, experts perform annotation of the candidate seed term-related data (ii.c in Figure 4.3), evaluating whether the sentence is "related" or "not related" to the target node (e.g., in the case study of this paper explained in this paper, the target node is NPP "training system"). In this same step, ii.c, inter-rater reliability is calculated using the kappa statistic (Cohen, 1960; Landis & Koch, 1977) to determine the level of agreement between annotators. See Appendix A for more details on the calculation of inter-rater reliability in this paper. The inter-rater reliability results of Cohen's kappa (Cohen, 1960) have been interpreted as: values ≤ 0 as indicating no agreement and 0.01–0.20 as none to slight, 0.21–0.40 as fair, 0.41– 0.60 as moderate, 0.61–0.80 as substantial, and 0.81–1.00 as almost perfect agreement (Landis & Koch, 1977; McHugh, 2012). A low level of agreement indicates ambiguity in candidate seed terms, lack of knowledge by the annotators, or theoretical inconsistencies between the Organizational Causal Input Model and the text data.

In Step ii.d, if the result of inter-rater reliability analysis is low, the results of annotation are not reliable enough to be used in the next step of the algorithm and so before moving to step ii.e, it is recommended that the annotators be trained to get a clear understanding of the meaning of the seed terms. Then, the same set of seed terms are used to generate another sample of data for the annotators to conduct the annotation until the inter-rater reliability rate is improved to a reasonable value. Step ii.e (ii.e in Figure 4.3) is a process to use the results of annotations to remove candidate seed terms that do not adequately identify data related to the target node category. If the number of target node-related data pertaining to a specific candidate seed term does not meet the analyst's threshold criteria (e.g., the ratio of number of target node-related data over number of all data in a sample of seed term queries is less than %30), a decision is made to remove the seed term. If more seed terms are required, additional candidate seed terms are generated (ii.g in Figure 4.3), and then another sample data is selected based on the updated set of candidate seed terms, and steps ii.c, and ii.e are rerun. This loop is repeated until adding more candidate seed terms does not provide the analyst a reasonable number of additional selected seed terms (i.e., most of added seed terms are removed in Step ii.e.). In this case, in Step ii.f., the analyst decides to stop this process and move to Step ii.h to call the resulted set of seed terms as "final." The final seed terms are used in Step iii that is discussed in Section 4.3.1.1.3.

4.3.1.1.3. Select features (Step iii of DT-SITE Element 2.1 in Figure 4.3)

Using the final seed terms from Step ii, a sample set of data that includes seed terms is queried (iii.a in Figure 4.3). In this paper, this sample set of seed term-queried data is referred to as the "silver standard." The assumption of the silver standard is that any entry containing a seed term is labeled as being in the target node category, while any entry that does not contain a seed term is labeled as not being in the target node category. Since the seed terms that are used for the generation of the silver standard are based on an interactive and annotation-based process in Step ii (explained in Section 4.3.1.1.2), it is reasonable to assume that all the data entries that are in the silver standard (i.e., the data entries that contain seed terms) are related to the target node category. However, assuming that the silver standard completely covers the target node category is not accurate for several reasons, namely, (i) the theory-based seed terms may not be comprehensive, and/or (ii) it is possible that some of the selected seed terms appear in the data as types of synonyms that are not known, and/or (iii) since our data is imbalanced/skewed, removing some of the seed terms in Step ii.d may lead to missing a reasonable number of data entries related to the target node category. According to Zipf's law, the word frequency of language typically follows a power law distribution (Zipf, 1935). While it is easy to identify the most frequent keywords using keyword searches, it is challenging to ensure that all the relevant keywords that appear in the long tail are also captured.

Machine learning models can be overfit to the initial data set if the entire vocabulary of a collection is used rather than a subset of informative features. One of the symptoms of overfitting is that the model produces accurate predictions on a training dataset but does not generalize to data in a new test set. Overfitting is problematic when working with text because the feature space is typically large (i.e. the vocabulary size can be in the order of tens of thousands) and because the feature space is sparse (i.e. most features are zeros because a data entry contains only a small subset of the vocabulary terms). To avoid over-fitting, informative features are selected that represent "characteristics" in data that are likely predictors of the target node category (Joachims, 2002). In Step iii.b of the feature selection process, entropy is calculated for every word in the dataset and based on the labels from the silver standard. Entropy is widely used in feature selection in machine learning (Yang & Pedersen, 1997). The reduction in entropy associated with each word (or term) can be used for word ranking, where words providing the greatest reduction in entropy are prioritized (Sui, 2013). In this paper, Eq. 4.1 in Yang and Pedersen (1997) is used to identify the most informative features (Yang & Pedersen, 1997).

$$G(t) = -\left[P(t)\sum_{i=1}^{m} P(c_i|t)\, log\, P(c_i|t) + P(\bar{t})\sum_{i=1}^{m} P(c_i|\bar{t})\, log\, P(c_i|\bar{t})\right] \tag{4.1}$$

where, $P(t)$ is the probability of word t existing in a document/entry, $P(c_i|t)$ is the conditional probability a document is in category i given word t in the document, $P(\bar{t})$ is the probability of word t not existing in a document, and $P(c_i|\bar{t})$ is the conditional probability a document is in category i given word t is not in the document. Eq. 4.1 is run for every word for all entries in the dataset. The words are ranked based on lowest entropy score, and using this ranking, in step iii.c, the analyst will select r ranked words with the lowest entropy as the final set of features that will be used in the classifier in Step iv.

4.3.1.1.4. Build and evaluate classifiers (Step iv of DT-SITE Element 2.1 in Figure 4.3)

The purpose of this step of the algorithm is to use the features (generated in Section 4.3.1.1.3) to build a predictive model (or function or classifier) that can best identify (or classify) the data related to the target node category. The assumption is that a function of these features would represent the characteristics that could lead to the identification/classification of the target category data, and the purpose of this step of the algorithm is to build the right function of the features. In order to build this function (or classifier), several candidate techniques (e.g. naïve Bayes, decision tree and SVM) are common. This paper uses SVM in the case study (Section 4.4). After a specific technique (e.g., SVM) is selected, k-fold cross validation (Anguita et al., 2009) is used to execute the technique on the data and evaluate the error rate of classifier performance. The underlying concept of k-fold cross validation is that k-1 folds of data (i.e., "training data"[9]) is used for building the classifier while one fold of data (i.e., "test data") is used for testing the classifier. This process is repeated k times (by changing the folds) so that each fold of data is used for testing. In this study, the k-fold cross validation is also run several times ("n" runs in the algorithm) to better validate the results and generate more randomness. These "n" runs try to check the model validity by capturing the epistemic uncertainty (i.e., uncertainty related to the lack of knowledge or confidence about a model (NRC, 2013b)) in the results that are detailed in Section 4.3.1.2 by developing the probability distribution of the number of data entries associated with the target node category.

In Step iv.a of Figure 4.3, the analyst defines the number of runs (n) that the k-fold cross validation needs to be repeated. In this paper, the number of runs is based on the analyst's opinion, but future work will discuss the sensitivity of the results to these number of runs. At the start of each run (Step iv.c in Figure 4.3), the entire dataset is shuffled and divided into 'k' mutually exclusive and approximately equal folds. In Step iv.e, the classifier is built using (a) the selected classifier building technique (e.g., SVM), (b) the features (from Step iii), and (c) the training data. In this step of the algorithm, the selected technique (e.g., SVM) is conducted on the training data (i.e., folds 1,2,…i-1, i+1,…k) to build a function of the features (i.e., a classifier) that can well present the characteristics of the category-related data (i.e., the label data) in the training data. In step iv.d of Figure 4.3, the remaining fold of the data that is not included in the training

[9] "Training data" is the data set that is used for building the classifier and is labeled by the silver standard and should not be confused with the "training system" causal model from DT-BASE or the target node category of "training system" in Section 4.

data (i.e., fold i) is used as the test set for the built classifier. The classifier is used to label data in the test set (fold i) as 'related to the target node category' or 'not related to the target node category' (Step iv.f in Figure 4.3). This process is repeated for each of the k folds (iv.g and iv.h in Figure 4.3), i.e., the test set would change among all k folds. In Step iv.i of Figure 4.3, to evaluate the performance of a classifier, a confusion matrix is used to calculate precision, recall, and accuracy for each run. Precision is the ratio of the number of data entries correctly predicted as being related to the target node category (i.e., data entries labeled as being related to the target node category by the classifier and are also in the silver standard) to the total number of data entries predicted by the classifier as being related to the target node category. Recall refers to the ratio of the number of data entries correctly predicted as being related to the target node category to the total number of data entries marked as being related to the target node in the silver standard. Accuracy stands for the ratio of correctly labeled data entries (i.e., the ratio of the summation of the number of agreements between the classifier predictions and the silver standard to the total number of data entries are recorded for each run. In Steps (iv.j and iv.k in Figure 4.3), this process is repeated for the rest of the n runs.

In Step iv.i, the performance of the classifier is tested against labels generated by the silver standard but it is known that the silver standard does not cover all target category data entries. If it was possible to annotate the entire database to find all the labeled data, it would be a better test of the performance of the classifier. Instead of annotating the entire dataset, in Step iv.l of Figure 4.3, a random sample of data is selected and annotated to generate a gold standard. In the literature, a gold standard can be generated by annotating either a complete annotation of the entire dataset (e.g., (Akhondi et al., 2014)) or a set of randomly sampled data (e.g., (Juckett, 2012)). Ideally, the gold standard should have a high inter-rater reliability score (Viera & Garrett, 2005). If an entire dataset is not used for the gold standard, then the number of samples for annotations in the gold standard is determined by the analyst, and annotations should also have a very high inter-rater reliability score (i.e., (Cohen, 1960; Landis & Koch, 1977)). In Step iv.m of Figure 4.3, the classifier predictions are evaluated against the gold standard using a confusion matrix for estimating precision, recall, and accuracy. The value of evaluation in Step iv.i is that a larger amount of data is used for testing the classifier since the folds are changed k times in the k-fold evaluation process and the k-fold runs are repeated "n" times, but the test in Step iv.m is only on one subset of data. The value of evaluation in Step iv.m is that the test is against the gold standard rather than silver standard. This paper proposes both of these evaluations in the algorithm to get more information on model performance, while avoiding the annotations of the entire dataset which requires extensive time and human resources.

4.3.1.2. Estimating Conditional and Marginal Probabilities Considering their Associated Uncertainties (Element 2.2 in Figure 4.3)

As it is mentioned at the beginning of Section 4.3.1, the purpose of Element 2.2 of DT-SITE is to estimate (from the results of text mining) the conditional and marginal probabilities of the BBN model developed in DT-BASE. These probabilities in Element 2.4 are integrated with the probabilities estimated in the DT-BASE using Bayesian updating. This paper only covers Element 2.1 (Text mining) and Element 2.2. In this paper, the scope of Element 2.2 is limited to estimating the target node probability of the BBN model because the text mining of this paper is limited to the target node. Future work will extend the text mining algorithm to other causal factors in the BBN model.

In this paper, in each of the n runs of Step iv in Element 2.1 (explained in Section 4.3.1.14), the number of data entries related to the target node category is predicted. The predicted number of data entries related to the target node is then divided by the total number of data entries in the collection, resulting in the probability of data being related to the target node for each run (Step 2.2.a in Figure 4.3). Based on the n probabilities estimated from n runs, an initial distribution family should be selected (Step 2.2.b in Figure 4.3) and fit to the n probabilities (Step 2.2.c in Figure 4.3). A statistical test (e.g., Kolmogorov-Smirnov test for a small sample size) is utilized to evaluate the goodness of fit of the selected distribution (Step 2.2.d in Figure 4.3). Additional details regarding assumptions for the selected statistical test are provided in Section 4.4.2. If the results of the statistical test are not acceptable, another distribution is selected and fit to the n probabilities (Step 2.2.c in Figure 4.3). However, if the results of the statistical test are acceptable, the fitted distribution is accepted. The distribution resulted from this process represents the epistemic uncertainty in the results of the algorithm that is captured through "n" runs in Section 4.3.1.1.4. Future research by the authors will focus on more advanced quantification of uncertainties in this study.

4.4. APPLYING THE DT-SITE METHODOLOGY TO ESTIMATE THE PROBABILITY OF TRAINING SYSTEM-RELATED EVENTS IN THE LICENSEE EVENT REPORTS OF NUCLEAR POWER PLANTS

This section applies Element 2.1 and 2.2 of the DT-SITE methodology (explained in Section 4.3.1) in a case study using LER data from the U.S. nuclear power industry. The case study uses an existing Organizational Causal Input Model for the "training system" at an NPP (see Figure 4.4), related to Node 7 in Figure 4.1. As Figure 4.2 demonstrates, the existing Organizational Causal Input Model in Element 1.5, built and quantified using Elements 1.1 to 1.4 of DT-BASE (Pence & Mohaghegh, 2018; Pence et al., 2019b), provides input to Step ii of Element 2.1. of DT-SITE (as it is explained in Section 4.3.1.1.2). The target node of the causal model in Figure 4.4 is the NPP "training system," which stands for the NPP organization's ability to provide adequate training to its workforce and is based on the Systematic Approach to Training (SAT) used at NPPs. Within the training system causal model (Figure 4.4), each factor and causal relationship is supported by either industry, regulatory, or academic sources (i.e., written evidence could be found to support the inclusion and placement of each sub-factor) (Pence & Mohaghegh, 2018).

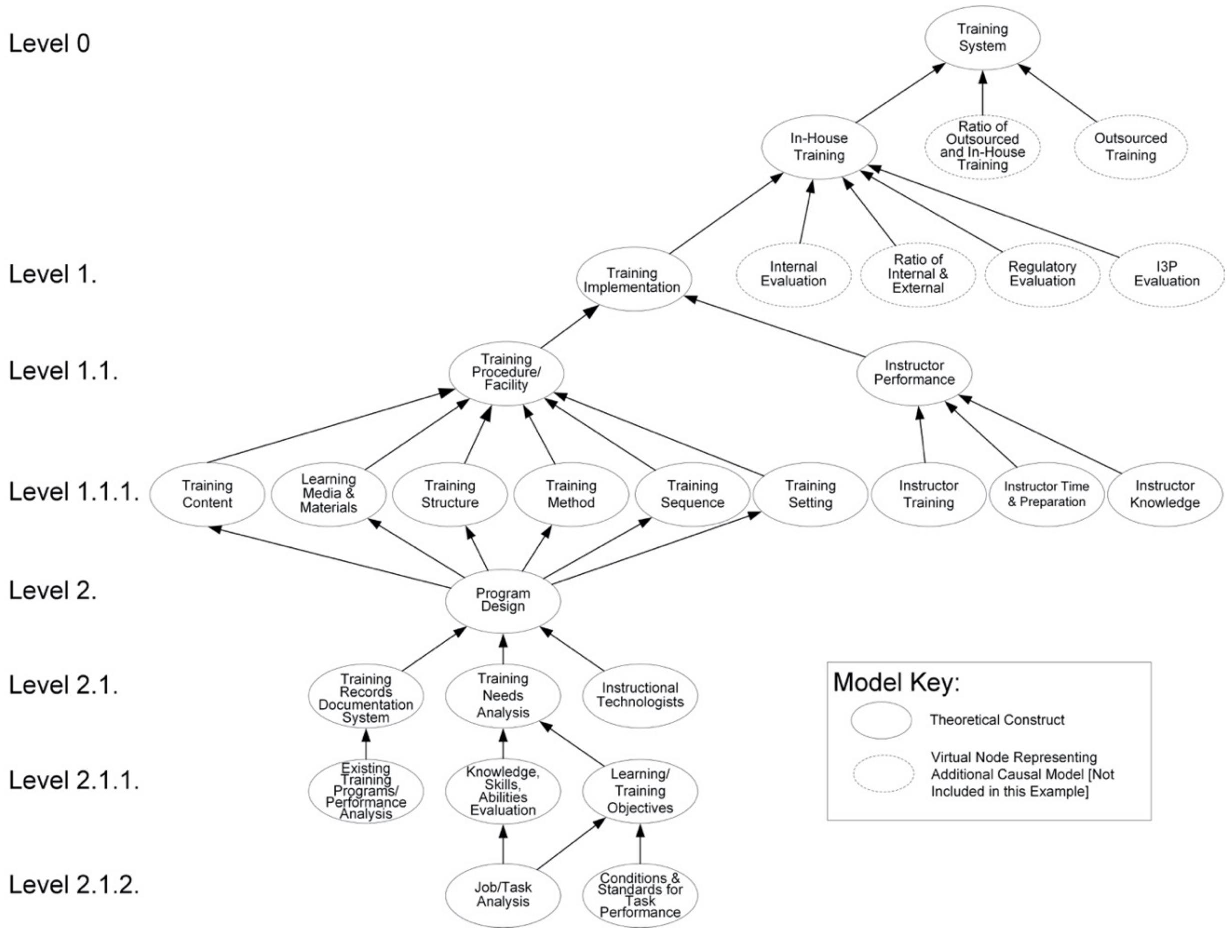

Figure 4.4: Training system causal model developed in Element 1 (i.e., DT-BASE) of the Data-Theoretic module of I-PRA methodological framework (Figure 4.2) (Pence & Mohaghegh, 2018; Pence et al., 2019b)

4.4.1. Applying Text Mining on the LER Database (Element 2.1 in Figure 4.2)

This case study applies the steps of Element 2.1, introduced in Section 4.3, including: (i) collect and pre-process unstructured free text data (Section 4.4.1.1), (ii) identify and evaluate theory-based seed terms from DT-BASE (Section 4.4.1.2), (iii) select features (Section 4.4.1.3), and (iv) build and evaluate classifiers (Section 4.4.1.4) using the LERs from "Event Date" 1/3/2000 to 1/9/2019, where there are 6,225 unique LERs accessed from the LERSearch dataset on the NRC website (https://lersearch.inl.gov).

4.4.1.1. Collect and pre-process unstructured LER data (Step i of DT-SITE Element 2.1 in Figure 4.3)

The data collection in this study refers to nodes A to D.3 in Figure 4.5, where LERs are downloaded from the public website using a python script for (A) setting the path and naming convention of data, (B) setting LER search parameters (e.g., date, NRC region), (C) running web browser automation using Selenium[10] and ChromeDriver,[11] (D) performing web scraping of LERs, where the 'View Text' hyperlink is used as a decision criteria (D.1), (D.2) LERs without an HTML file are skipped, and (D.3) the rest are downloaded to the file path with the naming convention. Once data collection is completed, pre-processing begins. For pre-processing, another python script was developed for: (E) section identification and extraction using headers in the free text LER (i.e., abstract and cause), (F) performing text cleaning to remove HTML, Unicode blocks and unnecessary spacing, (G) running the Stanford CoreNLP Sentence Splitter (Manning et al., 2014) on the cleaned dataset, and finally (H) developing a pre-processed LER dataset to be used in Step ii of DT-SITE Element 2.1.

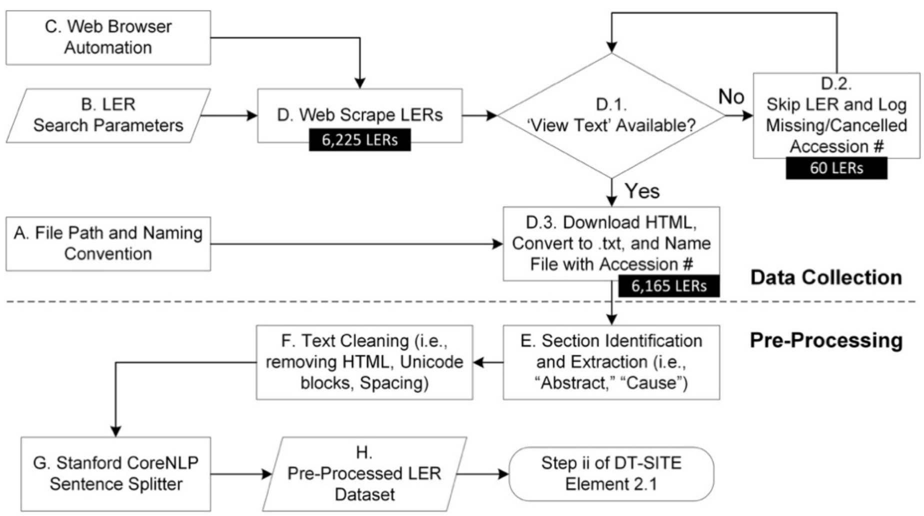

Figure 4.5: Data collection and pre-processing (Step i of DT-SITE Element 2.1) on LERs (number of LERs shown in black boxes)

The python script downloaded all text files associated with the LERs from 2000-2019. Among the LERs from 2000 to 2019, there were 60 that were marked "C" (Canceled), meaning that they were formally withdrawn, some having a cancelation letter. Two of the canceled reports (LER #s 3252008001 and 3342014003) have duplicate LER numbers (but with different ML numbers) and are not marked as canceled or reused in the LER database. The canceled LERs associated with LER numbers 3252008001 and 3342014003 were excluded from this study, but the non-canceled LERs associated with those same LER numbers are included in the study. All 60 canceled LERs and the two duplicates (listed in Appendix B) are excluded from the analysis, bringing the total dataset from 2000 to 2019 to 6,165 LERs. It should be noted

[10] https://www.seleniumhq.org/
[11] http://chromedriver.chromium.org/

that both the 'Abstract' and 'Cause' sections of LERs were used in this study. Out of the 6,165 LERs, there were 98 files where the 'Cause' section could not be extracted due to missing or incomplete header information (listed in Appendix C), and therefore only the 'Abstract' is used. For the 6,165 LERs, the abstract and cause sections (only using the abstract sections for LERs in Appendix C) were pre-processed and loaded into the Stanford CoreNLP sentence splitter.

4.4.1.2. Identify and evaluate theory-based seed terms from the DT-BASE training system causal model (Step ii of DT-SITE Element 2.1 in Figure 4.3)

In this step, the terms, definitions, synonyms, and relationships for factors in the training system Organizational Causal Input Model (Figure 4.4) are used. Based on keywords from DT-BASE (i.e., from (Pence et al., 2019b)), an initial set of candidate seed terms is generated (ii.a in Figure 4.3) to identify the "training system" target node (i.e., 'Level 0' in Figure 4.4). In this study, the bag of words assumption is used (Salton et al., 1975), which means that each feature in Step iii corresponds to a single word, and therefore keywords in this step are single words. A sample set of event data that have at least one of the candidate seed terms are selected and two independent experts provide annotations identifying if entries are related to the target node ("Yes") or not ("No"). Inter-rater reliability was calculated to determine the level of agreement between two annotators. In most cases, the independent annotation process requires annotation instructions, but in the current study, the training system causal model (shown in Figure 4.4) served as a guide for annotators. Two authors of this paper served as annotators, "Annotator A" and "Annotator B," independently reading and labeling 313 sentences from 282 LERs. Both annotators were familiar with industry language in the LER narratives, as well as with the training system causal model. Inter-rater reliability (see Table 4.4) was measured using the kappa statistic (Landis & Koch, 1977), resulting in a score of 0.96 that shows a high agreement. For the supplementary data of this annotation see (Pence et al., 2019a).

Table 4.4: Inter-rater reliability analysis for Annotators A and B on LERs

		Annotator B	
		Yes	No
Annotator A	Yes	182	3
	No	3	125

As mentioned in Section 4.3.1.1.2, identifying and evaluating candidate seed terms is an iterative process whereby experts evaluate sentences that contain seed terms in the context of a dataset, and either add or remove seed terms until the "final" set of seed terms is developed. Seed terms considered in this project are shown in Table 4.5. To generate Table 4.5, the sentences which contain a seed term and are related to the target node are identified as "Yes," while sentences that contain a seed term but are not related to the target node are identified as "No." The number of times the seed term is marked as "Yes" is divided by the total number of entries randomly sampled for each seed term ("Total") to provide a percentage of those entries that include a seed term and related to the target node ("%Yes"). During this process of evaluating candidate seed terms, experts remove candidate seed terms that do not identify the target node above a threshold of 0.3 (an assumption made by the analyst). For example, "train" was included as a candidate seed term, but in the contexts of LER reports, "train" refers to a redundant technical system (e.g., auxiliary feedwater train) and not human "training." In other cases, while several LERs reported that "procedures" were updated as a corrective action, 'procedure quality' differs from 'training quality.' In other words, in the reviewed LERs where inadequate procedural guidance was mentioned, they were only considered as 'training-related' in cases where the event narrative stated that there was a procedural violation. Therefore, if the narrative only refers to a procedural guidance deficiency, it does not imply training in all cases, unless stated as a procedure violation, and "procedure" was removed as a candidate seed term. These types of definitions and caveats were considered for all candidate seed terms and updated accordingly.

Each seed term evaluated independently for both the abstract and cause sections in Table 4.5. It should be noted that in these experiments, seed terms from the abstract and from the cause section were sampled separately, as it was not clear at the beginning if the language from these sections would differ; however the results showed that the same set of seed terms emerged from both sections, and therefore the abstract and cause sections were not separated in the next step.

Table 4.5: Candidate seed terms evaluated for the training system causal model

	Included in the Abstract Section?				**Included in the Cause Section?**				**Seed Term (Final)**
Candidate Seed Terms	**Yes**	**No**	**Total**	**%Yes**	**Yes**	**No**	**Total**	**%Yes**	
experience	3	17	20	15	0	20	20	0	No
experienced	0	20	20	0	1	19	20	5	No
familiar	0	0	0	0	10	8	18	56	Yes
familiarity	1	0	1	100	5	0	5	100	Yes
instructor	0	0	0	0	1	0	1	100	Yes
instructors	0	0	0	0	4	0	4	100	Yes
knowledge	17	3	20	85	16	4	20	80	Yes
qualification	4	16	20	20	5	15	20	25	No
requalification	14	1	15	93	20	0	20	100	Yes

Table 4.5 (cont.)

	Included in the Abstract Section?				Included in the Cause Section?				Seed Term (Final)
Candidate Seed Terms	Yes	No	Total	%Yes	Yes	No	Total	%Yes	
trained	20	0	20	100	19	1	20	95	Yes
training	20	0	20	100	20	0	20	100	Yes
unfamiliar	2	0	2	100	8	1	9	89	Yes

4.4.1.3. Select features from training-related LERs (Step iii of DT-SITE Element 2.1 in Figure 4.3)

For feature selection, words were converted to lower case, but stemming was not employed to prevent misidentification of terms (e.g., to ensure that 'training,' which refers to the target node, was treated separately from 'train'). Although the abstract and cause sections were considered separately to evaluate seed terms in Step ii, in this step, both the abstract and cause sections of LERs between 2000 and 2019 are used. The silver standard categorization is shown in Table 4.6, where a training-related LER is marked "Yes" if it contained at least one seed term in either the abstract or cause section, and an LER that is not training-related is marked "No." In order to develop features, entropy of all words in the LERs is calculated, considering categorization from the silver standard, and word ranking is done using Eq. 4.1.[12] As a result of word ranking, 500 words (the number defined by the analyst) with the lowest entropy were selected as the final set of features. Table 4.6 shows an example of six lowest-ranked features, pulled from a random set of LERs, to demonstrate the number of times a feature could appear in an LER. When a feature (i.e., a word) does not appear in the LER, a zero is recorded in the feature matrix. As with most text classification tasks, the feature matrix is sparse, which is also illustrated in Table 4.6 by the number of zeros, for example only one of the LERs included the term "training" (Column 2 in Table 4.6), and none of the LERs in this sample included the term "trained" (Column 4 in Table 4.6).

Table 4.6: Example of the six lowest-ranked features (out of 500)

LER #	training	knowledge	trained	personnel	licensed	expectations	…	Training-Related LER?
2802005003	0	0	0	0	0	0	…	No
5292005006	0	0	0	0	0	2	…	No

[12] Eq. 4.1 is performed using the Oracle Data Miner (version 12.2c).

Table 4.6 (cont.)

3342011001	0	1	0	1	0	0	…	Yes
4232010004	0	0	0	1	0	0	…	No
3532000003	0	0	0	0	0	0	…	No
2472000001	0	0	0	4	0	1	…	No
2852011005	0	0	0	0	0	0	…	No
3022006002	0	0	0	12	0	0	…	No
2602009006	2	0	0	2	1	0	…	Yes
3732017006	0	0	0	0	0	0	…	No

4.4.1.4. Build and evaluate classifiers for identifying training-related LERs (Step iv of DT-SITE Element 2.1 in Figure 4.3)

The SVM technique (Vapnik, 1999) was selected for classifying LERs in the DT-SITE sub-module since SVMs work well for text classification tasks where data is sparse and skewed (only 1,341 [22%] of the 6,165 LERs included a seed term). Data was stored in an Oracle Database 12c Enterprise Edition Release 12.2.0.1.0 and the linear SVM was used with Oracle default settings. In this study, 10-fold cross validation was used to evaluate the classifier. To perform 10-fold cross validation, LERs were shuffled and randomly assigned to ten (approximately) equal segments for each run. In 10-fold cross validation, the classifier is built using the first 9 folds of the data (i.e., 9/10$^{\text{ths}}$ of the total number of documents) and evaluated on the remaining 1/10$^{\text{th}}$ of the data (which is called the test set). A second classifier is then built using the first 8 folds and the 10$^{\text{th}}$ fold and then evaluated using the 9$^{\text{th}}$-fold. This process was repeated for each of the segments so that predictions for each LER in each test set are collected such that each LER had one prediction. The process of shuffling, random assignment, and prediction for each of the ten test sets, is a "run." Each run provides one prediction (either "training" or "not training") for each LER. Figure 4.6 shows the process of 10-fold cross validation for one run.

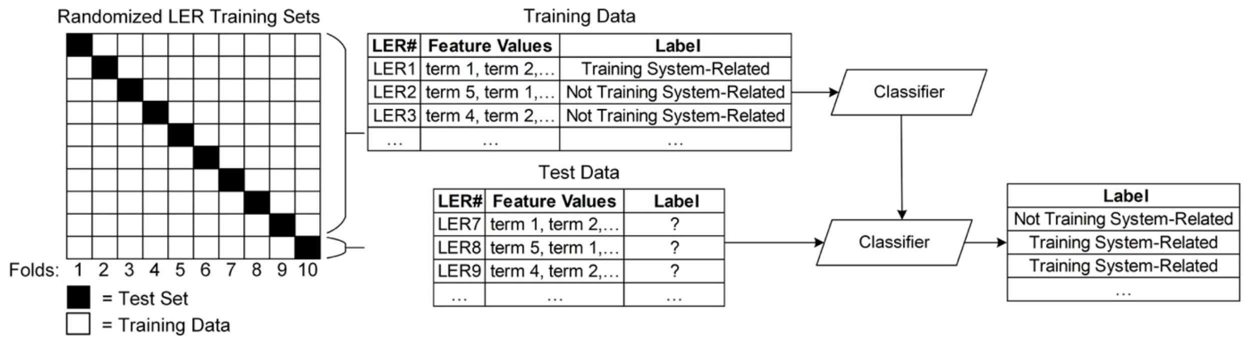

Figure 4.6: Example of 10-fold cross validation for one run

In order to represent some of the epistemic uncertainty associated with SVM accuracy, the 10-fold cross validation process was repeated 10 times (10 runs)[13]. Table 4.7 reports the classifier prediction on the number of LERs related to the target node category (i.e., training system-related LERs). The table also demonstrates the performance of the SVM classifiers, by reporting precision, recall, accuracy using silver standard.

Table 4.7: Reporting the classifier results and evaluating classifier performance based on the silver standard

Run ID	Precision	Recall	Accuracy	Estimate of Training System-Related LERs
1	0.941	0.932	0.972	1,329
2	0.939	0.928	0.971	1,325
3	0.940	0.929	0.972	1,325
4	0.939	0.930	0.972	1,328
5	0.936	0.936	0.972	1,341
6	0.932	0.934	0.971	1,345
7	0.935	0.924	0.970	1,325
8	0.942	0.924	0.971	1,315
9	0.942	0.928	0.972	1,321
10	0.936	0.923	0.970	1,322
Average	0.938	0.929	0.971	1,328

As Table 4.7 shows, the SVM classifiers showed high performance with respect to the silver standard; however, to further evaluate the SVM classifiers, independent sentence-level annotations (See

[13] In this study, the number of runs "n" and the number of folds "k" are both ten, however, these two do not have to be equal, as these are two independent numbers that are selected by the analyst.

Table 4.8) were performed on 200 randomly sampled LERs (with a total of 10,269 sentences) to develop a gold standard. Inter-rater reliability score was 0.96 using Cohen's kappa statistic (Cohen, 1960). For the supplementary data of this annotation see (Pence et al., 2019a).

Table 4.8: Consensus between Annotators A and B in manual annotation (gold standard)

		Annotator B	
		Yes	No
Annotator A	Yes	160	0
	No	13	10,096

The annotated samples were compared against the outputs of 10 SVM classifiers to generate the gold standard confusion matrix (Table 4.9). It should be noted that, in Table 4.9, predicted SVM classifier results are based on the aggregation of ten runs. In this table, "Actual" refers to the gold standard developed using manual annotations, and "Predicted" refers to the SVM classifier results. For example, in Table 4.9, 45 (Yes/Yes) represents the entries where the gold standard was annotated "Yes" and the SVM classifier predicted "Yes," showing agreement that the entry was training related. Using the confusion matrix in Table 4.9, the precision for the gold standard was 1, the recall was 0.672, and the accuracy was 0.890. One of the reasons for lower performance when comparing with the gold standard is that the features and classifiers are built in this study based on silver standard. Future work will generate more annotated data to provide possibilities to use a gold standard when evaluating features and classifiers. Future work will also focus on advancing uncertainty analysis in this algorithm to better use the classifier prediction outputs in presenting the uncertainty in the estimated probability in Section 4.4.2.

Table 4.9: Confusion matrix for the gold standard (manual annotations)

	Predicted (SVM Classifier Results)	
Actual (Based on the Gold Standard/Manual Annotations)	Yes	No
Yes	45	22
No	0	133

4.4.2. Estimating the Probability of Training System-Related Events in LERs (Element 2.2 in Figure 4.2)

This step uses the total number of LERs in the data collection period, 6,165, as the denominator, and uses the SVM estimation of all ten runs as a numerator to generate ten SVM-based probability estimates of LERs from 2000 to 2019 being in the target node category. In this study, the lognormal distribution was selected to represent the ten estimated probabilities. To evaluate the goodness of fit of the selected distribution, the Kolmogorov-Smirnov (KS) test was used. The KS test was evaluated at five levels of significance (α) (i.e., 0.2, 0.1, 0.05, 0.02, and 0.01) corresponding to five critical values (0.323, 0.369, 0.409, 0.457, and 0.489 (Hayter, 2012)), resulting in no rejections for a lognormal distribution with a test statistic of 0.234, and a p-value of 0.568 (i.e., threshold value of the significance level where the null hypothesis can be accepted for all values of (α) less than the p-value). Given the KS test results, the lognormal distribution is accepted. The Cumulative Distribution Function (CDF) and the Probability Distribution Function (PDF) are shown in Figure 4.7 and 4.8, respectively. The distribution resulted from this process represents the epistemic uncertainty in the results of the algorithm that is captured through “10” runs in Section 4.4.1.4. Future research by the authors will focus on more advanced quantification of uncertainties in this study. For example, one of the underlying assumptions in this study is that if an LER has a “sentence” related to the target node category, it is judged as a target node category-related LER. In other words, the judgment at the level of the sentence is assumed to be the judgment at the level of LER. Future work will evaluate the selectivity of the results with respect to this assumption.

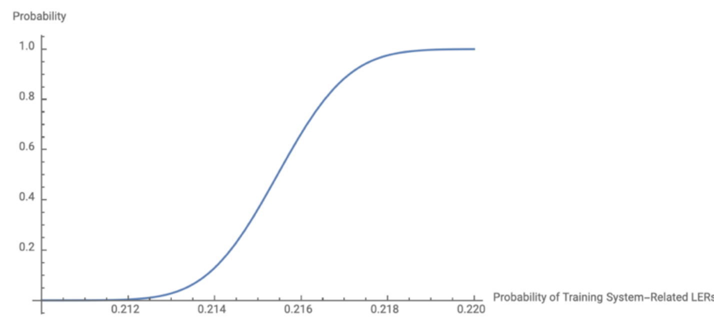

Figure 4.7: CDF for the probability of “Training System-Related” LERs from 2000 to 2019

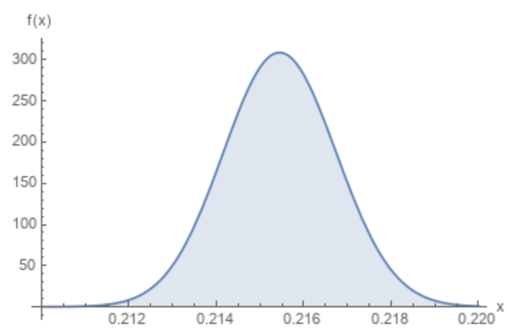

Figure 4.8: PDF for the probability of “Training System-Related” LERs from 2000 to 2019

The probability estimated in this section is the probability of having training system-related LERs. This probability is different from the probability of “Poor Training Quality,” P, which can be defined as of A'/N_{Demand}, where A' stands for the real number of events involving training as a contributor, during the data collection period and, N_{Demand} represents the total number of operator, operations, and maintenance demands during the data collection period. With this definition, P takes on values between 1.0 (every demanded action involves training issues) and 0.0 (training is never a contributor). Eq. 4.2 shows the relationship between P, which is the realistic probability of poor training quality, and the probability presented in Figure 4.8 (i.e., the probability of training system-related LERs) which is represented by A/N_{LER} (i.e., the ratio of training issues identified by DT-SITE [A], to all reported incidents during the data collection period [N_{LER}]). In Eq. 4.2, A'/A stands for the quality of the LER program in terms of accurately reporting training contributions. If all incidents involving training are correctly identified and reported A'/A = 1.

$$P = \frac{A'}{N_{Demand}} = \frac{A}{N_{LER}} \times \frac{N_{LER}}{N_{Demand}} \times \frac{A'}{A} \qquad (4.2)$$

Since N_{LER} in the case study is not constrained to any specific NPP, this study proposes an approach for calculating N_{Demand} that considers all NPPs in the U.S. by summing the steps of procedures during normal operation (S_{Proc_OP}), steps of procedures during the outage time (S_{Proc_OT}), and tasks during maintenance processes over a year (M_T), to create a 'nuclear industry-wide' estimate, as shown in Eq. 4.3.

$$N_{Demand} = n_Y \times \sum_{N_p} \left[M_T + n_d \times \sum_{Proc\_OP} S_{Proc\_OP} + \sum_{d'} \sum_{Proc\_OT_{d'}} S_{Proc\_OT_{d'}} \right]_p \qquad (4.3)$$

where, N_p is the total number of operating NPP units in the U.S. (e.g., 99) over the period of interest of n_Y years (e.g., the period of interest in this study is 2000-2019, n_Y = 19.02), n_d is the number of operating days per year (e.g., 318 days), d' is all days on outage per year, $Proc\_OP$ is the collection of all procedures conducted daily during normal operation (e.g., approximately 120 procedures as a rough estimate using information from (Thomas et al., 2016)), $Proc\_OT_{d'}$ is the collection of all procedures conducted on outage days (e.g., approximately 150 procedures as a rough estimate using information from (Thomas et al., 2016)). Eq. 4.3 assumes that the procedures (and steps of these procedures) for a plant are the same for every day that the plant is operating. However, this is not the case for days a plant is in outage, as it is assumed that the procedures vary over the duration of an outage based on the specific causes of the outage. Hence, $S_{Proc\_OT_{d'}}$ in Eq. 4.3 is the number of steps in the procedure $Proc\_OT_{d'}$ on day d'. It is assumed that M_T is the number of annual maintenance tasks (e.g., approximately 325,000 maintenance tasks per year as a rough estimate using information from (Thomas et al., 2015)). It should be noted that the details of Eq. 4.3 are not a complete consideration of all possible demands, and the examples provided are for demonstration, based on rough and conservative estimates from two reports (i.e., (Thomas et al., 2015; Thomas et al., 2016)). Using Eq. 4.3, the average total number of demands is estimated as 992,976,930 for the period of 2000-2019. Utilizing this number of demands, considering A'/A = 1 in Eq. 4.2, and using the results of 10 SVM runs (Table 4.7) for A (i.e., training system-related LERs), probability of "Poor Training Quality," P is estimated as 7.03E-07. Figure 4.9 shows the PDF for the probability of "Poor Training Quality."

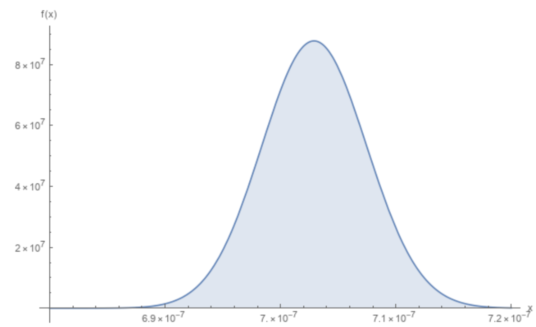

Figure 4.9: PDF for the probability of "Poor Training Quality"

For the sake of discussion, this paper makes a simplifying assumption that the steps associated with each procedure are similar for all NPPs throughout the U.S.; however, to improve the accuracy of this estimation, future research is required to provide details of procedures and their associated steps for each plant. Future work will also analyze how it is possible to have a more realistic estimate of A'/A. The probability of "Poor Training Quality" from text mining can be used to estimate the state of training-related PSFs in HRA, and that is the focus of ongoing research by some of the authors of this paper.

4.5. CONCLUDING REMARKS

Organizational factors remain elusive and latent contributors to incidents and accidents in high-consequence industries. This paper is the product of a line of research on the advancement of 'socio-technical' risk analysis to explicitly incorporate organizational factors into PRA/HRA. This paper advances the Data-Theoretic input module of the I-PRA framework (Figure 4.2) to support the quantification of underlying organizational factors using data analytic techniques. The Data-Theoretic (DT) input module of I-PRA has two sub-modules (i) DT-BASE, for developing detailed grounded theory-based causal relationships in SoTeRiA, equipped with a software-supported BASEline quantification utilizing information extracted from academic articles, industry procedures, and regulatory standards, and (ii) DT-SITE, using data analytics to refine and measure the causal factors of SoTeRiA based on industry event databases and using Bayesian updating to modify the baseline quantification. This paper focuses on the advancement of the DT-SITE methodology, specifically Elements 2.1 and 2.2 (see Section 4.3), contributing to the integration of text mining for the measurement of organizational factors and for PRA.

To clarify how the approach proposed in this paper fills the gaps in the existing studies, Section 4.2 provided a review of related studies in three different groups: (1) studies that utilize machine learning-related techniques for the measurement of organizational factors in safety/risk analysis from 2000 to 2018, (2) machine learning studies (not specifically for organizational factors) that have been conducted from 2000 to 2019 under the field of PRA, and (3) parametric studies that analyzed LERs from 2000 to 2018. The review of literature highlighted the gaps in the existing studies and the contributions of this paper, as follows:

- None of the reviewed studies (in the three groups) used a supervised machine learning process that is guided by a theoretical causal framework, and this paper offers a first-of-its-kind theory-guided machine learning method.
- There are a limited number of studies that leveraged machine learning for measuring organizational factors in safety/risk analysis. One of the reasons is that, for the measurement of organizational factors, methodologies should be capable of dealing with limited or unstructured data, as well as differentiate between a wide array of theoretical constructs. This paper develops and applies a machine learning method for the quantification of organizational factors in safety/risk analysis.
- In studies where machine learning was applied for measuring organizational factors, none were connected to or performed analysis for PRA frameworks. This paper is a first-of-its-kind PRA-related study that develops a machine learning method for the quantification of organizational factors
- The studies applying machine learning or NLP approaches for PRA primarily analyzed physical phenomena. Among the PRA-oriented machine learning/NLP studies, nine used historical event data rather than results of simulation codes. Among these nine studies, four used unstructured free text data, three of which used LERs, and among these three, one used NLP instead of machine learning. This indicates that there are limited studies using text mining approaches for PRA. The Data-Theoretic methodology in this paper offers a text mining approach for PRA, where the supervised machine learning process is conducted on unstructured free text data from LERs to perform classification using the SVM technique. SVM, compared to Logistic Regression (used by some of the existing studies), has been shown to perform better for highly imbalanced/skewed datasets such as LERs. Compared to the well-known/open source machine learning algorithms for SVM and Logistic Regression, the performance evaluations of commercial software packages (e.g., IN-SPIRE, IBM Watson Content Analytics [ICA]), used by some of the existing studies, are limited due to a lack of open source, repeatable, and reproducible evaluations. Additional research is

needed to compare the performance evaluation of machine learning techniques for unstructured data to justify the best selection for PRA.

- The majority of studies that conducted data analysis on LERs used coded LERs (structured data) and a parametric type of process. These studies did not consider the quality of human coders in their analysis. In this paper, LERs are "annotated" rather than coded. A theoretical causal model (developed in DT-BASE) is used to provide guides for annotators. In addition, the kappa statistic is used to measure the inter-rater reliability of annotators.
- Among all the studies that conducted data analysis on LERs, three of them used machine learning approaches. Among these studies, two applied the supervised machine learning process of classification for analyzing LERs; however, their process was not guided by a theoretical framework. The Data-Theoretic methodology introduced in Section 4.3 makes unique contributions to studies of LERs by offering a supervised machine learning process that is guided by a theoretical causal framework. With respect to application areas, most studies that analyzed coded and structured LER data were focused on analyzing equipment failure and human error. This paper proposes the first-of-its-kind machine learning method to quantitatively analyze LERs for the application area of organizational factors.

A case study (Section 4.4) leverages an existing DT-BASE causal model for the quality of an NPP "training system" (Figure 4.4 (Pence et al., 2019b)) to demonstrate the DT-SITE text mining step on a set of LERs from the U.S. nuclear power industry. A distribution was fit to the SVM classifier results to develop the distribution of the probability of "Training System-Related" LERs. A post analysis also is conducted to develop the distribution of the probability of having "Poor Training Quality" in NPPs. In this paper, several key assumptions are made which have the potential to contribute to uncertainty in the results; for example, future research is needed to analyze model uncertainty associated with different classification models (e.g., Decision Tree, Naïve Bayes). Another assumption is that LER labels are done based on sentence-level labels (i.e., if there is sentence related to training system in a LER, the LER is assumed to be related to training system). The accuracy of this and other assumptions needs to be evaluated in future studies.

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CHAPTER 5: GIS-BASED INTEGRATION OF SOCIAL VULNERABILITY AND LEVEL 3 PROBABILISTIC RISK ASSESSMENT TO ADVANCE EMERGENCY PREPAREDNESS, PLANNING AND RESPONSE FOR SEVERE NUCLEAR POWER PLANT ACCIDENTS[1]

ABSTRACT

In the nuclear power industry, Level 3 Probabilistic Risk Assessment (PRA) is used to estimate damage to public health and the environment if a severe accident leads to large radiological release. Current Level 3 PRA does not have an explicit inclusion of social factors, and therefore, it is not possible to perform importance ranking of social factors for risk-informing emergency preparedness, planning and response (EPPR). This paper offers a methodology for adapting the concept of social vulnerability, commonly used in natural hazard research, in the context of a severe Nuclear Power Plant (NPP) accident. The methodology has four steps: (1) calculating a hazard-independent social vulnerability index for the local population; (2) developing a location-specific representation of the maximum radiological, hazard estimated from current Level 3 PRA, in a Geographic Information System (GIS) environment; (3) developing a GIS-based socio-technical risk map by combining the social vulnerability index and the location-specific radiological hazard; and (4) conducting a risk importance measure analysis to rank the criticality of social factors based on their contribution to the socio-technical risk. The methodology is applied using results from the 2012 Surry Power Station (SPS) State-of-the-Art Reactor Consequence Analysis (SOARCA). A radiological hazard model is generated from MELCOR Accident Consequence Code System (MACCS), translated into a GIS environment, and combined with the Center for Disease Control (CDC) Social Vulnerability Index (SVI). This research creates an opportunity to explicitly consider and rank the criticality of location-specific SVI themes based on their influence on risk, providing input for EPPR.

5.1. INTRODUCTION

Probabilistic risk assessment (PRA) is a systematic methodology used in risk-informed regulation and policy setting by the U.S. Nuclear Regulatory Commission (NRC) (NRC, 2002). PRA provides a risk-importance ranking of safety-critical systems and components to more efficiently allocate resources for inspections, maintenance, operation, design, and regulation (Kee et al., 2013). For a nuclear power

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plant (NPP), PRA can be used to generate three levels of risk information, including risk from reactor core damage (Level 1 PRA), risk from loss of containment integrity (Level 2 PRA), and risk to the public and environment (Level 3 PRA). NPP license holders maintain plant-specific Level 1 PRAs to estimate core damage frequency (CDF) resulting from a combination of initiating events (IE) (e.g., loss of coolant accident (LOCA), fire, seismic), and system- and component-level failures. Level 1 PRA is used for regulatory oversight, licensing, inspections, and a variety of other applications (NRC, 2002, 2014b). Level 2 PRA expands Level 1 PRA results to estimate the mode of containment failure and associated large early release frequency (LERF), while specifying amounts and types of radionuclides which are released to the environment, referred to as 'source term' (NRC, 1983). Level 3 PRA uses the source term from Level 2 PRA to analyze the transport of radionuclides through the environment. Level 3 PRA estimates the short and long-term consequences of nuclear accidents on public-health (e.g., short-term injuries or long-term cancers), environmental contamination, and economic consequences (Miller, 2015). While population's social information is implicitly accounted for in Level 3 PRA in the determination of evacuation parameters for each site through evacuation time estimate (ETE) studies, the social factors are neither location specific nor explicitly incorporated; therefore, it is not possible to perform sensitivity analysis or importance ranking of social factors for risk-informing emergency preparedness, planning, and response (EPPR). In this research, a model is said to have an "explicit" incorporation/inclusion of a factor (e.g., a social factor) if the factor is a direct input variable in the governing equations that describe the model. In contrast, if the factor does not appear directly in the governing equations but is considered when assigning values to any of the input variables of the model, the corresponding model is considered to have an "implicit" incorporation of the factor.

The overall objective of EPPR, as defined by NUREG 0654, is "to provide dose savings (and in some cases, immediate lifesaving) for a spectrum of accidents that could produce offsite doses more than those that are included in the Protective Action Guides (PAGs)" (NRC, 1980). The PAG is defined as "the projected dose to an individual from a release of radioactive material at which a specific protective action to reduce or avoid that dose is recommended" (EPA, 2017). Protective actions may include shelter-in-place, relocation, potassium iodide pills, or evacuation (NRC, 2017a). An emergency planning zone (EPZ) sets the boundary for EPPR activities and assists decision-makers in identifying which of the recommended protective actions (e.g., evacuation or shelter-in-place) are appropriate for each area around an NPP. In the U.S., emergency planning regulations documented in 10 CFR 50.47(c)(2) require the establishment of two EPZs around each NPP: a 10-mile plume exposure pathway EPZ, and a 50-mile ingestion exposure pathway EPZ (NRC, 2017a). Determination of these existing EPZs (Collins et al., 1978) is based on dose calculations using sequence probabilities and source terms from the "Reactor

Safety Study" WASH 1400 (NRC, 1975). Within the EPZs, the corresponding EPPR must ensure that all necessary resources are available to protect the population from radiation exposure.

Performance-based EPPR oversight deals with limited data and prescriptive standards. The U.S. NRC has moved toward a risk-informed, performance-based philosophy on regulation (Apostolakis et al., 2012), but EPPR is one of the areas that has not been adequately addressed. Level 3 PRA research, specifically for risk-informing EPPR, is still evolving (Fleming & Nourbakhsh, 2003; Siu, 2006). Without risk-informed approaches, the cost of oversight and EPPR requirements may be high, with limitations for developing localized safety performance goals (Siu, 2006). While there are vast differences between empirical historical accidents and their practical insights for local geographies of NPPs, the fact remains that offsite response practices are not explicitly modeled or incorporated into Level 3 PRA consequence estimations to improve EPPR performance worldwide (NAS, 2014). More than 30 years after the Three Mile Island (TMI) accident, strong parallels can be seen in the 2011 Fukushima Daiichi accident, where there was "insufficient implementation of the emergency plan," "ill-defined delineation of responsibilities," and "insufficient collection, sharing, and dissemination of information" (Omoto, 2013). The demographics of the surrounding population (i.e., the attributes (e.g., age, location) of the various cohorts and their potential for being exposed to severe health effects) inform planning and analysis of offsite response actions (NRC, 2013a). Therefore, the explicit incorporation of location-specific social factors of the local population into Level 3 PRA, as it facilitates the analysis and ranking of these factors, can drastically affect decisions related to EPPR.

This paper is part of a line of research by the authors to explicitly incorporate location-specific social contributing factors into Level 3 PRA (Miller, 2015; Miller et al., 2015). There have been significant studies, by several authors of this paper, regarding the explicit incorporation of social and organizational factors into Level 1 PRA (Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2009a, 2009b; Pence et al., 2014; Pence et al., 2017). The goal of this study is to initiate the same paradigm of research for Level 3 PRA. This paper offers a methodology for combining the concept of social vulnerability (used in natural hazard research) with Level 3 PRA (used in severe nuclear accident research and practices) in a geographic information system (GIS) environment to "externally" and explicitly integrate social factors with Level 3 PRA. Parallel research by the authors focuses on developing a methodology to "internally" and explicitly incorporate social factors into Level 3 PRA (Bui, Ha et al., 2016; Bui et al., 2017; Pence, Justin et al., 2015).

Section 5.1.1 discusses state-of-the-art Level 3 PRA codes used in the U.S. nuclear power industry. Section 5.2 sets the theoretical ground for the explicit incorporation of social factors into Level 3 PRA by developing a macro-level socio-technical risk analysis causal framework and by framing the nuclear-oriented social vulnerability construct in the causal framework. Section 5.3 explains the proposed methodology for external-explicit integration of social factors with level 3 PRA of NPPs. The difference between “internal” and “external” methodological approaches for the incorporation of social factors is highlighted in Section 5.3. Section 5.4 demonstrates a case study implementing the methodology using results from the 2012 SOARCA study.

5.1.1. Level 3 Probabilistic Risk Assessment (PRA)

This section introduces the high-level modules of the MELCOR Accident Consequence Code System (MACCS) and WinMACCS; a computer code and user interface for Level 3 PRA applied in the U.S. Radiological source term inputs can be varied to generate initial conditions for multiple scenarios of radiological atmospheric transport and environmental dispersion (NRC, 2014a). The ‘EARLY’ calculation module in MACCS quantifies the accumulation of radiation dose for an evacuating population by considering doses they receive during normal activity, sheltering, and initial evacuation (Bixler et al., 2017). In a Level 3 PRA, the consequence model incorporates dose coefficients related to specific organs and tissues of the body from concentrations of radionuclides. Dose rate, which is the same as exposure rate, is usually measured as rems or Sieverts per hour. Level 3 PRA considers two types of exposures: acute and chronic. Acute exposure involves a significant exposure received over a short period, i.e., a high exposure rate. Chronic exposures involve exposure at a low rate received over an extended period over a lifetime (NRC, 2013a). This paper focuses on the inclusion of social factors in Level 3 PRAs, and therefore readers are directed to Refs. (Bixler et al., 2017; NRC, 2015, 2017b) for more details on hazard modeling in MACCS.

Census and economic data provide an input for the SECtor POPulation and Economic Estimator (SECPOP). SECPOP is a MACCS preprocessor to evaluate census, land use, and economic data to create a site file that can be used for different applications. Advancements to the economic analysis portion of SECPOP include the Regional Economic Accounting (REAcct) framework, a gross domestic product (GDP)-based model that can use GIS-linked data to perform analysis at multiple levels of resolution (Outkin et al., 2015). Currently, the population is modeled into cohorts; population segments which can be based on starting location and customized by time-related parameters such as delay to shelter, delay to evacuation, the speed of evacuation, duration of the beginning phase of evacuation, and duration of the middle phase of evacuation (NRC, 2013b). In EPPR practice, emergency alert system (EAS) sirens are used to notify the public about the emergency, and “an emergency notification message will be distributed to residents in the EPZ via text alerts, TV, and radio” (NRC, 2017c). In the 2012 Surry Power Station (SPS) State-of-the-Art Reactor Consequence Analysis (SOARCA) study, six cohorts were assigned, which included the general public, shadow evacuation, schools, special facilities (e.g., hospitals, nursing homes, prisons), tail evacuation, and non-evacuating population (NRC, 2013b). Newer Level 3 PRA studies have increased the number of cohorts, for example, there are nine cohorts in the 2017 Sequoyah SOARCA study (NRC, 2017c). In the Sequoyah SOARCA study, it is assumed that a portion of a cohort may disregard the EAS (NRC, 2017c). However, defining the governing parameters for each cohort, and specifically for the general public, is challenging.

Simulation is used to generate ETEs in MACCS using two methods: (a) radial simulation (i.e., all movement radially outward), and (b) network evacuation (i.e., traffic follows major roadways). A set of network evacuation speed multipliers are visualized in WinMACCS to “better reflect the spatial and temporal response of individual cohorts” (NRC, 2014a). Current approaches leverage existing ETE studies and national telephone surveys, but without a detailed understanding of emergent population evacuation behavior and road traffic patterns, assigned speeds may not provide the level of realism needed for Level 3 PRA estimations. The 2017 SOARCA study for Sequoyah has begun to address these concerns by including a seismic roadway impact analysis which considers the loss of roadways with bridges and potential flooding in low lying areas (NRC, 2017c). Further, the Sequoyah study considers ETEs based on the number of vehicles, available evacuation routes, and roadway capacity at the available exit points of the EPZ, leveraging information from multiple ETE studies, and confirmatory analysis using the RtePM code (NRC, 2017c). RtePM is a GIS-based web application that allows for on-the-fly analyses of evacuation routes and time estimates based on time of day, average demographic information, people per vehicles, percent evacuating, and percent going to shelters (VMASC, 2013).

5.2. THEORETICAL DEVELOPMENT FOR EXPLICIT INCORPORATION OF SOCIAL FACTORS INTO LEVEL 3 PRA

Lack of explicit incorporation of social factors in PRA may lead to (a) underestimating risk due to inadequate quantification of common cause failures (CCFs) (Sakurahara et al., 2017) and dependencies associated with shared organizational and social failure mechanisms, (b) inadequate risk management due to a lack of understanding of the underlying social risk contributing factors and their causal paths of influence on system risk, and (c) inefficient resource allocation due to lack of risk importance ranking of social factors. There are two key requirements for explicit incorporation of social factors into PRA: (i) the integration of a theoretical model of how socio-technical systems perform, considering causal factors with their corresponding level of analysis and relational links, and (ii) the adaptation of appropriate methodological techniques, 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 (Pence et al., 2017; Sakurahara et al., 2017). This section focuses on the development of the theoretical causal framework, and Section 5.3 introduces the methodology.

For many years, the explicit incorporation of underlying social and organizational failure mechanisms into Level 1 PRA has been a challenging area of research (Bier, 1999; Ghosh & Apostolakis, 2005; Mohaghegh & Mosleh, 2009a; Pence, J et al., 2015; Pence et al., 2017). The Socio-Technical Risk Analysis (SoTeRiA) framework (Mohaghegh, 2007; Mohaghegh & Mosleh, 2006; Mohaghegh & Mosleh, 2009a) (Figure 5.1), grounded on "theories" rather than on a set of factors or accident data, was developed to address this challenge. SoTeRiA theorizes multiple levels of 'internal' mechanisms, including individual, unit, group, and organization (Nodes 2 to 9 in Figure 5.1), and their interactions with the 'external' environment, including physical, regulatory, business, and sociopolitical climates (Nodes 10 to 16 in Figure 5.1), along with their causal influences on technical system risk (PRA; Node 1). Further details about the theoretical development and quantifications of SoTeRiA can be found in related publications by the authors (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a; Pence et al., 2017).

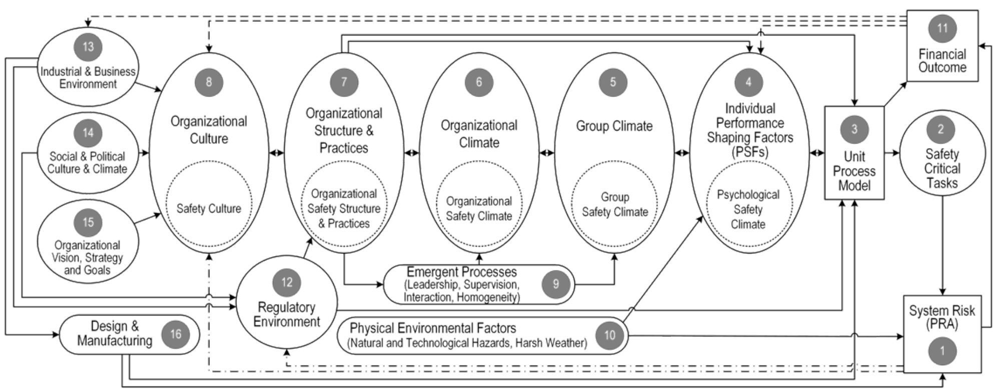

Figure 5.1: Socio-Technical Risk Analysis (SoTeRiA) Theoretical Framework

The scope of SoTeRiA (Figure 5.1) was limited to one organization (e.g., the NPP) and Level 1 PRA. In this research, the scope of SoTeRiA is expanded for use in EPPR applications. Figure 5.2 shows a 'macro-level' SoTeRiA theoretical framework, which extends the scope of SoTeRiA to the regional area surrounding an NPP to demonstrate the relationships between physical environmental factors (i.e., technological hazard in the phase of Level 3 PRA), onsite organizations modeled in SoTeRiA (Mohaghegh, 2007; Mohaghegh & Mosleh, 2009a), offsite response organizations (OROs), the population, and critical public infrastructure in relation to the three phases of PRA (Levels 1, 2, and 3). In Figure 5.2, the onsite organization (SoTeRiA) module stands for nodes 1-9, 11, and 13-16 from the SoTeRiA framework (Table 5.1), covering the human actions, team processes, and organizational factors that contribute to onsite performance.

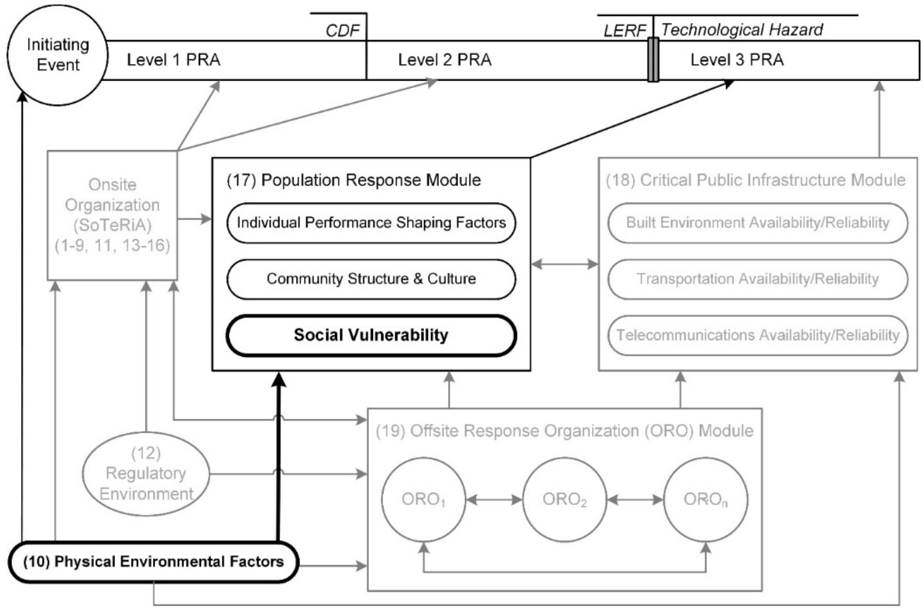

Figure 5.2: Macro-level Socio-Technical Risk Analysis Theoretical Framework for EPPR Applications

As Figure 5.2 indicates, one of the modules that interacts with population response is critical public infrastructure (Module 18), which includes the availability and quality of the built environment (e.g., energy and water systems, communication networks, transportation systems) and service infrastructure (hospitals, fire and police departments) (Nan et al., 2011; Zio, 2014). OROs (Module 19) support the population response (Module 17) by providing services, e.g., transportation management, firefighting, search and rescue, environmental cleanup, media relations, international affairs, financial management, mass care, resource support, public health, evacuation support, notification, recommendations, and tools and equipment (Sullivan et al., 2013). The performance of OROs and availability of critical public infrastructure will influence the population response to an accident (Module 17).

The population response module is designed to predict the behavior of large groups. The concept of performance shaping factors from human reliability analysis (Swain & Guttmann, 1983) can be used to consider the possible internal and external factors affecting human performance. Human reliability analysis (HRA) is mainly developed for individual-level (Kirwan, 1994; Swain & Guttmann, 1983) and crew-level (Parry et al., 2013) performance modeling, and the expansion of HRA to the regional-level human performance prediction requires further research. The focus of this paper, however, is on framing and operationalizing social vulnerability as a construct among others within the population response module (Module 17), where several factors influence the behavior of a population during a severe nuclear accident. Other modules, e.g., offsite physical environmental factors (Module 10), also affect the influencing factors of population response (Module 17), which include the social vulnerability construct.

In the nuclear power domain, vulnerability can be categorized into two areas: (i) vulnerability as a measurement of 'risk' (e.g., regional risk assessment (Baklanov & Mahura, 2001; Baklanov et al., 2013; Baklanov et al., 2008; Rigina & Baklanov, 2002) and post-accident mental health effect assessment (Kunii et al., 2016; Mashiko et al., 2017; Solomon & Bromet, 1982)), or (ii) vulnerability compared with NPP risk assessments, where exposure to risk is viewed from the perspective of the local population (e.g., environmental justice, NPP siting (Alldred & Shrader-Frechette, 2009; Cousins et al., 2013; Kosmicki, 2013; Kyne, 2015; Kyne & Bolin, 2016; Satterfield et al., 2004; Shrader-Frechette, 2013)). This paper, however, adapts the concept of social vulnerability, developed by Cutter et al. (2003) in the context of natural hazards (Bakkensen et al., 2017; Cutter et al., 2003), for the context of a severe nuclear accident. Cutter et al. have defined social vulnerability as a representation of social factors that "influence or shape the susceptibility of various groups to harm and that also govern their ability to respond," which "also includes place inequalities – those characteristics of communities and the built environment, such as the level of urbanization, growth rates, and economic vitality, that contribute to the social vulnerability of places" (Cutter et al., 2003). Section 5.3 explains the methodological approach for the quantification and mapping of the social vulnerability construct, and its integration with a radiological hazard in the context of a severe nuclear accident.

Given the large-scale nature of the macro-level SoTeRiA framework (Figure 5.2) and rare-event characteristics of NPP accidents, it is difficult to validate the framework empirically, and therefore, it is essential that the causal factors and relationships be based on theoretical foundations and principles so that the framework is theoretically valid (Mohaghegh, 2007). This theoretical validation was a key consideration in the development of SoTeRiA (Table 5.1) for Level 1 PRA. The focus of this paper is on the operationalization of the social vulnerability construct of macro-level SoTeRiA (Figure 5.2), and future publications will report on theoretical justification and operationalization of the other elements in Figure 5.2.

5.3. METHODOLOGICAL DEVELOPMENT FOR EXTERNAL-EXPLICIT INTEGRATION OF SOCIAL FACTORS WITH LEVEL 3 PRA

In this research, a methodological spectrum (Figure 5.3) is introduced regarding the operationalization and quantification of incorporating social factors (explained in Section 5.2) into Level 3 PRA of nuclear power plants. As mentioned in Section 5.1, current Level 3 PRA of NPPs have implicit incorporation of social information, represented by the left end of the spectrum in Figure 5.3. In Level 3 PRA, the implicit incorporation of population response is reflected through ETE analysis. The lack of explicit and location-specific incorporation of social, political, and community information may result in an incomplete response model. For example, evacuation efficiency is highly location-specific and socially and behaviorally dependent (Cova & Church, 1997; Dash & Gladwin, 2007; Goldblatt & Weinisch, 2005; Lindell & Prater, 2007; Miller, 2015; Miller et al., 2015). Without realistic modeling of population performance in the evacuation module of the Level 3 PRA code, the time estimates, resource allocations, and decisions that are made based on the outputs of these models may be inaccurate. If the social data contained in the evacuation model is input as a lump sum (i.e., the social data is incorporated implicitly in the evacuation model), there are limitations for updating information about new policies, procedures, and plans, or when demographic changes occur that would modify the way the public reacts in an emergency.

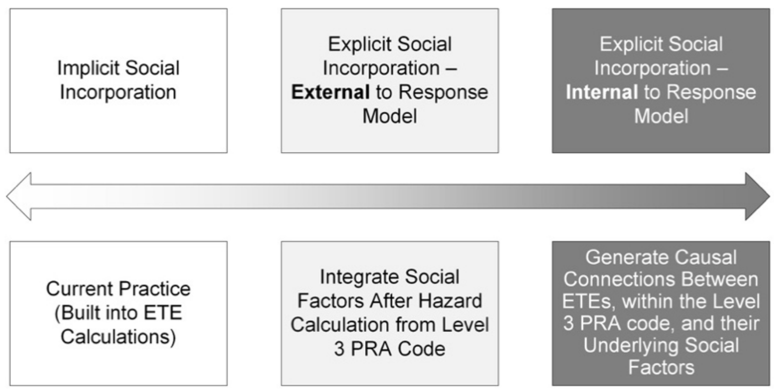

Figure 5.3: A methodological spectrum for the incorporation of social factors into EPPR models

To overcome the limitations of implicit incorporation of social factors in current Level 3 PRA tools, the authors proposed two methodological approaches for explicit incorporation: (a) internal (shown on the right side of the spectrum in Figure 5.3), and (b) external (shown in the middle part of the spectrum in Figure 5.3). A more accurate approach is an internal method (the right side of the spectrum in Figure 5.3) that requires developing advanced simulation environment to operationalize the macro-level SoTeRiA causal model (Figure 5.2) in order to quantify the effects of underlying social contributing factors, associated with the population response module (Module 17), on the evacuation parameters (e.g., mobilization time estimates, transient and transient-dependent populations, etc.) in the Level 3 PRA code. Developing the internal-explicit methodology is the focus of a parallel research study by the authors (Bui, H. et al., 2016; Bui et al., 2017; Pence, Justin et al., 2015).

As shown in the middle of the spectrum in Fig 3, an approach that is somewhere in-between the two ends of the spectrum is the explicit integration of social factors externally to the Level 3 PRA code. The focus of this paper is on this external-explicit integration. Demographic aspects are implicitly considered in MACCS via cohort modeling; however, there are no input parameter in MACCS that can be adjusted to explicitly and internally reflect social vulnerability. Since MACCS parameters and social vulnerability data are inherently spatial, a GIS-based methodology is proposed in this research to create an external-explicit integration, including the following steps:

(1) Calculating a hazard-independent social vulnerability index;

(2) Developing a location-specific representation of the maximum radiological hazard, estimated from current Level 3 PRA, in a GIS environment;

(3) Developing a socio-technical risk map by combining the social vulnerability index and the location-specific radiological hazard;

(4) Conducting a risk importance measure analysis to rank the criticality of social factors based on their contribution to risk.

The following sub-sections further explain each of the above steps.

5.3.1. Calculating a Hazard-Independent Social Vulnerability Index

There are several methods for developing a social vulnerability index which can be used to quantify the social vulnerability construct (a construct within Module 17 in Figure 5.2). For example, the Social Vulnerability Index (SoVI®), developed by Cutter et al., (2003), offers a method for processing demographic data to generate a measure of social vulnerability to environmental hazards (Cutter et al., 2003). SoVI® is a widely-used technique which mainly focuses on age and sociodemographic conditions (Tarling, 2017). Another class of social vulnerability index includes the Center for Disease Control (CDC) Agency for Toxic Substances and Disease Registry (ATSDR) Social Vulnerability Index (SVI), developed by ATSDR Geospatial Research, Analysis, and Service Program (GRASP) (ATSDR, 2018). The CDC SVI provides a simplified method that puts more focus on socioeconomic attributes (Flanagan et al., 2011). Both SoVI® and the CDC's SVI use statistical analysis of demographic data to determine which areas of the population are most vulnerable to hazards. A comprehensive review of these methods can be found in (Tarling, 2017). In this research, the CDC's SVI is selected because it (i) focuses on socioeconomic attributes, which can provide insights into the population's access to resources, for example, private transportation, (ii) is supported and maintained by federal agencies, which helps to promote data transparency, and (iii) includes American Community Survey (ACS) data (ATSDR, 2018), which provides information from 2012 to 2016 to support analysis with more current outputs. The CDC SVI is based on the four high-level themes and associated factors shown in Table 5.1.

Table 5.1: The CDC SVI Themes and Census Variables (ATSDR, 2018)

ID	Themes	Variables
1	Socioeconomic Status	Below Poverty
		Unemployed
		Income
		No High School Diploma
2	Household Composition & Disability	Aged 65 or Older
		Aged 17 or Younger
		Civilian with a Disability
		Single-Parent Households
3	Minority Status & Language	Minority
		Speak English "Less than Well"
4	Housing & Transportation	Multi-Unit Structures
		Mobile Homes
		Crowding
		No Vehicle
		Group Quarters

The CDC SVI has four sub-steps for calculation (Flanagan et al., 2011):

(1) Each of the 15 variables (except income) is ranked, from highest to lowest, across census tracts in the region of analysis. Income is ranked lowest to highest, since a higher value indicates less vulnerability.

(2) A percentile rank is calculated for each census tract over each of the 15 variables. The percentile rank of each given value refers to the ratio of the number of values, lower than the given value, over the count of all values in the set, excluding that given value. In other words, the percentile rank can be calculated using Eq. 5.1 from Ref. (Flanagan et al., 2011):

$$Percentile\ Ranking = \frac{Rank-1}{N-1}, \qquad (5.1)$$

where N = the total number of data points, and "Rank" refers to the ranking that is generated for each variable across census tracts in Step 1.

(3) A percentile rank is calculated for each theme, shown in Table 5.1, by adding the tract-level percentile ranks of the variables (estimated in Step 2) associated with that theme.

(4) The overall percentile rank of each tract is estimated by the summation of the percentile ranks of the four themes for that tract. Percentiles range from 0 to 1, where higher values indicate greater social vulnerability.

5.3.2. Developing a Location-Specific Representation of the Maximum Radiological Hazard, Estimated from Current Level 3 PRA, in a GIS Environment

The scope of Level 3 PRA and EPPR is inherently spatial, with interrelated events that have strong spatial components, and therefore "geographical space is a valuable framework for reasoning about many problems that arise in the context of emergency management" (Cova, 1999). Originally used by geographers, GIS has been incorporated into many areas of research applicable to emergency management, such as natural hazard analysis (Ferretti & Montibeller, 2017), identification of evacuation routes, and infrastructure planning (Cova, 1999). GIS tools are well suited for storing and analyzing data relating to the built environment, and the vulnerability of the built environment to natural hazards. GIS is a powerful tool for querying data, measuring spatial entities, transforming data, creating new data, interpolation, generating values of discrete objects, point and route optimization, geostatistical analysis, pattern analysis, relationship analysis and geovisualization (Burrough et al., 2015; Peggion et al., 2008).

In the nuclear domain, GIS techniques have been applied to map radiological hazards, health effects, protective action locations, and economic areas (Hammond & Bier, 2015; Mercat-Rommens et al., 2015; Silva et al., 2017; Tsai et al., 2012). GIS has been used to analyze and visualize field data from historical accidents (Van der Perk et al., 1998), and generate spatial risk analysis based on postulated hazards (Rigina & Baklanov, 2001; Rigina & Baklanov, 2002). Several radiological hazard codes are designed to generate outputs usable in GIS geodatabase and 'shapefile' formats (Grabowski et al., 2009; Rentai, 2011; Rigina & Baklanov, 2001; Rigina & Baklanov, 2002). For example, the NRC's Radiological Assessment Systems for Consequence AnaLysis (RASCAL) tool can produce shapefiles for GIS (NRC, 2012a). RASCAL, however, is a methodology for representing the early phase of a nuclear incident, while MACCS is used to consider short and long-term scenarios (OECD & NEA, 2016).

In this paper, there are two primary benefits of utilizing GIS: (1) combining diverse streams of data (i.e., social vulnerability data and radiological hazard data from MACCS) into one geographically-coordinated environment, and (2) visualizing risk analysis results for communicating EPPR to decision-makers and the larger population. In this step of the proposed methodology, GIS provides the environment for a location-specific representation of the maximum radiological hazard estimated from Level 3 PRA. As discussed in Section 5.1.1, MACCS is a Level 3 PRA code that is used by the U.S. nuclear industry and regulator to model scenarios of radiological atmospheric transport and environmental dispersion (NRC, 2014a). Peak dose is an output from MACCS, calculated at an (r, θ) location, representing the accumulated (total) dose at a given location. The location-specific dose is the result of all direct exposure pathways at that location (not including the ingestion pathway) (NRC, 1997). This location-specific peak dose represents the hazard to any persons located in the area. MACCS generates peak dose estimate information for the region surrounding an NPP which can be exported as comma-separated values (CSV) (Miller, 2015).

In this step of the methodology, the Level 3 PRA code is run without executing any population response module. Since the population response model is the only part of Level 3 PRA code that implicitly contains social information, there are some dependencies involved in running Level 3 PRA code with evacuation module and then integrating the social factors in Step 3 externally to the results. Therefore, in this research, the Level 3 PRA code is run with no population response considerations. The output of Level 3 PRA code, without executing evacuation module, is based on the source term, plume rise, transport, dispersion, and deposition only; thus, the result can be thought of as completely independent of the population's reaction to the radiological hazard. The estimated peak dose from this step of the methodology represents the "maximum" radiological hazard to any persons located in the area because it is considered that the population do not evacuate and are in one place the entire part of the EARLY module of MACCS (EARLY is seven days in the SOARCA study).

As currently implemented, the MACCS code has an internal geographically coordinated system and can use GIS-compatible data but is not compatible with external user-added models through commercial and open source GIS platforms. The following sub-steps are used to convert MACCS results for GIS compatibility:

1. <u>Convert and transpose peak dose data:</u> this sub-step transposes the CSV outputs of peak dose values from MACCS into single records for each index radius and index angle pair (r, θ). In this process, several fields which form the attribute information are added, calculated, and removed using the 'Transpose Fields' tool in ArcGIS Pro.
2. <u>Create the polar grid in GIS:</u> this sub-step uses a Python script to create a polar grid using the polar grid resolutions from NUREG-1150 (NRC, 1990, 2014a).

3. Join peak dose data to the polar grid in GIS: this sub-step conducts a 'table join' of peak dose data with each cell of the polar grid, linking location-specific hazard information with the polar grid feature class.

5.3.3. Developing a Socio-Technical Risk Map by Combining the Social Vulnerability Index and the Location-Specific Maximum Radiological Hazard

Several hazard analysis studies use the relationship shown in Eq. 5.2 for relating hazard and vulnerability (Blaikie et al., 2014; Dwyer et al., 2004), in order to estimate the risk of a specific natural hazard, at a specific location, and considering the population's location-specific vulnerability.

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \qquad (5.2)$$

This research makes a parallel between PRA and hazard analysis. In this research, the maximum radiation dosage frequency at each location is used as "Hazard" in Eq. 5.2. The maximum radiation dose frequency at each location is calculated by multiplication of the location-specific maximum radiation dose (estimated in Step 2 of the methodology; Section 5.3.2) and LERF (i.e., the output of Level 2 PRA code which is the input frequency to the Level 3 PRA code). SVI (estimated in Step 1 of the methodology; Section 5.3.1) is used for "vulnerability" in Eq. 5.2 as an indicator of hazard progression. The accumulated dose in the population relates to a "degree of hazard progression in the population" (i.e., the vulnerability of the population to the hazard) that is associated with population evacuation deficiencies. In other words, the "vulnerability" term in Eq. 5.2 is used as a surrogate for the population's ability to evacuate efficiently. Since SVI is an aggregation of many social factors, and because it can act as a term for damage susceptibility for diverse groups of people, in this research, the SVI term can be considered as a surrogate for population's ability to evacuate efficiently. If SVI at a location is 1 (i.e., the most vulnerable population), the estimated socio-technical risk from Eq. 5.2 is equal to the maximum radiation dose frequency at that location. This is reasonable because the location-specific maximum radiation dose (estimated in Step 2 of the methodology; Section 5.3.2) is calculated by running the Level 3 PRA code, assuming that there is no population evacuation or protection. On the other hand, if SVI is less than 1 (i.e., a less vulnerable population), the estimated socio-technical risk from Eq. 5.2 proportionally reduces (i.e., less accumulation of dose in population).

Since both radiation hazard and social vulnerability are location-specific, their multiplication (based on Eq. 5.2) is performed in a GIS-based environment to estimate and visualize a socio-technical risk. An ArcGIS Pro model is developed to calculate the socio-technical risk values using the 'intersect' geoprocessing tool to combine overlapping spatial areas of the polar grid segments and census tracts to create a new field for the socio-technical risk and multiply feature class information for CDC SVI and peak dose at each unique location. It should be noted that most census tract areas are larger than polar grid segments, and therefore the granularity of intersected areas more closely follow the polar grid regions, meaning that CDC SVI values are distributed across several intersected areas. In future research, increased spatial resolution of CDC SVI data can improve the accuracy of this intersection.

5.3.4. Conducting a Risk Importance Measure Analysis to Rank the Criticality of Social Factors Based on their Contribution to Risk

For the socio-technical risk (estimated in Step 3 of the methodology) to be used in risk-informed decision making in EPPR and resource allocation, it is valuable to rank the criticality of location-specific social factors with respect to their influence on risk. While sensitivity analysis has been conducted for SoVI® for the context of natural hazards (Schmidtlein et al., 2008), this step of the proposed methodology demonstrates the use of importance measure (IM) analysis to obtain a ranking of CDC SVI themes based on their contribution to overall socio-technical risk.

The IM methodology for this research is developed based on the concept of Fussell-Vesely IM, commonly used in classical PRA (Van der Borst & Schoonakker, 2001; Vesely et al., 1983), which indicates the importance of each risk contributor in terms of contribution to risk reduction. As discussed in Section 5.3.1, the CDC SVI has four themes, each with corresponding variables which compose the total percentile rank for each theme. In this research, the risk importance measure of theme i for location l, shown as $IM_i^{(l)}$, is formalized by Eq. 5.3:

$$IM_i^{(l)} = \frac{R_0^{(l)} - R_{i-}^{(l)}}{R_0^{(l)}}, \quad (5.3)$$

where $R_0^{(l)}$ is the nominal socio-technical risk value for location l, estimated by considering each theme with its nominal/realistic percentile rank, and $R_{i-}^{(l)}$ is the socio-technical risk value for location l computed with a partial (e.g., ten percent) decrease in the percentile rank of the theme $i,\ i \in \{1,2,3,4\}$ in Table 5.1. Conceptually, Eq. 5.3 assesses how much the socio-technical risk value decreases when the percentile rank of each theme is decreased; hence, indicates the location-specific importance of each theme in terms of reducing the socio-technical risk. Because existing Level 3 PRA is "implicit" with respect to social factors, it is not possible to perform this type of importance ranking of social factors. This type of ranking is an important benefit of the "explicit" incorporation of social factors into Level 3 PRA and can be valuable for risk-informing EPPR.

5.4. APPLICATION OF THE METHODOLOGY FOR THE SURRY POWER STATION

In this section, the methodology (explained in Section 5.3) is applied in a case study for SPS using the 2012 SOARCA study to provide the input parameters for the radiological hazard model (NRC, 2013b), and the 2016 CDC SVI data for the state of Virginia (CDC et al., 2018).

<u>Step (1) Calculating Social Vulnerability Index for the SOARCA study:</u>

Full documentation on the CDC SVI can be found in (ATSDR, 2018). Figure 5.4 shows the total population for the region surrounding the SPS. In this paper, the method of graduated colors is used in all maps to provide the reader with an idea of how the distribution of values are spread over the 10-mile EPZ. As a caveat, the bounds of each graduated level are given on each map, and the ranges for each of the quantiles are not the same. It should also be noted that the 'James River' is a labeled water feature and is excluded from the analysis.

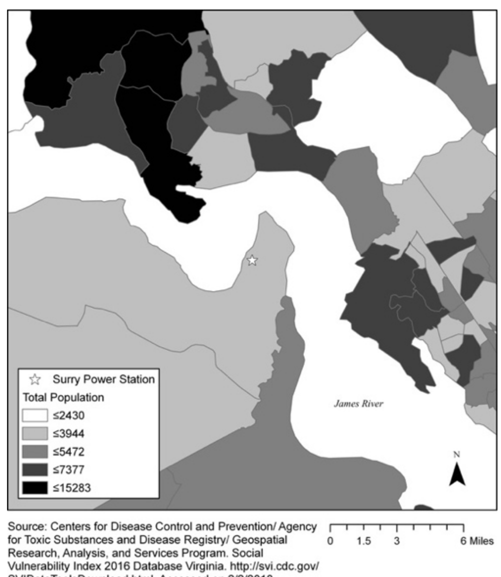

Figure 5.4: Total Population Surrounding the Surry Power Station (Source: CDC SVI)

Figure 5.5 shows a map of the CDC SVI for Virginia focused on the region surrounding SPS. Census-tract percentile rankings show only a relative value, given the location within the state of Virginia (Bakkensen et al., 2017). The color scheme used in Figure 5.5 is based on splitting the range of possible CDC SVIs into quantiles classified using natural breaks (Jenks) in ArcGIS Pro. The CDC SVI shown in Figure 5.5 is hazard independent, using demographic and ACS data (CDC et al., 2018).

Source: Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program. Social Vulnerability Index 2016 Database Virginia. http://svi.cdc.gov/SVIDataToolsDownload.html. Accessed on 2/2/2018

0 1.5 3 6 Miles

Figure 5.5: Social Vulnerability Census Tracts for the State of Virginia: The Region Near Surry Power Station

<u>Step (2) Developing a location-specific representation of the maximum radiological hazard for the SOARCA study:</u>

The SPS SOARCA study provides the inputs for generating peak dose estimates. The SOARCA study claims that while PRA results are specific to SPS, they also serve as a useful representation of other operating pressurized water reactor NPPs in the US (NRC, 2012b). In this example, dose in Sv (Sieverts) is used as a measure of the radiation hazard. MACCS generates a polar grid of location-specific peak dose estimates. The radial distances (0.16, 0.52, 1.21, 1.61, 2.13, 3.22, 4.02, 4.83, 5.63, 8.05, 11.27, 16.09 kilometers) (r) and angular dimensions (64 angles (θ) and 12 radii) for the polar grid resolution are provided by the MACCS Best Practices Guide for the SOARCA study (NRC, 2014a).

To consider the total risk of a severe nuclear event, a range of accident scenarios are considered, sampling from all source terms in the radionuclide inventory. The nuclides are considered at plant shutdown from each accident, so source terms are consisted of the same isotopes but differed in the respective percentages of each isotope. Other differences between accident scenarios include plume release times, plume heat contents, plume release heights, plume mass density, plume mass flow rate, and plume segment durations. The scenario in this application is based on the SOARCA Unmitigated long-term station blackout (LTSBO) scenario and the representative source term that is part of the SOARCA study (NRC, 1990, 2012b). The unmitigated LTSBO is chosen because it represents the largest contribution to CDF, estimated to be 2×10^{-5} per reactor year (NRC, 2013b).

To generate a location-specific representation of a radiological hazard, MACCS is used to model atmospheric phenomena, radionuclide decay, and exposure pathways. Protective measures (i.e., evacuation, relocation, shelter-in-place, potassium iodide (KI) pills) are excluded to make the results independent of OROs and population response. For the SOARCA study, 28 plume segments are used for the LTSBO accident (NRC, 2013b). The plume parameters are given in Volume 2 of the Surry SOARCA study (NRC, 2013b). A critical part of the scenario for plume modeling is the explicit consideration of weather conditions for a given geographic location. Weather sampling and incorporation of uncertainty for MACCS parameters allow for detailed and probabilistic scenarios of hazard progression to be developed.

For this application, no dose threshold mitigative actions are included in MACCS. MACCS is run a total of 24 times to produce output files that cover 10 miles of the plume exposure EPZ, which are binned into the polar grid resolution listed above. In this example, it is assumed that one individual is stationary throughout the entire EARLY module of MACCS (EARLY is seven days in SOARCA), estimating the maximum dose they would receive. The second sub-step from Step 2 (introduced in Section 5.3.2) is applied a Python script to create a polar grid (Figure 5.6) using the resolutions from NUREG-1150 as previously mentioned (NRC, 1990, 2014a).

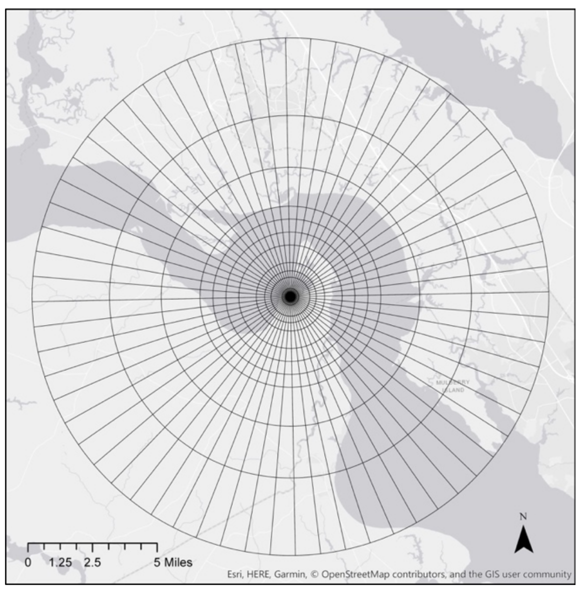

Figure 5.6: Grid System Generated by the Python Script in ArcGIS Pro

The third sub-step from Step 2 (introduced in Section 5.3.2) is used to join peak dose data with the polar grid to generate the location-specific representation of a radiological hazard in GIS (Figure 5.7).

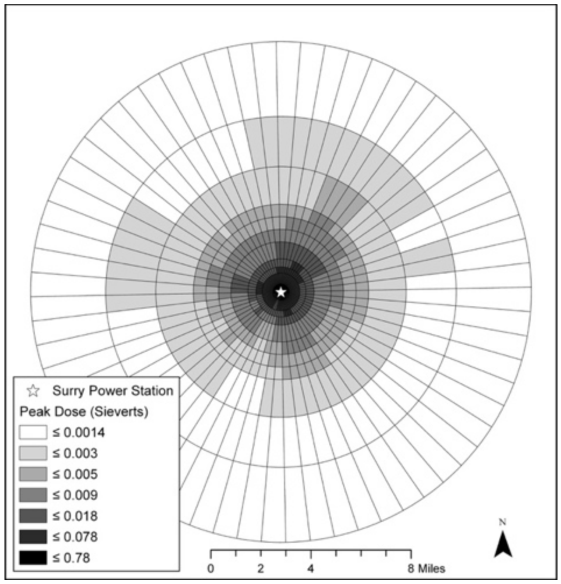

Figure 5.7: Map of Radiological Hazard around Surry Power Station due to LTSBO Event

The results shown in Figure 5.7 indicate that a radiological hazard from SPS is not spatially uniform. As seen in Figure 5.7, the radiation hazard is highest near the plant, and because of weather sampling, higher levels of peak dose are seen in the northeast, southeast, and west. The GIS-compatible hazard data is then combined with the social vulnerability data in the next step to produce a socio-technical risk map.

Step (3) Developing a socio-technical risk map for the SOARCA study:

Based on Step 3 of the methodology (introduced in Section 5.3.3) an ArcGIS Pro model is applied to intersect overlapping spatial areas of the polar grid and census tracts, which resulted in 742 unique areas within the 10-mile EPZ. Using this approach, an external-explicit integration of social factors with Level 3 PRA is demonstrated by the intersection of hazard and the CDC SVI. Figure 5.8 shows that radiation risk to the public is highest near the plant. The two highest categories of risk exist within three miles of the plant. The middle level of risk is encompassed within a five-mile range, with the exception being the western region, which has been expanded due to higher social vulnerability, as well as a higher probability of wind in that direction. There are areas in the 7 to 10-mile radial ring that vary between the lowest and second lowest levels of risk.

The numbers that are generated by the intersection of hazard and vulnerability in Figure 5.8 are based on Sieverts (Sv), which should be multiplied by LERF (2×10^{-5}) to represent dose frequency. The mean CDC SVI (a percentile rank of combining all four themes) within the 10-mile EPZ shown in Figure 5.8 is 0.63 (from a range of 0 to 1). With the statistical information for these areas, decision-makers can rank specific populations by different criteria related to hazards or social factors to focus their planning efforts. For example, the first 128 intersect areas most at risk lie within the first two radial rings used in WinMACCS (within 0.52 km of SPS).

All regions that are associated with risk greater than the mean are within 1 mile of the plant. Ranking areas outside of 1 mile, decision-makers can find neighborhoods within their area of governance to provide extra resources for emergency preparedness purposes. The scope of CDC SVI data at the census tract-level does not provide block-level data for developing highly granular risk indicators. Increased spatial resolution would improve the analysis and means to communicate the results with decision-makers and constituents of larger geographical areas defined by political boundaries. The socio-technical risk values could also be used to compare the surrounding regions at different NPPs.

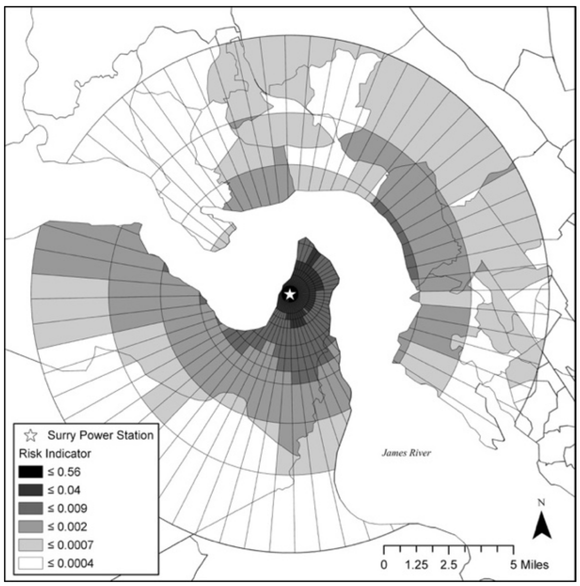

Figure 5.8: Socio-technical risk map of radiological hazard and social vulnerability.

<u>Step (4) Conducting a risk importance measure analysis:</u>

Using Eq. 5.3, the IM analysis is conducted for all locations within the EPZ to rank location-specific CDC SVI themes based on their influence on the socio-technical risk indicator. Table 5.2 shows the IM results for each census tract within the 10-mile EPZ of SPS. Locations, where peak dose is the dominant risk contributor (i.e., closest to the NPP), are excluded from a detailed interpretation of the IM results.

Table 5.2: Importance Measure Results

Census Tract	Theme 1 IM	Theme 2 IM	Theme 3 IM	Theme 4 IM
320.01	10%	23%	10%	6%

Table 5.2 (cont.)

Census Tract	Theme 1 IM	Theme 2 IM	Theme 3 IM	Theme 4 IM
30.02	7%	11%	6%	7%
320.05	10%	10%	4%	5%
320.06	3%	2%	1%	2%
320.07	5%	4%	2%	5%
321.13	4%	5%	2%	7%
321.23	8%	6%	2%	6%
321.24	10%	9%	7%	4%
321.24	5%	5%	3%	4%
321.31	10%	9%	8%	7%
321.32	6%	7%	4%	6%
322.11	8%	9%	6%	6%
322.12	2%	2%	1%	2%
322.23	6%	4%	4%	6%
322.25	2%	1%	1%	2%
322.26	3%	2%	1%	2%
323	8%	4%	3%	7%
324	7%	7%	2%	7%
503.06	8%	11%	3%	9%
505	4%	3%	1%	4%
509	8%	6%	3%	5%
510	7%	7%	2%	6%
511	12%	10%	7%	2%
801.01	6%	13%	3%	14%
801.02	2%	1%	1%	2%
802.02	7%	16%	3%	10%

Table 5.2 (cont.)

Census Tract	Theme 1 IM	Theme 2 IM	Theme 3 IM	Theme 4 IM
802.03	7%	9%	3%	11%
802.05	4%	4%	2%	5%
802.06	6%	10%	3%	11%
803.03	9%	15%	7%	15%
803.04	5%	12%	2%	15%
2801.01	7%	6%	1%	6%
3701	10%	7%	3%	10%
3702	7%	5%	3%	6%
3703	8%	3%	2%	8%
8601	7%	6%	1%	4%
8602	10%	7%	2%	8%

The results of this analysis reveal that the CDC SVI theme contributions to socio-technical risk can vary significantly by location. For instance, for the census tract 320.01 of Newport News county (location l_1), $IM_i^{(l_1)} = \{10\%, 23\%, 10\%, 6\%\}$, which indicates that Theme 2 (Household Composition & Disability) is the most critical risk contributor. For the census tract 803.03 of James City county (location l_2), $IM_i^{(l_2)} = \{9\%, 15\%, 7\%, 15\%\}$, indicating that Themes 2 (Household Composition & Disability) and 4 (Housing & Transportation) are the two most critical risk contributors. This ranking could support risk-informed EPPR to help make more efficient decisions with respect to resource allocation. The locations where a specific theme (e.g., Household Composition & Disability, Housing & Transportation) is the greatest contributor to risk may require decsion-makers to run more detailed evaluations and perform additional data collection and analysis to generate long-term prevention strategies that can address the sources of vulnerability (e.g., transportation options, services to support those living with disabilities). Future work will perform IM on each variable of the CDC SVI (Table 5.1), in addition to each theme, to more comprehensively identify the most critical location-specific social factors contributing to risk.

5.5. CONCLUDING REMARKS

This paper is a part of a line of research by the authors to explicitly incorporate location-specific social contributing factors into Level 3 PRA (Miller, 2015; Miller et al., 2015). There have been significant studies, by several authors of this paper, regarding the explicit incorporation of social and organizational factors into Level 1 PRA (Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2009a, 2009b; Pence et al., 2014; Pence et al., 2017). The goal of this study is to initiate the same paradigm of research for Level 3 PRA. In the nuclear power domain, Level 3 PRA is used to estimate damages to public health and the environment in the case of a severe accident leading to large radiological release. Explicit incorporation of social factors, most specifically location-specific social factors into Level 3 PRA, can drastically affect decisions related to emergency planning, preparedness, and response (EPPR). In the aftermath of the Fukushima Daiichi accident in 2011, there were concerns about the population's ability to respond to a radiological hazard (NAS, 2014), and therefore, understanding the implications of the social makeup of the population near an NPP has the potential to give decision-makers information about the effects of their decisions.

This paper adapts the concept of social vulnerability, originally developed in the context of natural hazards (Bakkensen et al., 2017; Cutter et al., 2003), for the context of a severe nuclear accident. The paper sets the theoretical ground by developing a macro-level socio-technical risk analysis causal framework and by framing the nuclear-oriented social vulnerability construct in the causal framework. The methodology offered in this paper operationalizes the social vulnerability construct, and makes an external-explicit integration of social vulnerability and Level 3 PRA of NPPs, following four steps: (1) calculating a hazard-independent social vulnerability index for the local population, (2) developing a location-specific representation of the maximum radiological hazard estimated from current Level 3 PRA in a geographic information system (GIS) environment, (3) developing a GIS-based socio-technical risk map by combining the social vulnerability index and the location-specific radiological hazard, and (4) conducting a risk importance measure analysis to rank the criticality of social factors based on their contribution to the socio-technical risk.

The methodology is applied using results from the 2012 Surry Power Station (SPS) State-of-the-Art Reactor Consequence Analysis (SOARCA). A radiological hazard model is generated from MELCOR Accident Consequence Code System (MACCS), translated into a GIS environment, and combined with the Center for Disease Control (CDC) Social Vulnerability Index (SVI). The results of this analysis reveal that the CDC SVI theme contribution can vary significantly by location. In affected locations, different themes such as 'household composition & disability,' and 'housing & transportation' can be greater contributors to socio-technical risk estimates. These results can be used to provide location-specific information to help EPPR for creating plans to evacuate individuals with special needs and the elderly while estimating the amount and type of supplies that are needed like food, water, medicine, and bedding (ATSDR, 2018). This research helps to visualize location-specific radiological risk around an NPP that improve risk communication with public and policymakers. Developing an internal-explicit methodology to more accurately incorporate social factor into Level 3PRA and first responders' performance model is the focus of a parallel research study by the authors (Bui, H. et al., 2016; Bui et al., 2017; Pence, Justin et al., 2015).

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CHAPTER 6: THEORETICAL AND METHODOLOGICAL DEVELOPMENT FOR THE EXPLICIT INCORPORATION OF SOCIAL FACTORS INTO EVACUATION TIME ESTIMATION AND LEVEL 3 PROBABILISTIC RISK ASSESSMENT OF NUCLEAR POWER PLANTS[1]

ABSTRACT

The 2011 Fukushima Daiichi accident revealed several gaps in the U.S. Level 3 Probabilistic Risk Assessment (PRA) of Nuclear Power Plants (NPPs); for example, the need to explicitly consider and analyze (i) unanticipated socio-technical factors influencing the communication of the Offsite Response Organization (ORO) and (ii) the influence of social and psychological factors on the performance of an evacuating population. This paper advances a macro-level theoretical causal framework that covers the socio-technical factors influencing population and ORO performance given man-made and natural hazards. While the long-term goal of this research is to operationalize the full scope of the macro-level theoretical causal framework, this paper focuses on population protective action performance and presents a new use of Human Reliability Analysis (HRA) for theorizing and quantifying a new indicator for Population Error (PE) associated with departure time delay. The methodological developments include (A) building and validating an HRA-based Population Departure Time Model (PDTM) using data from NPP Evacuation Time Estimate (ETE) studies to provide the distribution of population departure time, (B) Integrating PDTM with an evacuation transportation model to generate distributions of evacuation time and average speed, (C) Integrating the coupled PDTM-transportation model with the Level 3 PRA model (i.e., MELCOR Accident Consequence Code System (MACCS)) of NPPs to create the distribution of radiation risk, and (D) conducting sensitivity analysis to rank the criticality of input factors with respect to their influence on risk. The integrated methodological framework is demonstrated in a case study using information from the 2017 Sequoyah NPP State-Of-the-Art Reactor Consequence Analysis (SOARCA) study.

6.1. INTRODUCTION

The Nuclear Regulatory Commission (NRC) defines emergency preparedness as the last line of defense in a defense-in-depth philosophy for protecting the population from the consequences of a severe Nuclear Power Plant (NPP) accident with radiological release to the environment (NRC, 1983). The

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Federal Emergency Management Agency (FEMA) is responsible for understanding preparedness for "all-hazards" under Presidential Policy Directive 8 and the U.S. National Preparedness Goal (DHS, 2015). The U.S. Radiological Emergency Preparedness (REP) program, administered by FEMA, provides state, local, and Tribal governments "relevant and executable planning, training, and exercise guidance and policies necessary to ensure that adequate capabilities exist to prevent, protect against, mitigate the effects of, respond to, and recover from incidents involving commercial NPPs" (FEMA, 2016). Under the REP, each NPP is required to have a Radiological Emergency Response Plan (RERP) (NRC & FEMA, 2019). The planning basis for the REP considers that accident phenomena and the impact of REP improvements on offsite consequences should continually be assessed through NRC's State-of-the-Art Reactor Consequence Analyses (SOARCA) research (NRC & FEMA, 2019), that uses "Level 3" Probabilistic Risk Assessment (PRA).

PRA is a "systematic, disciplined theory and language for dealing with rare events, for quantifying risks, and making decisions in the face of the uncertainties attendant to these events" (Kaplan & Garrick, 1981). Level 1 PRA corresponds to socio-technical system scenarios (i.e., the combination of human errors and equipment failures) leading to core damage (measured as Core Damage Frequency [CDF]), Level 2 PRA depicts the time and mode of containment failure that leads to the release of radioactivity from an NPP (measured as Large Early Release Frequency (LERF) and source term), and Level 3 PRA models the transport of radiological plumes and their potential consequences to humans and the environment. MELCOR Accident Consequence Code System (MACCS) is the Level 3 PRA model used in the U.S. and has three modules for phenomenological modeling: ATMOS (i.e., atmospheric transport, dispersion, deposition, and radioactive decay of the radiological hazard), EARLY (i.e., the emergency phase protective actions, up to seven days, or a maximum of forty days after radiological release), and CHRONC (i.e., intermediate [after the emergency phase up to one year] and long-term [after the intermediate phase and up to several decades] protective actions, consequences and economic costs) (NRC, 1997). This paper focuses on theoretical and methodological advancements associated with the EARLY module. In the EARLY module, an analyst can make assumptions about emergency response scenarios that include evacuation, sheltering, and dose-dependent relocation (NRC, 1997).

Some of the key inputs to MACCS (e.g., evacuation strategies, the number of cohorts that refer to segments of the population, departure times, and evacuation speeds) are based on the results of Evacuation Time Estimate (ETE) studies. U.S. NPP licensees are required to conduct ETE studies (considering variations in time of year, day of the week, time of day demand estimations, roadway capacities, and trip generation times) to aide in pre-planning and protective action decision-making (NRC, 2011a, 2013a, 2013b). As an established practice in the SOARCA report NUREG-1935, licensees leverage information from ETE studies to provide key input parameters into MACCS in order to generate site-specific Level 3 PRA models (NRC, 2012). ETE studies include telephone surveys that provide information on departure time delays for various scenarios and include transportation model runs that are leveraged in MACCS to set network evacuation speeds to "better reflect the spatial and temporal response of individual cohorts" (NRC, 2014).

Despite the progress that has been made for Level 3 PRA, there are still several gaps to address; for example, the need to "explicitly" consider and analyze (i) unanticipated socio-technical factors influencing the communication of the Offsite Response Organization (ORO) (NAS, 2014), and (ii) the influence of social and psychological factors on the performance of an evacuating population, for example, as highlighted in (Pence et al., 2018). This paper is part of a line of research on the advancement of socio-technical risk analysis for "explicitly" incorporating organizational/social factors into Level 1 PRA and Human Reliability Analysis (HRA) (Bui et al., 2019b; Mohaghegh, 2007; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2009a, 2009b; Pence et al., 2020; Pence et al., 2015; Pence et al., 2014; Pence et al., 2019; Pence et al., 2017; Sakurahara et al., 2019), as well as into Level 3 PRA (Pence et al., 2018). In this research, a model is said to have "explicit" (rather than "implicit") incorporation of a social factor if it is a direct input variable in the governing equations that describe the model (Pence et al., 2018). In previous Level 3 PRA research by some of the authors of this paper, a methodological spectrum (Figure 6.1) was introduced to characterize the level of integration of social factors in Level 3 PRA (Miller et al., 2015; Pence et al., 2018). The spectrum (Figure 6.1) depicts the concept of "implicit" of social factors in NPP ETE studies on the left, and "explicit" incorporation of social factors into Level 3 PRA on the right. For studies that consider social factors implicitly, they typically include social factors as a lump sum (e.g., population density), and do not consider location-specific variation in social vulnerability and demographic factors. Implicit incorporation creates limitations for updating information about new policies, procedures, and plans, or when demographic changes occur that would modify the way the public reacts in an emergency. The advancement towards explicit, or model-based incorporation of social factors can be considered from two perspectives: (i) internal (on the right side of the spectrum in Figure 6.1), and (ii) external (the middle of the spectrum in Figure 6.1). Internal incorporation implies the development of advanced modeling and simulation to quantify the effects of underlying factors on the parameters in Level 3 PRA. External incorporation implies the quantification of independent models, where the results are combined after the hazard calculation in a separate modeling environment, for example, Pence et al., (2018) generated an explicit-external integration (i.e., the center of the spectrum in

Figure 6.1) of Center for Disease Control (CDC) Social Vulnerability Index (SVI) with Level 3 PRA (MACCS) radiological hazard outputs in a Geographical Information System (GIS) environment.

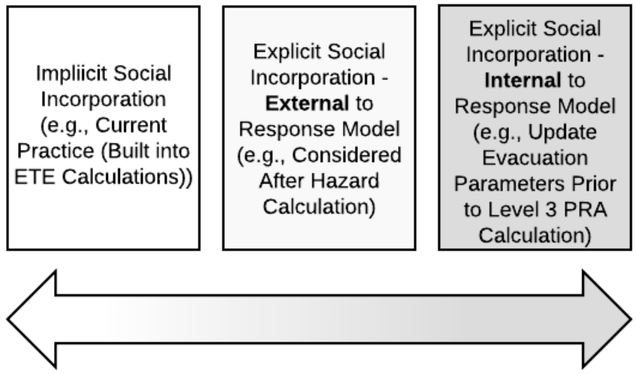

Figure 6.1: Methodological spectrum on the incorporation of social factors into evacuation models (Miller et al., 2015; Pence et al., 2018)

This paper continues the line of research toward an "explicit-internal" incorporation of social factors into Level 3 PRA (i.e., an advancement toward the right side of the spectrum in Figure 6.1), and makes theoretical and methodological contributions as follows:

- Section 6.2 expands the macro-level theoretical causal framework for socio-technical risk analysis of severe nuclear accidents, previously introduced by the authors (Pence et al., 2018), to advance the coverage of the socio-technical factors that influence population and ORO performance. The advanced theoretical framework contributes to the comprehensiveness of Level 3 PRA by considering a broader set of influencing factors and their multi-level interrelationships, providing opportunities for improved root cause analysis and development of the RERP. One element of this causal framework (i.e., population protective action performance) is further expanded in Section 6.2.1.1, where an HRA-based theoretical representation of Population Error (PE) is introduced for pre-evacuation departure performance. Population departure times, the time it might take for a segment of the population to depart in an evacuation (NRC, 2017), are important in determining the overall performance of an evacuation (Herrera et al., 2019; Tamminga et al., 2011). In NPP radiological emergencies, social factors, such as social context (i.e., activities of the population and their location) and social structure (i.e., nature of family ties and social networks) can be significant contributors to departure times (Johnson, James H., 1985, 1986; Johnson, J. H. & Zeigler, 1986; Sorensen, J., 1991); however, social factors are only implicitly considered in the existing ETE surveys. Without explicit consideration of social factors, it would be hard to analyze their effects on the population departure time to impove emergency response.

- While the long-term goal of this research is to operationalize the full scope of the macro-level theoretical causal framework[2] introduced in Section 6.2, the methodological developments of this paper focus on the population protective action performance. Section 6.3 introduces a methodological framework for (A) building and validating the HRA-based Population Departure Time Model (PDTM), and (B) integrating it with the transportation evacuation model to generate model-based ETEs and evacuation speed estimates as inputs to (C) MACCS. This integrated methodology makes an advancement toward the explicit incorporation of social factors into Level 3 through the explicit incorporation of social factors into departure time and evacuation speed estimations. The integrated methodology can help (i) create a more realistic estimation of risk from MACCS by contributing to a more realistic representation of population evacuation performance and (ii) provide the opportunity to conduct importance ranking of the social factors, influencing departure time and evacuation speed, with respect to their impacts on risk. The results provide location-specific insights that can be useful in improving the RERP for areas where higher PE potential exists for the departure stage of an evacuation.
- In Section 6.4, the integrated methodology is applied in a case study using results from the 2017 Sequoyah SOARCA study.

6.2. THEORETICAL DEVELOPMENT FOR THE EXPLICIT INCORPORATION OF SOCIO-TECHNICAL FACTORS INTO LEVEL 3 PRA

In the aftermath of the 2011 Fukushima Daiichi accident, the National Academy of Sciences (NAS) made the following recommendations for enhancing PRAs for U.S. NPPs: (a) scenarios of offsite response should consider damage to critical offsite infrastructure (e.g., communication and transportation network disruptions), (b) larger scale, regional, and multi-hazard (i.e., natural hazards, such as large earthquakes, large floods, and geomagnetic disturbances) and man-made hazards (e.g., the dispersion of radioactive materials beyond the 10-mile Emergency Planning Zone (EPZ)) should be expected, (c) the social impacts of protective actions should be considered, specifically for special populations such as children and the elderly (e.g., a major issue with evacuation was due to a lack of detailed planning for vulnerable populations), (d) offsite health (e.g., death, injury, and mental distress resulting from evacuations) and social consequences (e.g., disruptions to families and communities, loss of trust) should be considered, and (e) PRAs should include quantitative uncertainty estimates for failure event

[2] The macro-level theoretical framework considers a region-level (i.e., multiple census tracts) spatial scale, and depicts global/generalized phenomena that are composed of multidisciplinary intracomponent interactions (e.g., (Fromm, 2004))

probabilities (i.e., not prematurely screening out events without scientific justification) (NAS, 2014). The NAS mentioned that the "results of PRAs are limited by experts' ability to recognize all relevant phenomena, including potentially important external hazards, and by uncertainties and incompleteness of estimates of accident probabilities and consequences" (NAS, 2014). The recommendations from "a" to "d" are related to the deficiencies in Level 3 PRA, more specifically associated with the inadequate consideration of socio-technical factors influencing ORO and population performance. This section focuses on advancing a multidisciplinary framework, equipped with a "theoretical" validation (see (Pence et al., 2019)), to provide more comprehensive coverage of the socio-technical causal factors influencing ORO and population performance. When this theoretical framework is quantified with proper methodological techniques (the focus of Section 6.3), it can explicitly analyze and rank the effects and criticality of the influencing factors and their associated uncertainties (this contributes to recommendation "e" mentioned above).

In a previous research study, some of the authors of this paper began developing a multidisciplinary framework for understanding the role of social factors in offsite NPP emergencies and emergency response (Pence et al., 2018). The theoretical framework depicted the relationships between physical environmental factors (i.e., hazard), onsite organizations, OROs, the population, and critical public infrastructure in relation to the three phases of PRA (Levels 1, 2, and 3) (Pence et al., 2018). The goal of the framework in (Pence et al., 2018) was to depict the relationship of social vulnerability to a radiological hazard, and did not consider the influence of natural hazards on NPP condition, the onsite emergency response influence on NPP condition, the NPP condition influence on critical infrastructure availability, the differences between various infrastructures (i.e., social infrastructure, utility infrastructure, and transportation infrastructures), the influence of radiological hazard on the ORO, etc. This section advances the framework from (Pence et al., 2018) into the macro-level theoretical causal framework (Figure 6.2) (and the associated processes and tasks shown in Figure 6.3 and Figure 6.4)) to have more comprehensive coverage of the influencing factors and their multi-level causal relationships.

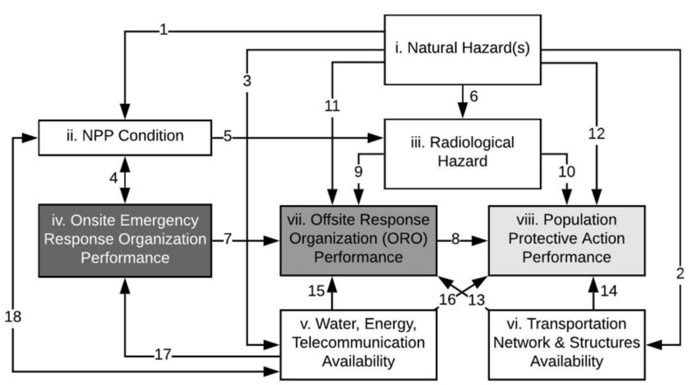

Figure 6.2: Macro-level theoretical causal framework of factors influencing population and ORO performance given man-made and natural hazards

Given the multidisciplinary nature of the macro-level framework and rare-event characteristics of NPP accidents, it is difficult to validate the framework empirically; therefore, it is essential that causal factors and relationships are built based on theoretical foundations so that the framework is theoretically valid (Mohaghegh, 2007; Pence et al., 2018). Development of the macro-level framework follows the theory-building process presented in (Pence et al., 2019); identifying literature associated with each factor, manually extracting evidence from literature (i.e., academic articles, regulatory and industry documents), locating each factor within the framework, building causal constructs, and justifying their directional links from literature. As shown in Table 6.1, the reasoning for each node (factors "i" to "viii" in Figure 6.2) as well as the associated directional causality (edges 1 to 18 in Figure 6.2) is justified based on literature of emergency response studies related to natural and technological hazards. For succinctness, only three references for each edge that connects two theoretical constructs in Figure 6.2 (i.e., an influencing factor to target factor) are provided in Table 6.1. In the development of the framework, it was found that existing studies are mainly focused on one causal relationship at a time, or do not consider broader factors such as the built environment, or do not address multi-hazard interactions in radiological emergencies. For example, most natural hazard-related frameworks neglect interactions among different typologies of hazards (Lettieri, 2009). Although the existing Level 3 PRA model (MACCS) for nuclear hazards explicitly considers the effects of some of the factors in Figure 6.2 (i.e., factors ii, iii, and vi), the influences of other critical factors (e.g., factors i, iv, v, vii and viii) are only implicitly considered. The goal of the theoretical development in this section is to address these gaps and to improve the comprehensiveness and explicitness of the existing Level 3 PRA model with respect to the causal factors influencing radiological emergency response.

Natural hazards (factor i in Figure 6.2) are defined as geophysical processes in the environment that can create the potential for damage or losses (Bobrowsky & Bobrowsky, 2013). Types of natural hazards include meteorological (e.g., storm, tornado, hurricane), hydrological (e.g., flood), geological (e.g., earthquake, volcano, tsunami), and extraterrestrial (e.g., meteor strike, geomagnetic disturbance) (Bobrowsky & Bobrowsky, 2013). Natural hazards can affect NPP condition (edge 1 in Figure 6.2) and are included as "external hazard" initiating events in Level 1 PRA (NRC, 2009a). NPP condition (factor ii in Figure 6.2) refers to the severity of damage to one NPP and the status of the core (e.g., "core damage" as modeled in Level 1 PRA) and containment (e.g., "large early release" as modeled in Level 2 PRA), which provides the frequency and characterization of radiological source term (NRC, 2013d). The radiological hazard (factor iii in Figure 6.2) considers atmospheric transport, dispersion, deposition, and radioactive decay of the technological hazard resulting from the NPP accident condition (i.e., source term). Natural hazards can damage transportation networks and the built environment (edge 2 in Figure 6.2), as well as water, energy, and telecommunications infrastructures (edge 3 in Figure 6.2), and availability for the functions of emergency response (e.g., flooding-induced road inundation) (edge 11 in Figure 6.2). The NPP condition will be monitored (edge 4 [factors ii to iv] in Figure 6.2) by the Onsite Emergency Response Organization (ERO) (NRC, 2011b) (factor iv in Figure 6.2). The onsite ERO is responsible for taking mitigating actions to recover the NPP from an accident condition using Emergency Operating Procedures (EOPs) and Severe Accident Management Guidelines (SAMGs) (NEI, 2016a) (edge 4 [factors iv to ii] in Figure 6.2). When the NPP condition/radiological source term enter the environment (edge 5 in Figure 6.2), the atmospheric transport and deposition of the radiological hazard (factor iii in Figure 6.2) begins. In the environment, meteorological natural hazards can influence the trajectory and dispersion of the radiological hazard (edge 6 in Figure 6.2). The onsite ERO (factor iv in Figure 6.2) declares a General Emergency (GE), which fans out and activates the ORO (factor vii in Figure 6.2). The quality and timing of information from the ERO to the ORO will affect ORO performance (edge 7 in Figure 6.2) (NRC, 2015). The ORO makes Protective Action Decisions (PADs) and provides Protective Action Recommendations (PARs) to the population and performs emergency response functions to assist the public in the performance of protective actions (edge 8 in Figure 6.2). Significant work has focused on whether or not people will evacuate when directed; however, little work has been conducted on choice of protective action alternatives (Sorensen, J.H., 2000). Section 6.2.2.1 provides more details on the population protective action performance (factor viii).

The radiological hazard will be monitored in the field by the ORO and can also affect ORO Emergency Worker (EW) health through dose exposure (edge 9 in Figure 6.2). The radiological hazard will also influence the physical health of the population, which is estimated as dose accumulation (edge 10 in Figure 6.2). The natural hazard can affect human performance (e.g., low visibility in severe weather) of both the ORO (edge 11 in Figure 6.2) and the population (edge 12 in Figure 6.2). Transportation network unavailability can impact ORO (edge 13 in Figure 6.2) and population performance (edge 14 in Figure 6.2). Water, energy, and telecommunication infrastructure unavailability can impact ORO performance (edge 15 in Figure 6.2) and population performance (edge 16 in Figure 6.2) (e.g., mobile communication disruptions). Energy and telecommunication availability can affect onsite emergency response (edge 17 in Figure 6.2) (e.g., in scenarios of loss of offsite power and for communicating to the ORO). Lastly, NPP condition can contribute to the loss of power to the energy grid or energy grid disruption (edge 18 [factors ii to v] in Figure 6.2), and loss of offsite power can contribute to NPP condition (edge 18 [factors v to ii] in Figure 6.2). For example, in the Fukushima Daiichi accident, "prolonged unavailability of offsite electrical power and the failure of on-site power systems was a significant contributor to the damage to the reactors and release of radioactivity" (IAEA, 2012). The U.S. has responded to this issue with the addition of guidance for diverse and flexible coping strategies (FLEX) (NEI, 2012b).

Table 6.1: Theoretical justification of the macro-level theoretical causal framework in Figure 6.2

Edge	Influencing Factor	Target Factor	Supporting References
1	i. Natural Hazard	ii. NPP Condition	(Cruz et al., 2004; Katona & Vilimi, 2017; NRC, 2009a)
2	i. Natural Hazard	vi. Transportation Network & Structures Availability	(Katona & Vilimi, 2017; Lindell et al., 2019; NEA, 1998)
3	i. Natural Hazard	v. Water, Energy, Telecommunication Availability	(Cavallin et al., 1994; Katona & Vilimi, 2017; Preston et al., 2016)
4	ii. NPP Condition	iv. Onsite Emergency Response Organization Performance	(McKenna, Thomas J., 2000; NEI, 2012a, 2016b)
4	iv. Onsite Emergency Response Organization Performance	ii. NPP Condition	(IAEA, 2015; INPO, 2015; NEA, 2018)
5	ii. NPP Condition	iii. Radiological Hazard	(McKenna, T. J. & Glitter, 1988; NEA, 2016; NRC, 2009b)
6	i. Natural Hazard	iii. Radiological Hazard	(Levin & Chaves, 2015; Lucas et al., 2017; Yoshikane et al., 2016)
7	iv. Onsite Emergency Response Organization Performance	vii. Offsite Response Organization (ORO) Performance	(FEMA, 2013a; INPO, 2015; NRC & FEMA, 2019)
8	vii. Offsite Response Organization (ORO) Performance	ii. Population Protective Action Performance	(IAEA, 2006; Lindell, 2000; NRC & FEMA, 2019)
9	iii. Radiological Hazard	vii. Offsite Response Organization (ORO) Performance	(NEA, 2015; NRC, 1991, 2008)
10	iii. Radiological Hazard	viii. Population Protective Action Performance	(Bromet, 2014; Cardis & Hatch, 2011; Tokonami et al., 2012)
11	i. Natural Hazard	vii. Offsite Response Organization (ORO) Performance	(Gray & Collie, 2017; Osofsky et al., 2011; Weinhold, 2010)
12	i. Natural Hazard	viii. Population Protective Action Performance	(Lindell Michael & Prater Carla, 2007) (Alaeddine et al., 2015; D'Orazio et al., 2014)

Table 6.1 (cont.)

13	vi. Transportation Network & Structures Availability	vii. Offsite Response Organization (ORO) Performance	(Pederson et al., 2006; Schiff, 1995; Zio & Ferrario, 2013)
14	vi. Transportation Network & Structures Availability	viii. Population Protective Action Performance	(Chang, L. et al., 2012; Cova & Johnson, 2003; Lindell et al., 2019)
15	v. Water, Energy, Telecommunication Availability	vii. Offsite Response Organization (ORO) Performance	(GAO, 2009; Kruchten et al., 2007; Pederson et al., 2006)
16	v. Water, Energy, Telecommunication Availability	viii. Population Protective Action Performance	(El Khaled & McHeick, 2019; Kruchten et al., 2007; Pederson et al., 2006)
17	v. Water, Energy, Telecommunication Availability	iv. Onsite Emergency Response Organization Performance	(Pederson et al., 2006; Son et al., 2015; Zio & Ferrario, 2013)
18	ii. NPP Condition	v. Water, Energy, Telecommunication Availability	(Boegli et al., 1978; IAEA, 2012; Kosai & Unesaki, 2017)
18	v. Water, Energy, Telecommunication Availability	ii. NPP Condition	(IAEA, 2012; NRC, 2003; Thompson et al., 2019)

The macro-level framework (Figure 6.2) covers high-level paths of causality and requires further theory building to generate more detailed causal factors, sub-factors, and interrelationships. Section 6.2.1 focuses on factors iv (highlighted in dark grey), vii (highlighted in grey), and viii (highlighted in light grey) from Figure 6.2 to develop a more detailed sequence of work processes and tasks associated with ORO performance and population response. Future research will be needed to theoretically expand the other factors in Figure 6.2.

6.2.1. Theorizing Offsite Response Organization and Population Protective Action Performance

In this section, the causal relationships between factors iv, vii, and viii from Figure 6.2 are expanded in Figure 6.3, based on the combination of three studies (Lindell, 2000; Mileti, D. et al., 1985; NRC, 2015), to provide more details on the sequence of the related processes in order to explicitly elaborate the phenomenology of information transfer between onsite and offsite organizations and the public during the early emergency phase (i.e., the early evacuation period up to seven days after radiological release) of an NPP accident. Section 6.2.1.1 further expands factor viii from Figure 6.2

(focusing on events c.1 and c.2 from Figure 6.3) to provide more details related to the population's tasks before departure.

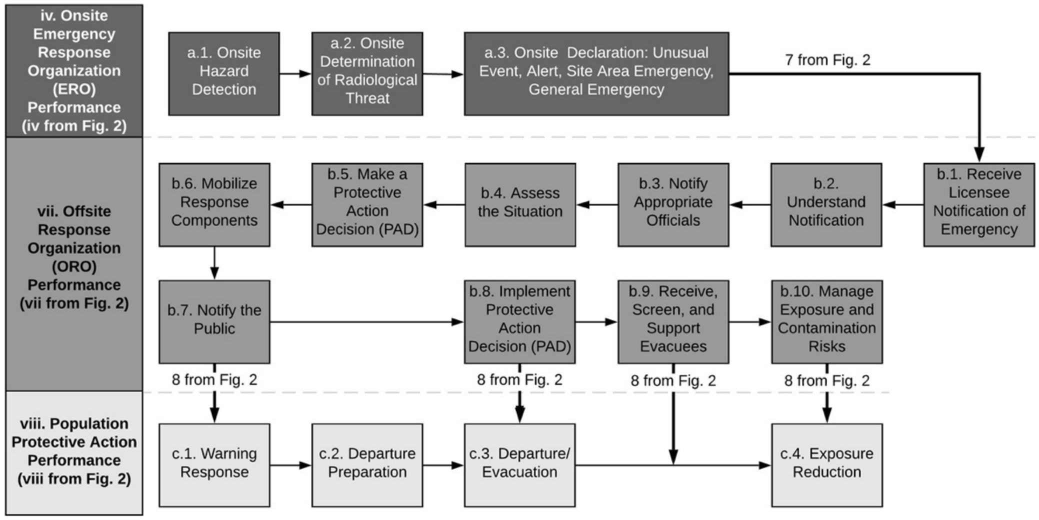

Figure 6.3: Process Model of Onsite Response, Offsite Response, and Population Response in the Early Emergency Phase

Figure 6.3 does not go into detail about the onsite ERO (factor iv in Figure 6.2) but considers three onsite actions (i.e., hazard detection (a.1 in Figure 6.3), determination of radiological threat (a.2 in Figure 6.3), and declaration of emergency (a.3 in Figure 6.3)) suggested by (Mileti, D. et al., 1985) that would be taken immediately after the occurrence of an NPP accident, leading to the declaration of a notification of emergency (according to the NRC's emergency classification system) (NRC & FEMA, 2019). When the NPP condition (factor ii from Figure 6.2) transitions to an accident state (e.g., core damage), onsite ERO performance (factor iv from Figure 6.2) responds with events a.1 to a.2 (in Figure 6.3), which are events leading to the Onsite Declaration of a General Emergency (a.3. in Figure 6.3). Event a.3 results in the communication of information about the NPP accident (edge 7 from Figure 6.2) to the ORO (factor vii from Figure 6.2), where the ORO will Receive the Licensee Notification of an Emergency (b.1. in Figure 6.3) and initiate ORO events (b.1. to b.10. in Figure 6.3), derived from (NRC, 2015). The ORO function for Notifying the Public (b.7. in Figure 6.3), results in an emergency warning communicated to the population (edge 8 from Figure 6.2), initiating Population Protective Action Performance (factor viii from Figure 6.2), leading to population Warning Response (c.1. in Figure 6.3), Departure Preparation (c.2. in Figure 6.3), Departure/Evacuation (c.3. in Figure 6.3), and Exposure Reduction (c.4. in Figure 6.3), derived from (Lindell, 2000). ORO functions also contribute to performance of evacuations (8 from Figure 6.2; b.8 to c.3 in Figure 6.3), supporting evacuees, and managing exposure to the population (8 from Figure 6.2; b.10 to c.4 in Figure 6.3), but these functions are not covered in this paper and will be included in future research.

As shown in Figure 6.3, the ORO is not activated until the ERO declares a General Emergency, and population protective actions are not activated until the ORO notifies the public. Therefore, in the early emergency phase, the timing of ERO and ORO functions impact the population's ability to initiate protective actions in a timely manner. Based on a review of the literature, Sorensen (1990) stated that officials are often slow to make decisions, and delayed decisions can prevent timely warning to the public (Sorensen, J.H., 2000). In the 2011 Fukushima Daiichi accident, miscommunication between onsite and offsite organizations contributed to misunderstandings and a lack of confidence about emergency response efforts, and coordination among central and local governments was hampered by limited and poor communication (NAS, 2014). Based on the lessons learned from the Fukushima Daiichi accident, the NAS made recommendations for the U.S. nuclear industry to revise or update plans for communicating with affected populations in response to long-duration scenarios that include widespread loss of critical offsite infrastructure including communications, transportation, and emergency response infrastructures, and to improve communication and coordination between onsite and offsite support facilities (NAS, 2014).

Once the ORO has notified the public, population warning response (c.1 in Figure 6.3) will be initiated, resulting in processes of population protective action decision-making and preparation (c.2 in Fig 2), followed by response (c.3 in Figure 6.3), which includes performing the PAR, or deciding to perform an alternative action. PARs are communicated to the population, instructing individuals on how to reduce their exposure to radiation, taking into account best estimates of the dynamically evolving radiological hazard (plume) (i.e., factor iii from Figure 6.2). The next section focuses on population protective action performance (i.e., factor viii from Figure 6.2), specifically focusing on population departure, after receiving the ORO's notification (i.e., edge 8 from Figure 6.2, and b.7 to c.1 in Figure 6.3).

6.2.1.1. Theorizing Population Departure in Protective Action Performance Given Radiological Hazards

Golshani et al., (2019) provide a summary of studies on evacuation departure time and destination choice (Golshani et al., 2019a, 2019b), and categorize existing studies on evacuation decision-making into two groups (i) descriptive statistics, and (ii) predictive modeling (Golshani et al., 2019b). In an attempt to generate a predictive model for departure time, this section theorizes tasks and performance shaping factors associated with population departure (i.e., factor viii from Figure 6.2, specifically c.1 and c.2 from Figure 6.3), considering the influences of location-specific social vulnerability and demographics. This theoretical representation is equipped with proper methodological techniques in Section 6.3 to be quantified to (i) generate the predictive model for estimating the population departure time distribution and (ii) enable the explicit incorporation of the associated social vulnerability factors into Level 3 PRA. The theoretical representation of departure time is developed based on the following logical statements:

I. In NPP ETE studies (NRC, 2005), descriptive statistics are derived from surveys of the population within a 10-mile EPZ. ETE studies include information on the percentage of the population that intend to depart at specific time intervals in the early emergency phase, based on survey responses. This paper specifically focuses on ETE survey results, where a household representative was asked to assume that if all household members were at home, for example, at night or on the weekend, how long it would take for their household to depart after receiving an emergency notification. ETE survey results provide the percentage of the population in each time window, which can be considered as the probability of the specific departure time window for that NPP. Time window intervals in the ETE studies considered in this paper are; zero to twenty minutes, twenty to forty minutes, forty to sixty minutes, sixty to ninety minutes, and more than ninety minutes. These time windows and their associated probabilities represent the distribution of departure time for one NPP, based on survey results.
    - The goal of this section is to develop a theoretical basis for creating a model that can predict the probability distribution of the departure time (for a given plant) or the Probability Mass Function (PMF) of the predefined departure time window intervals.

II. For each NPP, the reason that the probability varies over the departure time window intervals is proposed to be due to variation of the Population Error (PE) probability within the 10-mile EPZ.
    - PE probability indicates a deviation from ideal or normal conditions and is considered to be influenced by social vulnerability and demographic factors that impact the population's performance in the tasks before evacuation begins. Because social vulnerability and demographics vary within the 10-mile EPZ, PE probability also varies within the 10-mile EPZ.

III. The percentage of the population departing in a specific time window can be considered to share a specific range of PE.
    - For each NPP, the probability of each departure time window shows the percentage of the population that has the range of PE associated with that time window. Therefore, the PMF of departure time for an NPP can be considered as the PMF of the "range of PE" associated with time windows for that plant. This process is explained in more detail in Section 6.3 and depicted in Figure 6.7.
    - It is assumed that the population with greater error (greater PE probability) will have a greater delay in departure time.

IV. Based on the ETE studies, the probability of each departure time window varies across NPPs, and, in this paper, this variation is proposed to be because the PE range associated with each time window varies across plants.

   - The PE range variation across plants is due to the variation of social vulnerability and demographic factors across NPPs.

V. By having (i) the plant-specific probability distribution of PE within the EPZ and (ii) the expected range of PE for each time window of NPPs, it is possible to develop the probability distribution of the departure time or the Probability Mass Function (PMF) of the departure time windows for a given plant.

   - In the rest of this section, existing HRA concepts are adapted to establish an HRA-based theoretical representation that helps with the development of the plant-specific probability distribution of PE within the EPZ. An algorithm is offered in Section 6.3.1 to utilize the ETE survey results along with the HRA-based model to generate the expected range of PE for each departure time window for NPPs.

VI. HRA is commonly used to theorize and estimate the probability of humans correctly performing a task within a required time period in a given scenario (Mosleh & Chang, 2004; Swain & Guttmann, 1983). There are a wide-range of HRA approaches (Boring et al., 2010; Hendrickson et al., 2012); however, all of them include (i) a qualitative phase (i.e., task analysis and identification of PSFs), where human error is theorized based on the deviation of internal PSFs (e.g., fatigue, cognitive mode) and external PSFs (e.g., physical work environment, teamwork, managerial and organizational factors) from nominal conditions (Swain & Guttmann, 1983) along with (ii) a quantitative phase to estimate the human error probability. This section covers the qualitative phase of HRA for PE probability, while the quantitative phase is covered in Section 6.3 as a part of the integrated methodology. In this paper, HRA is adapted for PE analysis, as follows:

   - Task Analysis: Task analysis is where actions are broken down into tasks and subtasks based on pre-defined characteristics for HRA (Swain & Guttmann, 1983). PEs, however, do not have pre-defined characteristics, and therefore, literature is used to identify tasks and subtasks. There have been limited studies that explain individual variation in response to emergency warnings (Sorensen, J.H., 2000), especially for NPP accidents. Lindell and Perry (1992) provided a characterization of a community's behavioral steps for a warning response to general hazards (natural or technological), which included risk identification (i.e., does the threat exist?), risk assessment (i.e., is protection needed?), risk reduction (i.e., is protection feasible?), and protective response (i.e., what action to take?) (Lindell & Perry, 1992). Similarly, Mileti and Sorensen (1990) characterized the generic processes of a population responding to any type of emergency as; hearing the warning, understanding the warning, believing credibility of the warning, personalizing the warning, confirming the warning, and responding with a protective action (Mileti, D.S. & Sorensen, 1990). Lindell and Perry (2012) theorized the Protective Action Decision Model (PADM) for environmental hazards and disasters by a generic multistage model of psychological processes (i.e., pre-decisional expectations, perceptions of threats, and protective action decision making) that influence individual's behavioral response (Lindell & Perry, 2012). Getting some insight from the existing literature (summarized above), the following generic tasks are proposed for the population following PAR and mapped to the generic HRA task types: (i) observation of the notification (i.e., diagnosis task), (ii) the orientation and interpretation of the associated risk (i.e., diagnosis task), (iii) the protective action decision (i.e., diagnosis task), and (iv) the performance of the protective action (i.e., action task). HRA event trees (Swain & Guttmann, 1983) are used to depict the sequence of tasks, considering the success paths (branching to the left) and error paths (branching to the right). Recovery paths are considered for each task, meaning when there is an error in Task A (to the right of Figure 6.4), there is a possibility for the population to recover, back to task a, with some error (delay). These recovery paths create the opportunity for 16 end states, with varying degrees of error, as represented by the success end state, S, and end states E_1 (worst case) to E_{15} (less than total success) in Figure 6.4. Task "1" in Figure 6.4, observe notification, is similar to the type of information input and elaboration tasks in HRA (e.g., (Chang, Y.H.J. & Mosleh, 2007)). In Task "1" skill-based errors (slips) (e.g., (Reason, 1990)) can occur, where individuals hear the GE siren, observe the EAS from their landlines and mobile devices, or in some cases, observe the notification from media reporting, social media, or social interactions. Task "2" in Figure 6.4, orient and interpret risk, can be considered as a knowledge-based error (e.g., (Reason, 1990)), and is similar to the type of problem-solving or perception tasks in HRA, where individuals, or households, arrive at a risk perception of the radiological hazard based on prior knowledge of the NPP and its associated emergency response programs. Task "3" in Figure 6.4, decide protective action, is similar to the type of decision-making tasks in HRA (e.g., (Chang, Y.H.J. & Mosleh, 2007)). In Task "3", individuals and households consider the ORO notification and EAS information in their decision-making process. In this research, it is assumed that the PAR is evacuation for the entire EPZ. Task "3" can be considered as a rule-based error (mistake), where individuals and households decide on their process for evacuation, considering scenarios associated with the location of other family members, and preferences for evacuating after waiting for all members to arrive home. Each sub-event scenario associated with Task "3" can add to departure time and are therefore lumped into the error category of Task "3." Task "4," perform protective action, can be considered as a skill-based error (e.g., (Reason, 1990)), and is similar to the type of action tasks in HRA (e.g., (Chang, Y.H.J. & Mosleh, 2007)). In Task "4," individuals or households will initiate their process of packing food, clothes, and belongings, wait for family members, or embark on additional pre-evacuation travel activities (e.g., picking up school children or relatives) (Lämmel et al., 2016). For example, based on a national survey of households living in NPP EPZs, Walton and Wolshon (2010) found that families desire to evacuate together, and emergency plans should anticipate parents attempting to pick up their children from school (Walton & Wolshon, 2010). Related to Task "4," Urbanik (2000) provided an event sequence associated with trip generation actions for NPP scenarios for individuals at work (i.e., warning receipt, departure from work, arrival at home, departure from home) (Urbanik, 2000), which remains the most commonly used event sequence for pre-evacuation actions in ETE studies. Future work can use Urbanik (2000) to expand Task "4" to more sub-tasks in the HRA-based analysis of PE. After Task "4", all pre-evacuation tasks for population departure are completed, and the stage of evacuation begins.

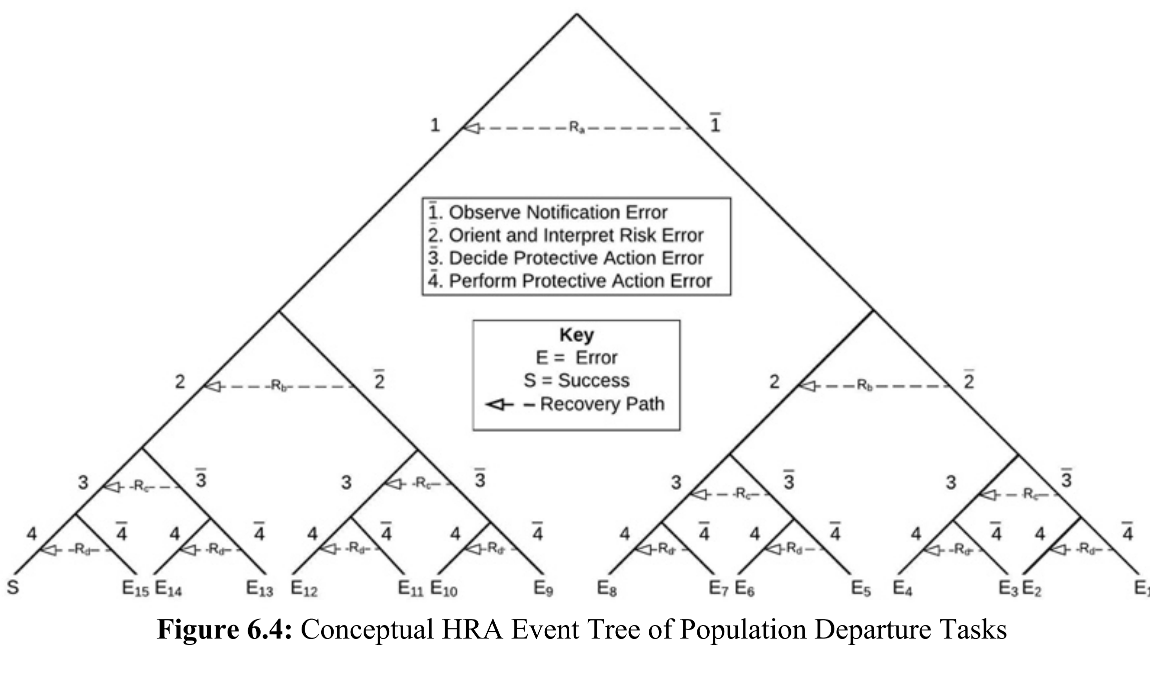

Figure 6.4: Conceptual HRA Event Tree of Population Departure Tasks

- Identification of PSFs: PSFs influence the performance of each task; therefore, they change the error probability of that task. In Table 6.2, for each task (i.e., Task "1" (Observe), Task "2" (Orient), Task "3" (Decide), Task "4" (Act)), selected attributes from social vulnerability (ATSDR, 2018) and U.S. Census data are considered as PSFs and justified by the literature. For succinctness, only one reference for each PSF is provided in Table 6.2. For PSF-1, considering social vulnerability and demographic attributes, a surrogate factor of people over age five who speak English "less than well" is considered for Task "1" (observe), where the language barrier may cause a delay in observing or understanding the warning (Sorensen, J.H., 2000), thereby creating a delay (error) in Task "1." For PSF-2, the elderly (i.e., age 65 and above) have greater potential to not receive warning information (Cutter & Barnes, 1982), for example, due to lack of audibility or access to technology. In Lindell's (2000) framework of factors influencing population preparation and response, it is stated that household resources, for example, the availability of a credit card or ready cash, are important in PAR compliance (Lindell, 2000). Therefore, for Task "2," PSF-3, household income, indicated by per capita income, is considered as a factor which could influence the orientation (e.g., a level of discomfort due to the inability to evacuate to a hotel, and having to go to a mass care facility) of an individual or household about the PAR of evacuation. For Task "3," PSF-4 considers that the decision to evacuate will be influenced by the lack of access to a personal or household vehicle (Lindell & Perry, 2012), where households with no vehicle will require additional time to seek alternative transportation options. PSF-5 considers that noninstitutionalized households with individuals with a disability may have an influence on decision-making (Dash & Gladwin, 2007; Lim et al., 2013). Redlener et al., (2008) found that sixty-three percent of parents "would disregard an evacuation order and go directly to their child's school in an attempt to collect their children," from findings that are consistent across the U.S. and independent of household income, education, age, or gender (Redlener et al., 2008). Therefore, for Task "4" in Figure 6.4, PSF-6, having school children is considered to increase the departure time for some parents that attempt to pick up their children from school. For PSF-7, commuters are likely to return home before evacuating as a family or group (NRC, 2005). Both PSF-6 and PSF-7 are indicators of pre-evacuation actions that would add additional local travel times (e.g., (Murray-Tuite & Mahmassani, 2003)) before initiating the actual evacuation.

Table 6.2: Performance Shaping Factors (PSFs) for each population departure task

Task	Performance Shaping Factor (PSF)	References
(Task "1") Observe	(PSF-1) Less than well English speaking	(Sorensen, J.H., 2000)
	(PSF-2) Persons aged 65 and older	(Cutter & Barnes, 1982)
(Task "2") Orient	(PSF-3) Per Capita Income	(Lindell, 2000)
(Task "3") Decide	(PSF-4) No Vehicle	(Lindell & Perry, 2012)
	(PSF-5) Non-institutionalized Population with a Disability	(Dash & Gladwin, 2007)
(Task "4") Act	(PSF-6) School children	(Liu et al., 2012)
	(PSF-7) Commuters	(NRC, 2005)

6.3. METHODOLOGICAL DEVELOPMENT FOR THE EXPLICIT INCORPORATION OF SOCIAL FACTORS INTO LEVEL 3 PRA

While the ideal goal of this research is to quantify the entire macro-level theoretical framework in Figure 6.2, in this paper, an integrated methodology (Figure 6.5) is developed to quantify a specific scope of the macro-level framework by coupling Population Departure Time Model (PDTM) (A in Figure 6.5) and transportation model (B in Figure 6.5) with Level 3 PRA (MACCS) (C in Figure 6.5). As discussed in Section 6.2, MACCS considers the explicit effects of some of the factors in Figure 6.2 (i.e., factors ii, iii, and vi), but the influences of other critical factors (e.g., factors i, iv, v, vii and viii) are only implicitly considered. The proposed integrated methodology improves the explicit consideration of factor viii (population protective action performance) and edge 14 (the influence of the transportation network [factor vi] on population protective action performance [factor viii]) from Figure 6.2. In MACCS, population departure time is based on survey responses from a sample set of the population in the EPZ. The integrated methodology uses a model-based approach (A in Figure 6.5) for leveraging social vulnerability and demographic data to estimate population departure times. MACCS uses a transportation model where evacuation movement is considered in discrete increments or "jumps" from one point to another considering distance and speed from one point to another (NRC 1997); while the integrated methodology utilizes a transportation model (B in Figure 6.5) to explicitly model traffic flow.

The integrated methodology connects the PDTM output distribution to a transportation model for evacuation (i.e., c.2 to c.3 from Figure 6.3), and the results of the transportation model are incorporated into a Level 3 PRA simulation (i.e., c.3 to c.4 from Figure 6.3). Because departure time influences evacuation speed, without an explicit model of evacuation, the treatment of dependencies between departure time and a data-driven evacuation speed estimation is challenging. Therefore, to consider the effects of social factors (in PDTM; A in Figure 6.5) on risk, the dependency between departure time and evacuation speed is considered by explicit modeling of both departure time and evacuation speed and integrating their coupling with MACCS Level 3 PRA code. In MACCS, there are two types of evacuation simulations: radial evacuation (all movement is radially outward) and network evacuation (traffic movement follows major roadways). Keyhole evacuation is a setting for both types of evacuation simulations, where site-specific protective actions based on wind direction be considered when the entire EPZ is not being evacuated. In this paper, the network evacuation is used without the consideration of a keyhole evacuation (i.e., in the case study, it is assumed that the entire EPZ is to be evacuated). MACCS inputs also include source term (C.2 in Figure 6.5), weather data (C.3 in Figure 6.5), dose coefficient (C.4 in Figure 6.5), and notification time (C.5 in Figure 6.5).

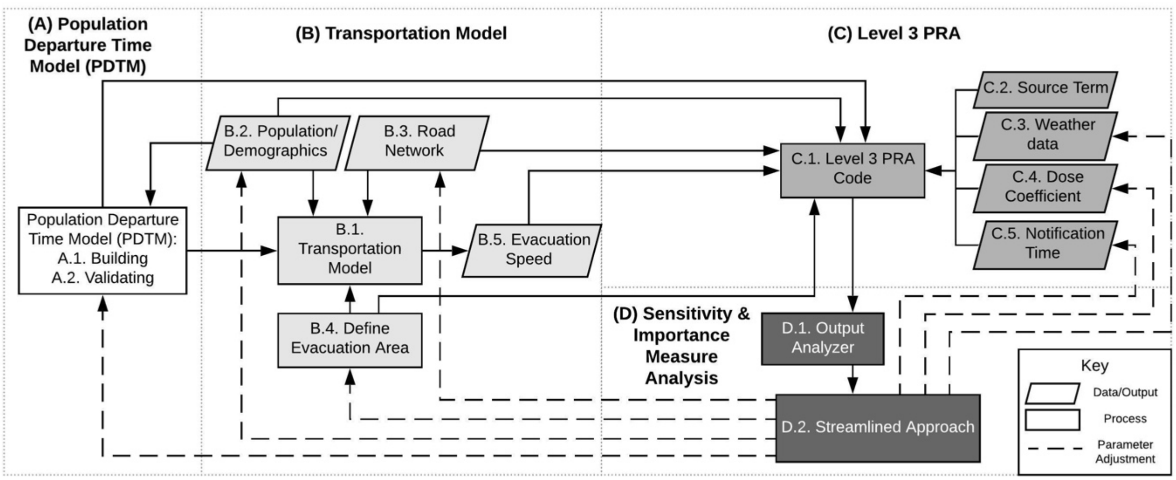

Figure 6.5: Integrated Methodology for Coupling Population Departure Time Model and Transportation Model with Level 3 PRA

Figure 6.5 also shows a set of generic inputs for the transportation model, which includes population and demographic data (e.g., population density, number of vehicles per household) (B.2 in Figure 6.5), road network data (i.e., link-node and geometry data) (B.3 in Figure 6.5), and a geographically defined evacuation area (B.4 in Figure 6.5). Using these inputs, the transportation model produces a distribution of average individual vehicle evacuation speeds (B.5 in Figure 6.5) that serve as an input to Level 3 PRA (C.1 in Figure 6.5). Based on the reviewed NPP ETE studies in this paper, both macroscopic (i.e., Dynamic Network Evacuation (DYNEV)) and mesoscopic (i.e., PTV Vision) transportation models have been used. None of the reviewed studies developed an explicit-internal incorporation of an ABM transportation model with Level 3 PRA input parameters to estimate risk. Because of the dependency between population departure and evacuation speed, the resolution for individual vehicle speeds in the simulation is critical, and therefore, an ABM model provides the most granular analysis of individual travel speeds. Further, because the population departure model incorporates social factors at a more granular level of analysis and produces a distribution of departure time considering the variations across the population within the EPZ, ABM is selected for the transportation model to generate a distribution of average evacuation speed that considers evacuees optimizing their personal evacuation route (i.e., considering speed calculations for each vehicle in the simulation). The integrated methodology analyzes Level 3 PRA outputs (D.1 in Figure 6.5) and conduct importance risk ranking with respect to Level 3 PRA input parameters and regarding the input factors in PDTM and the transportation model. The importance ranking provides useful information for risk-informed emergency planning and response. The following sub-sections provides more detailed information regarding modules of the integrated methodology.

6.3.1. Population Departure Times Model (A in Figure 6.5)

The PDTM (A in Figure 6.5) leverages the task analysis and PSF identification from Section 6.2.1.1 to provide a predictive model for population departure time distribution. This section covers the methodological approaches for two phases of the model: building the model (A.1 in Figure 6.5) and validating the model (A.2 in Figure 6.5). Section 6.4 implements these two phases using NPP databases. The validated model is also applied for the Sequoyah NPP in Section 6.4.

(A.1) Building the Population Departure Time Model: the computational flowchart for this step is shown in Figure 6.6. First, the NPPs to be included in the study ($k = 1, \dots, N_k$) are identified by the analyst (A.1.1 in Figure 6.6). NPP ETE survey data are collected for all NPPs included in the study (A.4 in Fig 6). Most NPP ETE survey data include EPZ departure times, where respondents are told to assume that if all household members were at home, for example, at night or on the weekend, and are asked how long it would take for their household to depart after receiving the emergency notification. As discussed in Section 6.2.1.1, the NPP ETE survey-generated probabilities are binned into five time window intervals, $T_l, l = 1, 2, \dots, 5$, where T_1 to T_5 represent (0, 20], (20, 40], (40, 60], (60, 90], and (90, 180], respectively (the unit of time is [minutes]).

For each NPP (A.1.2 in Figure 6.6), the plant center point is located using GIS, and a 10-mile buffer around the center point is generated for the EPZ (A.1.3 in Figure 6.6). Using CDC SVI (CDC et al., 2018) and U.S. 2010 Census data (B.2 in Figure 6.5), information on each attribute i ($i = 1, \dots, I$) for each census tract j ($j = 1, \dots, J$) within the EPZ of each NPP k ($k = 1, \dots, K$), denoted as a_{ijk}, can be exported using GIS (A.1.4 in Figure 6.6).

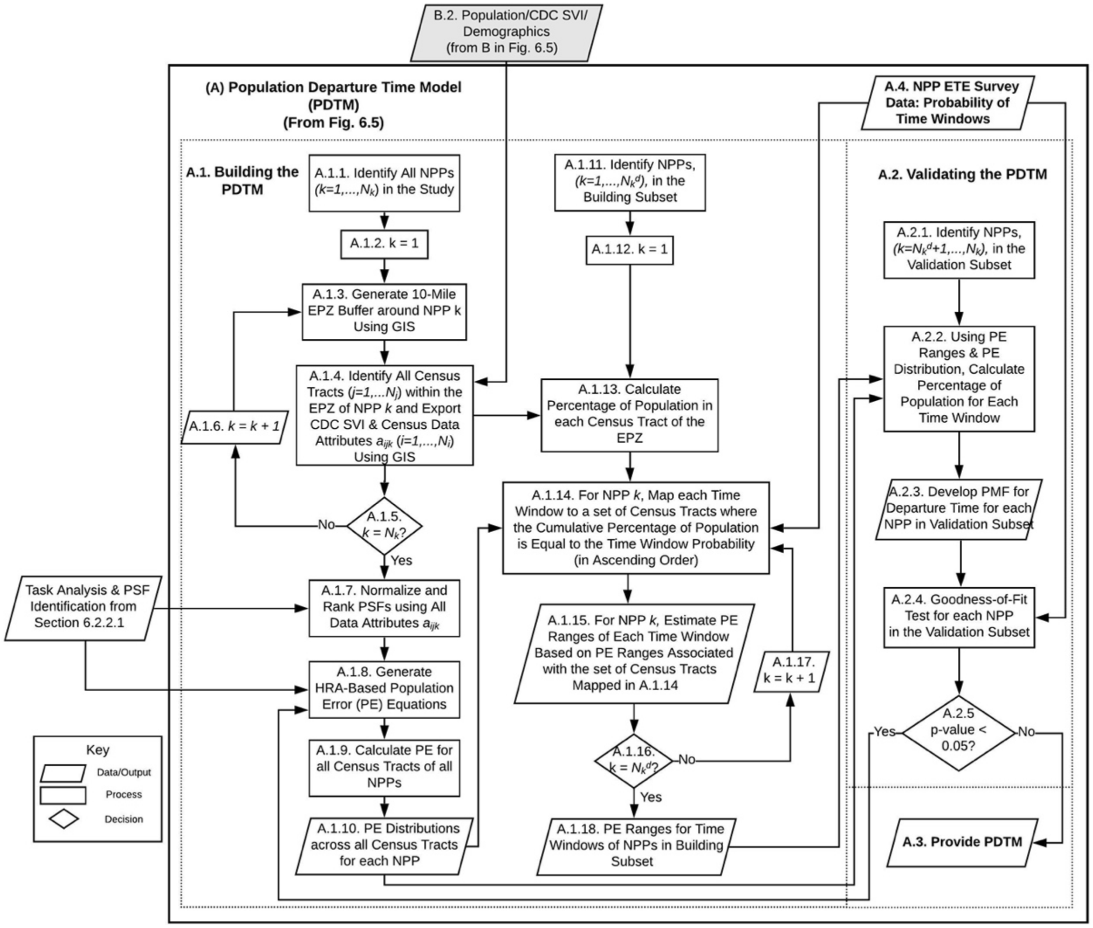

Figure 6.6: Sub-Steps for (A.1) Building (A.2) and Validating the PDTM

This loop is repeated for each NPP (A.1.5 and A.1.6 in Figure 6.6), resulting in a database of all NPP EPZ census tract attribute data. All extracted attribute data points a_{ijk} are then normalized, and their normalized values are used as the correspondent PSFs (A.1.7 in Figure 6.6), as described below. The use of PSFs is adapted from common practice in the existing HRA techniques, and PSFs are derived from CDC SVI and census data to provide a location-specific indicator of population performance. In the existing HRA techniques, the human error/success probability for human action is computed as a function of the nominal (or baseline) human error/success probabilities and PSFs. For instance, in the Success Likelihood Index Methodology (SLIM) (Embrey et al., 1984), the success rate and human error rate are computed by Eq. 6.1 and 6.2, respectively:

$$log_{10}(SP) = a_S(SLI) + b_S \tag{6.1}$$

$$log_{10}(FP) = a_F(FLI) + b_F \tag{6.2}$$

where SP: Success Probability; FP: Failure Probability; SLI: Success Likelihood Index; a_S and b_S: calibration constants for SLI obtained from two baseline cases (i.e., two sets of known SP and SLI); FLI: Failure Likelihood Index; a_F and b_F: calibration constants for SLI obtained from two baseline cases (i.e., two sets of known FP and FLI). SLI and FLI can be computed by using different forms of functions of the associated PSFs, e.g., linear summation or multiplication of the PSFs. In the context of the offsite population response, no information on {SP, SLI} or {FP, FLI} that can be used to calibrate Eqs. 6.1 and 6.2 is found. Therefore, this study assumes that the SLI computed based on scenario 'S' in Figure 6.2 or the FLI computed based on scenario 'E_1' in Figure 6.2 can be used as an approximate representation of the population performance in the pre-evacuation action (i.e., delay in their evacuation) and can be calibrated against the population departure time distribution. Future research is needed to establish a theoretical and methodological basis for estimating the nominal/baseline human error/success probabilities and incorporate them into the PDTM. SLI and FLI approaches are considered as two alternate models, and their prediction capability is evaluated and compared in model validation (A.2 in Figure 6.5) using the goodness-of-fit test.

To quantify SLI for scenario 'S' in Figure 6.2, "success PSFs" are first computed. For each attribute data point a_{ijk} collected from census tract j within the EPZ around plant k, its normalized "success" PSF value, PSF_{ijk}^S, is calculated using Eq. 6.3:

$$PSF_{ijk}^S = \frac{\max_{j,k} a_{ijk} - a_{ijk}}{\max_{j,k} a_{ijk} - \min_{j,k} a_{ijk}} \tag{6.3}$$

where $i = 1, 2, \dots I$; $j = 1, 2, \dots J$; and $k = 1, 2, \dots K$; with I, J, and K being the total number of attributes (i.e., PSFs), the total number of census tracts for plant k, and the total number of plants considered in the study. Eq. 6.3 is formulated in a way that, the lower the associated attribute data a_{ijk} in Eq. 6.3, the higher the value of SLI is. For example, in calculating PSF-6 (School Children), the success PSF indicates that, if there are less school children in census tract j, less parents will be inclined to pick up their children, and therefore increase the SLI, leading to higher SLI and SP. The SLI for population in census tract j of plant k is then computed assuming a multiplicative model for PSF_{ijk}^s, as follows:

$$SLI_{j,k} = \prod_{i=1}^{I} PSF_{ijk}^{s} \tag{6.4}$$

This SLI is used as a PE indicator below to build and validate the PDTM.

Similarly, to quantify FLI for scenario ‘E_1’ in Figure 6.2, “failure PSFs” are first computed. For each attribute data point a_{ijk} collected from census tract j within the EPZ around plant k, its normalized “failure” PSF value, PSF_{ijk}^{F}, is calculated using Eq. 6.5:

$$PSF_{ijk}^{F} = \frac{a_{ijk} - \min_{j,k} a_{ijk}}{\max_{j,k} a_{ijk} - \min_{j,k} a_{ijk}} \tag{6.5}$$

Eq. 6.5 is formulated in a way that, the higher the associated attribute data a_{ijk} in Eq. 6.5 is, the higher the value of FLI is. For example, for PSF-1 (Less than well English speaking), the higher number of individuals with less than well English speaking in a census tract may indicate a higher probability of error when observing or interpreting emergency notifications, leading to higher FLI and FP. The FLI for population in census tract j of plant k is then computed assuming a multiplicative model for PSF_{ijk}^{F}, as follows:

$$FLI_{j,k} = \prod_{i=1}^{I} PSF_{ijk}^{F} \tag{6.6}$$

This FLI is used as a PE indicator below to build and validate the PDTM.

The result of A.1.9 is a distribution of the PE indicator (i.e., SLI or FLI) for each NPP in the study (A.1.10 in Figure 6.6), which represents the variability across all census tracts in the EPZ that will be reflected in the departure time distribution. Once the PE distributions are generated, the development subset ($k = 1, \dots, N_k^d$) is selected by the analyst (A.1.11 in Figure 6.6). For each NPP (A.1.12 in Figure 6.6), the probability of each time window (i.e., zero to twenty minutes, twenty to forty minutes, forty to sixty minutes, sixty to ninety minutes, and more than ninety minutes) is extracted from ETE survey data (A.4 in Figure 6.6). The percentage of the population in each census tract of the EPZ is calculated (A.1.13 in Figure 6.6). Census tracts are sorted in ascending order of PE, and for each NPP, each time window (from ETE survey data) is mapped to a set of census tracts where the cumulative percentage of the population is equal to the time window probability (A.1.14 in Figure 6.6). This loop is performed for each NPP (A.1.16. and A.1.17. in Figure 6.6), resulting in PE ranges for time windows of all NPPs in the building subset (A.1.18 in Figure 6.6).

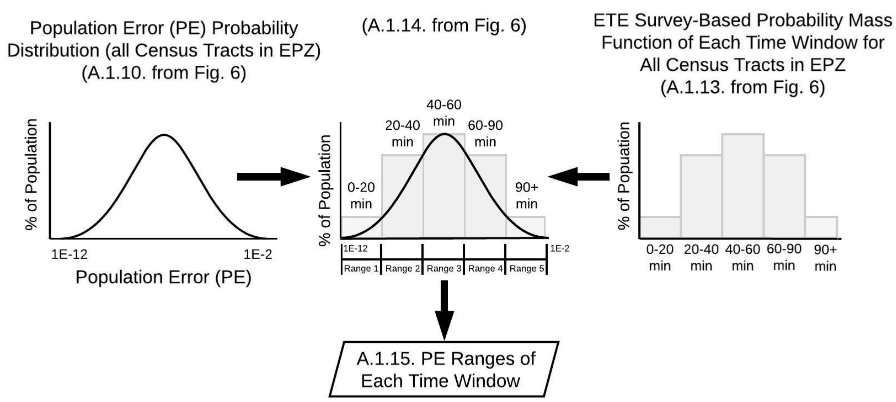

Figure 6.7: Assignment of PMF-Based Time Window Bins to the Population Error Distribution for each NPP

<u>(A.2) Validating the Population Departure Time Model</u>: The HRA-based PDTM is run for the remaining subset of NPPs that were not used in the building subset to serve as the validation subset ($k = N_k^d + 1, \dots N_k$) (A.2.1 in Figure 6.6) for predicting the PMF of the time windows. Then, the HRA-based PDTM is validated by checking whether Logical Statement V from Section 6.2.1.1 can be achieved within a reasonable level of prediction error.

Using the PE ranges from A.1.18 and the PE distribution from A.1.10, the percentage of the population for each time window is predicted (A.2.2 in Figure 6.6). Ranges of overlap (i.e., PE values that fall in-between two ranges) are considered by assigning a probability weight (i.e., assuming 50% chance for either time window). The estimation of PMF for each time window can be regarded as parameter estimation for a multinomial process, and using the maximum likelihood estimates, the point estimation of PMF for time window T_l and for plant k can be obtained as follows:

$$\hat{p}_{k,l} = \frac{y_{k,\tau \in T_l}}{N_{j,k}} \tag{6.7}$$

where $y_{k,\tau \in T_l}$ is the population-adjusted count of the census tracks in EPZ of plant k falling within time window T_l; while $N_{j,k}$ is the total number of census tracks in EPZ of plant k. Eq. 6.7 may generate misleading results since, for some of the NPPs, (i) the total number of census tracts is relatively small (e.g., less than 20) and (ii) the numerator of Eq. 6.7 can be zero for larger time windows. To address these challenges, this paper uses the point estimate based on Bayesian inference using the Dirichlet-multinomial conjugate. Assuming that the prior distribution for $\hat{p}_{k,l}, l \in \{1, 2, \dots, 5\}$, is represented by a 'flat' Dirichlet distribution, where all parameters, α_{kl}, are set to 1. Considering the population-adjusted count of the census tracks, $y_{k,\tau\in T_l}, l \in \{1, 2, \dots, 5\}$, as evidence, the likelihood function can be modeled by a multinomial distribution. Using the Dirichlet-multinomial conjugate property, the posterior distribution is also a Dirichlet distribution with updated parameters, calculated as follows:

$$\alpha_{kl} = 1 + y_{k,\tau\in T_l} \tag{6.8}$$

In this paper, the mean value of the posterior distribution, calculated by Eq. 6.9, is used as the point estimate of the time window probability:

$$\hat{p}_{k,l} = \frac{1 + y_{k,\tau\in T_l}}{\sum_{l=1}^{5}\left(1 + y_{k,\tau\in T_l}\right)} \tag{6.9}$$

The result of this calculation (A.2.3) are time window probabilities for each NPP in the validation subset (A.2.3 in Figure 6.6).

To evaluate the probability estimations for each NPP, a goodness-of-fit test is performed (A.2.4 in Figure 6.6). Leveraging the probabilities of each time window from the NPP ETE survey data (A.4), the PMFs for departure time (A.2.3) are evaluated using a goodness-of-fit test, for example Chi-square, to determine the level of reasonable error (i.e., the p-value is greater than 0.05) for the PDTM (A.2.5 in Figure 6.6). If the goodness-of-fit test is not successful (i.e., the p-value is less than 0.05), the analyst can generate an alternative HRA-based PE equation (A.1.8 in Figure 6.6) and re-run the building and validation of PDTM. If the goodness-of-fit test is successful (i.e., the p-value is greater than 0.05), the PDTM is provided for use. For example, Model 1 and Model 2 discussed above were tested, and Model 2 had a better goodness-of-fit and is therefore used in Section 6.4. In this paper, a reasonable error associated with the PDTM is assumed to be acceptable since the model helps to compensate for a lack of data (e.g., for outdated survey results, or in evaluating the EPZ for a new NPP design), and compliments surveys by providing more context for departure time estimations based on social vulnerability and demographic factors.

Once the validation (A.2 in Figure 6.5) is successfully executed, the PDTM model (i.e., the HRA-based PE equation used in A.1.8 and the PE ranges in A.1.18 from Figure 6.6) can be used. In Section 6.4, the processes of building and validating the model are executed using a set of NPP data, and then the validated PDTM is applied for Sequoyah NPP.

6.3.2. Transportation Models (B in Figure 6.5)

In order to select a proper transportation model for the integrated methodology (Figure 6.5), this research conducts a review of NPP-related studies from 2000 to 2019 that discuss evacuation models (or include the development or application of evacuation models) to analyze the challenges of transportation modeling for NPP evacuations. For an overview of evacuation models before 2000, see (Longo, 2010). The reviewed NPP-related studies fall into four categories:

a. Studies that discussed NPP evacuations but did not utilize a transportation model: Murray-Tuite and Wolshon (2013) provided a review of transportation modeling and identified factors contributing to NPP evacuations. Herrerra et al., (2019) evaluated the impact of population sizes and network topologies on trip generation times in ETE studies (Herrera et al., 2019). Hammond and Bier (2015) evaluated evacuation boundaries and compared them to keyhole evacuation strategies (Hammond & Bier, 2015). Four studies utilized optimization-based approaches for evaluating population evacuation routes (Guo et al., 2015; Huang et al., 2017; Lv et al., 2013; Zou et al., 2018). Goldblatt and Weinisch (2005) provide an overview of computer modeling for evacuation simulations for NPPs (Goldblatt & Weinisch, 2005). Deng et al., (2018) develop a parametric model to estimate an evacuation index associated with different evacuation alternatives to support decision making for NPPs (Deng et al., 2018).

b. Studies that used macroscopic transportation modeling: Macroscopic transportation models consider collective and aggregated (rather than individual) vehicle dynamics (i.e., density and velocity for a given location and time) (Helbing et al., 2002). In macroscopic models, traffic is represented as a flow (Bayram, 2016), where slowing down processes of fast-moving vehicles (encountering slower moving vehicles) and a relaxation process (i.e., adjusting speed towards a desired speed) determine flow rates in the model (Paveri-Fontana, 1975). DYNEV is a macroscopic transportation model that simulates traffic patterns over a road network during evacuations (Urbanik et al., 1988a). DYNEV parameters include vehicle population, network capacity, loading time, capacity reduction factor, time intervals, and free-flow velocities (Urbanik et al., 1988b). PTV Visum is a macroscopic transportation model that uses Origin-Destination (O-D) matrices as inputs for planning routes and forecasting traffic (Fellendorf et al., 2000). A benefit of macroscopic models is their ability to reduce application run times. Sixty-five NPP ETE studies from 2004 to 2018 that were available on NRC ADAMS were reviewed (See Appendix D), where 48 studies used versions of the DYNEV macroscopic simulation approach (i.e., (Urbanik, 2000)). DYNEV was developed by KLD Associates in the 1980s for FEMA (Urbanik et al., 1988a). DYNEV is a macroscopic traffic and evacuation simulation based on a gravity model that considers inputs of supply (e.g., evacuation routes, number of lanes, road capacity) and demand (e.g., permanent residents, employees, transients, special events), and can include multimodal transport (i.e., car and bus) (Weinisch & Brueckner, 2015). I-DYNEV differed from DYNEV in the way it computed the number of vehicles leaving a roadway segment. DYNEV II computes evacuation times and speeds for each link in 5-minute intervals (Cohen & Weinisch, 2015). DYNEV II was used to conduct ETE studies for 75% percent of the operating nuclear reactors in the U.S. (Cohen & Weinisch, 2015). Leveraging NPP ETE studies from 2011 and 2012, Weinisch and Brueckner (2015) used DYNEV to evaluate how varying the percentages of the shadow population (i.e., the population within 5 miles outside of the EPZ that would voluntarily evacuate) would affect ETEs (Weinisch & Brueckner, 2015). Cohen and Weinisch (2015) used DYNEV-II with FEMA's HAZards US (HAZUS) natural hazard loss estimation software to assess the impact of a natural hazard on evacuation (Cohen & Weinisch, 2015).

c. Studies that used mesoscopic transportation modeling: Mesoscopic transportation models consider a combination of both macroscopic and microscopic models, and are typically developed by disaggregating segments of macroscopic models into smaller segments (Bayram, 2016; Zhang et al., 2013). Mesoscopic models can produce indicators of traffic congestion and queuing (Zhang et al., 2013). PTV Vision combines Visum and Vissim (a microscopic transportation model) into a mesoscopic model through a methodology for bridging its different layers (i.e., the O-D matrix can be translated to Vissim) (Walker et al., 2012). An example of a mesoscopic model is TRANSIMS, which has been used to support evacuation modeling (e.g., (Pasupuleti et al., 2009)). As mentioned previously, sixty-five NPP ETE studies from 2004 to 2018 that were available on NRC ADAMS were reviewed (See Appendix D). 17 of the reviewed ETE studies used a combination of microscopic and macroscopic with the PTV Vision toolkit (i.e., (VISION, 2015)).

d. Studies that used microscopic transportation modeling: Microscopic transportation models consider individual vehicle movements on a second-by-second basis for analyzing traffic performance of road networks (FHWA, 2004). Microscopic models can consider specific driver and vehicle performance characteristics as well as behavior (Zhang et al., 2013). Compared to macroscopic models, microscopic models can require more effort to code, have larger volumes of data, and have long run times (Herrera et al., 2019). PTV Vissim a type of microscopic transportation model that is a discrete, stochastic, and time-step-based, where each vehicle is a single entity that follows rules based on Weidemann (1974) (i.e., four driving modes; free driving, approaching, following, braking (Wiedemann, 1974)) (Fellendorf & Vortisch, 2001, 2010). For a review of microscopic transportation models used in disaster research, see (Henson et al., 2009). Lee et al., (2016) utilized PTV Vissim (microscopic simulation), using surveys of the local population to generate traffic generation time estimates (Lee et al., 2016). Tuncer (2018) used PTV Vissim to evaluate the impact of shadow evacuation on NPP clearance times (Tuncer, 2018). Novacko et al., (2014) used PTV Vissim to evaluate the time of evacuation for the Krško NPP in Slovenia (Novacko et al., 2014). Agent Based Modeling (ABM) is a type of microscopic transportation modeling technique for simulating actions and interactions of autonomous individuals, so that emergent behavior can be observed (Zheng et al., 2013). ABMs are defined by bottom-up rules to govern individual agent behavior and decision-making, where traffic performance can feed back to modify agent behavior (Zheng et al., 2013). Hwang and Heo (2019) used the ABM software NetLogo and an extended GIS module to evaluate agent behavior patterns in NPP evacuations (Hwang & Heo, 2019). Alexis-Martin (2017) used Netlogo for a hypothetical case study to integrate population agents (i.e., nighttime population density from census data), radiological plume agents (i.e., generated by the Probabilistic Accident Consequence Evaluation (PACE) Numerical Atmospheric Modelling Environment (NAME) code), and countermeasure agents (i.e., shelters) to explore gender and radiation exposure, as well as demographic subgroup characteristics in hypothetical emergencies (Alexis-Martin, 2017). One study applied ABM using the software AnyLogic to simulate the number of residents evacuating over time (Amir et al., 2017). One study discussed the use of ABM for an NPP evacuation but did not provide information on their methodology (Kyoungseok & Lee, 2016).

The literature review in this section highlights the following results:

(i) Of the sixty-five reviewed NPP ETE studies, three consulting companies were the main authors of the reports (one company authoring 74% of the studies) and applied three types of macroscopic and mesoscopic transportation modeling software (see Appendix D). The review of NPP ETE studies indicates a lack of multidisciplinary and academic involvement in research on the topic of population evacuation for NPPs. As discussed in Section 6.1, licensees can leverage information from ETE studies to provide input parameters for MACCS, such as evacuation strategies, evacuation speeds, and the number of cohorts (i.e., segments of the population) (NRC, 2012), however, the explicit-internal incorporation of social factors beyond surveys and demographic data have not been considered (i.e., model-based approaches of population departure performance).

(ii) There are a limited number of studies that applied ABM for NPP-related evacuations (i.e., (Alexis-Martin, 2017; Amir et al., 2017; Hwang & Heo, 2019)). Of the ABM studies, one used a hypothetical location to conduct the case study (i.e., (Alexis-Martin, 2017)), and two solely relied on demographic data without using survey data to inform the assumptions on population behavior or evacuation time estimations (i.e., (Alexis-Martin, 2017; Amir et al., 2017)). One ABM study created an explicit-external incorporation of population evacuation with a static radiological plume model using PACE-NAME code (Alexis-Martin, 2017), however, an explicit-internal incorporation has not been demonstrated in the literature.

(iii) Most of the reviewed studies have generated an external model for evacuation and are not connected to a radiological hazard model. One study that did include a radiological hazard (i.e., using the NRC's Radiological Assessment Systems for Consequence AnaLysis (RASCAL) tool (Hammond & Bier, 2015)) did not include a microscopic, macroscopic, or mesoscopic transportation model. Another study that included a radiological hazard (i.e., using PACE-NAME (Alexis-Martin, 2017)) generated a static plume that was exported in a GIS environment to create an explicit-external integration with the ABM population evacuation model (Alexis-Martin, 2017). These studies have not developed an explicit-internal incorporation of social factors (i.e., updating evacuation parameters in Level 3 PRA).

In this paper, MultiAgent Transport Simulation (MATSim) is selected as the ABM microscopic transportation model (C in Figure 6.5), and the MATSim Evacuation extension (Lämmel et al., 2016) is used in the case study demonstration in Section 6.4. MATSim models start with a synthetic population of randomly generated individuals informed by census data (Lämmel et al., 2010). Each synthetic population member (agent) starts with one or several plans or "intentions" to be tested in the traffic flow simulation and scored (Lämmel et al., 2010). For example, part of the agent's plan can include their delay to departure and their predetermined route to safety. The road network (B.3. in Figure 6.5) includes the accessible areas for evacuees, where each street is a link that has parameters of length, capacity, and free flow speed (Lämmel et al., 2010). Traffic flow in MATSim is a queue simulation, where each link considers a first-in-first-out queue with three restrictions; (i) each agent remains for a certain time on the link based on free speed travel time, (ii) link flow capacity limits outflow, and (iii) link storage capacity limits agents per link (Lämmel et al., 2010). In MATSim, agents choose a travel plan, which initiates a network leading calculation, agents then score their simulated route and have the option for re-planning in order to optimize their path (Horni et al., 2016). In the evacuation simulation, individuals can optimize their routes based on two routing solutions: (a) shortest path based on Dijkstra's shortest path (Dijkstra, 1959), and (b) Nash equilibrium, where agents iterate route selection that is most optimal, considering congestion (Lämmel et al., 2010). Leveraging the information from these iterations, agents score each plan (i.e., shorter the travel time, the higher the score), and keep the score in their memory for comparing further iterations (Lämmel et al., 2010). Agents are also able to consider experienced travel plans from previous runs to generate new plans and decide if previous plans should be used again, or if new random plans should be generated (Lämmel et al., 2010). Mobility simulation, scoring, and re-planning are repeated in an analysis-defined number of iterations so that performance improvements can be observed

(Lämmel et al., 2016). The MATSim Evacuation extension uses a GIS-based time analysis to compute evacuation time and clearance time per each cell in a spatial grid in the user-defined evacuation area (Lämmel et al., 2016). Additional details on the operationalization of the MATSim Evacuation extension are included in Section 6.4. For more information on MATSim, see https://matsim.org/the-book. Once the transportation model is selected (i.e., MATSim), inputs are provided, the transportation model is run, and the distribution of average evacuation speed is calculated to prepare for integration with the Level 3 PRA code (C in Figure 6.5).

6.3.3. Sensitivity & Importance Measure Analysis (D in Figure 6.5)

The output analyzer (D.1 in Figure 6.6) is used for interpreting MACCS outputs as risk indicators. In this paper, risk is defined by the level of exceedance beyond U.S. Environmental Protection Agency (EPA) Protective Action Guidelines (PAGs) (EPA, 2017). It should be noted that PAGs are not an established risk criteria, and are not a legal representation or regulation for safe or unsafe conditions (EPA, 2017). The EPA PAG for the early phase is used as a risk indicator in this paper for demonstrative purposes. The EPA PAG for the early phase, which includes dose during an evacuation PAR, is 1 to 5 rem (10 to 50 mSv) total effective dose over four days (EPA, 2017). Risk is therefore calculated by the cumulative dose exceedance based on the EPA PAG.

The methodological framework proposes an integrated sensitivity analysis (D in Figure 6.5) that provides a streamlined approach (D.2 in Figure 6.5), similar to the concept introduced by Bui et al., (2019) for Integrated PRA applied for Level 1 PRA (Bui et al., 2019a). The streamlined approach provides an initial quantitative screening of influential parameters in Level 3 PRA for identifying the level of detailed modeling needed in the (A) PDTM and (B) transportation model. Sensitivity and importance measure analysis provide useful information to support decision making. Through the explicit inclusion of social factors in the PDTM, importance ranking of social factors can provide useful information to support risk-informed emergency preparedness, planning, and response. The following provides additional details on the streamlined approach (D.2).

D.2. Streamlined Approach: the Morris Elementary Effects (EE) method (Campolongo et al., 2007; Morris, 1991) is used for quantitative screening of MACCS input parameters (e.g., average speed and departure time) to identify the most influential factors based on their contribution to MACCS outputs (i.e., offsite risk indicators), for example, the probability of radiation dose exceeding 10 mSv. The Morris EE method uses the difference quotient of the model output as a sensitivity measure and can address the uncertainty of input parameters, non-linearity, and interactions among input parameters using the individually-randomized One-At-a-Time (OAT) design (Morris, 1991). In the OAT design for EE computation, the input space is discretized into a p-level grid. In each replication, the initial point in the input space is randomly selected from the p-level grid, and additional sampling points are generated by varying each input parameter by a preset jump (denoted as Δ) in an OAT manner. For each replication, thus, $(k + 1)$ simulation runs are required, where k is the number of input parameters considered in the Morris EE analysis. The EE calculation by this procedure is repeated for r times using different initial points randomly selected from the p-level grid. The mean value of the EEs indicates the main effects, while the standard deviation of the EEs indicates the degree of non-linearity and interactions among input parameters. The 95% confidence intervals for the EE mean and standard deviation estimators are constructed by the Bootstrapping method (DiCiccio & Efron, 1996). In this research, the p-level grid in the quantile space is generated using the R package 'sensitivity' (Iooss et al., 2020) and is transformed for the input space by the inverse transform method. For the scope of this paper, several MACCS input parameters associated with the public evacuation that could significantly impact the risk outputs or could induce large uncertainty are selected based on the authors' expert judgment, and for each of the selected input parameters, the upper and lower bounds are determined based on the insights from Sequoyah NPP ETE, After Action Report (AAR), and SOARCA studies (ARCADIS, 2013; FEMA, 2013b).

The results of the streamlined approach can help to provide justification for the prioritization of underlying models in the methodological framework so that an adequate scope and level of detail is included in the explicit models of social factors in Level 3 PRA. Using the insights from the streamlined approach, an analyst can determine which elements of the methodological framework should be advanced by developing explicit models, for example, the PDTM, as discussed above. Future work will include the development of an advanced importance measure approach that can be used to rank the underlying contributing factors of the PDTM (A in Figure 6.5) and transportation model (B in Figure 6.5) based on their contribution to risk outputs of Level 3 PRA (D.1 in Figure 6.5).

6.4. APPLYING THE INTEGRATED METHODOLOGY FOR THE SEQUOYAH NUCLEAR POWER PLANT

In this section, the methodological framework from Section 6.3 is applied, first implementing D.2 from Figure 6.5 to justify the explicit model-based approaches of PDTM and the transportation model, and then starting from A in Figure 6.5 to apply the full methodological framework. The Sequoyah NPP 2017 SOARCA study (herein referred to as "SOARCA 2017") (NRC, 2017) is used to provide the scenario information and key input parameters in MACCS. SOARCA 2017 provides the Level 3 PRA scenario information and input parameters for source term, dose coefficient, and notification time. In SOARCA 2017, "Realization 554" is a scenario of early containment failure induced by a large burn in a lower compartment that propagated to the dome that is considered to be "maximum-risk" with the highest risk source term and earliest release (i.e., 3.6 hours after the initiating event) (NRC, 2017). Realization 554 considers that radiological release occurs one hour after the GE siren, and the second release occurs six hours after the GE siren (NRC, 2017). Realization 554 is used in this case study. The scenarios in SOARCA 2017 include Short-Term Station Blackout (STSBO) and Long-Term Station Blackout (LTSBO), where, based on a FEMA exercise AAR (FEMA, 2013b), it was determined that an onsite GE would likely be declared two hours after the accident (NRC, 2017) (see a.3 in Figure 6.3). Once the onsite GE declaration is made (7 from Figure 6.2), the ORO sequence of tasks would begin (see b.1 to b.7 in Figure 6.3). Based on the FEMA AAR (FEMA, 2013b), the time between the ORO receiving the licensee notification (b.1 in Figure 6.3) and sounding the GE sirens to notify the public (b.7 in Figure 6.3) was estimated at 45 minutes, putting the GE siren and notification of the public at 2.75 hours from the accident (NRC, 2017).

The weather data used in the case study are the same as the data used in SOARCA 2017. Sequoyah weather data from 2012 was provided by the Tennessee Valley Authority, which included hourly wind direction and speed, precipitation rate, and atmospheric stability class. Using SecPop (NRC, 2018), demographic data from the 10-mile EPZ is fit to a concentric mesh to provide the population input file for MACCS. In the MACCS evacuation module, the network evacuation option was selected without keyhole evacuation, and the evacuation directions in the concentric mesh were set based on SOARCA 2017. Several assumptions were made to develop the case study in MACCS. Delay to shelter was set to zero minutes because the case study assumes a nighttime or weekend scenario, where it is likely that most household members are at home. A 10-mile EPZ was used as the evacuation boundary in the case study. Because the focus of the case study is on evacuation, normal and hot spot relocation parameters were not included. The exposure period (exposure duration) was changed from seven days to four days to compare with EPA PAG guidance of 10 millisieverts (mSv) per four days (EPA, 2017). In MACCS, the population can be modeled into cohorts; population segments which can be based on starting location and customized by time-related parameters such as delay to shelter, delay to evacuation, the evacuation speed, duration of the beginning phase of evacuation, and duration of the middle phase of evacuation (NRC, 2013c). In this study, the majority of general cohorts were combined into one group that is expected to start evacuating when the GE siren and emergency notification is provided by the ORO. In this case study, long-term consequences are not being calculated in MACCS, instead, early dose calculations from the EARLY module are being used to demonstrate risk in the early phase as a function of changes in input parameters. In this paper, an “early phase” risk metric is considered as the probability that the EPA PAGs is exceeded (i.e., 1 to 5 rem (10 to 50 mSv) total effective dose over four days). The EPA PAGs are designed to prevent the acute effects of radiological hazards and help to balance protective actions to reduce risk (EPA, 2017).

Considering Realization 554, the STSBO and LSTSBO scenario timeframes from SOARCA 2017, and the assumptions mentioned above, the case study for the Sequoyah NPP is implemented by the following:

1. Perform the streamlined approach (D.2 in Figure 6.5) quantitative screening of a selection of MACCS input parameters from SOARCA 2017 to rank the most influential factors;
2. Run the PDTM (A in Figure 6.5) for the Sequoyah NPP and generate a model-based population departure time distribution;
3. Run the transportation model (B in Figure 6.5) using the PDTM distribution to generate an average evacuation speed distribution;
4. Run MACCS Level 3 PRA (C in Figure 6.5) using SOARCA 2017 inputs, the PDTM distribution, and average evacuation speed distribution;
5. Interpret MACCS outputs using the output analyzer (D.1 in Figure 6.5).

<u>1. Perform the streamlined approach (D.2 in Figure 6.5) quantitative screening a selection of MACCS input parameters from SOARCA 2017 to rank the most influential factors;</u> using the SOARCA 2017 scenario described above, the streamlined approach (D.2 in Figure 6.5) is performed in MACCS, considering the six input parameters (X1 to X6) in Table 6.3. These six input parameters are identified, based on the authors' expert judgment, as the potentially influential factors in terms of the risk contribution or the potentially significant sources of uncertainty. In this paper, the probability of radiation dose exceeding 10 mSv is selected as a risk metric and is used as a model output of interest in the Morris EE analysis. This paper focuses on the offsite evacuation and radiation dose to the public during evacuation; hence, the MACCS input parameters associated with other processes and aspects (e.g., cancer risk-related factors, relocation factors) are not considered. In the OAT design for EE calculation, the 12-level grid ($p = 12$) is generated within the upper and lower bounds specified in Table 6.3, and the jump level is set at $\Delta = 6$. The number of replications r is selected based on the convergence study, where the Morris EE analyses are run with multiple selections of r, and $r = 20$ is selected in this study as it removes an overlap of the 95% confidence intervals between the influential and non-influential factors. In the OAT sampling, three shielding coefficients (i.e., cloud shine, ground shine, and inhalation/skin) are treated as a completely correlated random variable, represented by X4 in Table 6.3. Similarly, four vertical dispersion linear coefficients (i.e., Classes A/B, C, D, and E/F) are treated as a correlated random variable, represented by X5 in Table 6.3.

Table 6.3: Selected MACCS input parameters considering lower bound and upper bound estimates

ID	Parameter		Lower Bound	Upper Bound
X1	GE Siren[3]		147 min	201 min
X2	Departure Time[4]		1 min	180 min
X3	Evacuation Speed[5]		1 mph[6]	61.4 mph[7]
X4	Shielding Coefficients		Cloud Shine: 0.6	Cloud Shine: 0.95
			Ground Shine: 0.095	Ground Shine: 0.359
			Inhalation/Skin: 0.25	Inhalation/Skin: 0.98
X5	Weather Data: Vertical Dispersion Linear Coefficient	A/B	0.0144 m	0.0903 m
		C	0.0814 m	0.0509 m
		D	0.1054 m	0.6590 m
		E/F	0.0985 m	0.6158 m
X6	Total Population		Data sampled from 2009 to 2020[8]	

Figure 6.8 shows the results of the streamlined approach using the Morris EE method. Among the six selected MACCS input parameters in Table 6.3, X3 (Evacuation Speed) is identified as the most influential factor in terms of the impact on the risk output (i.e., the probability of radiation dose exceeding 10 mSv). The further analysis of the Morris EE outputs demonstrate that the risk output is highly sensitive to the lower subspace of X3 (around 1-4 mph), while it is less sensitive to the other subspaces of X3. This observation indicates that the risk output is a highly non-linear function of X3, and the results in Figure 6.8 are dominated by the model behavior with extremely small values of X3. To investigate the model behavior when X3 does not have an exceptionally small value, another run of the Morris EE analysis is conducted by setting the lower bound of X3 at 5 mph (while the settings of the other input parameters are identical to Table 6.3). The results, shown in Figure 6.9, indicate that, when X3 is greater than 5 mph, the departure time is the most influential factor for the risk output. These results provide scientific justification for advancing the estimation of the departure time and evacuation speed by developing the model-based approach, as described below.

[3] Assuming that the time from ORO receipt of the GE declaration to sounding of the GE sirens (base value: 36 minutes (FEMA, 2013b)) can vary by a factor of two in both decreasing and increasing directions, i.e., 18 minutes and 72 minutes, respectively (NRC, 2017)

[4] Departure time bounds are from the Sequoyah ETE study (ARCADIS, 2013)

[5] Based on Table 6-6 from SOARCA 2017 (NRC, 2017)

[6] Lower bound evacuation speed comes from SOARCA 2017 (NRC, 2017)

[7] Upper bound evacuation speed comes from the Sequoyah ETE study (NRC, 2017)

[8] Population data was calculated from 2010 demographic data by SecPop (Ref, NRC SecPop). The annual population growth rate is set at 0.412% based on SOARCA 2017.

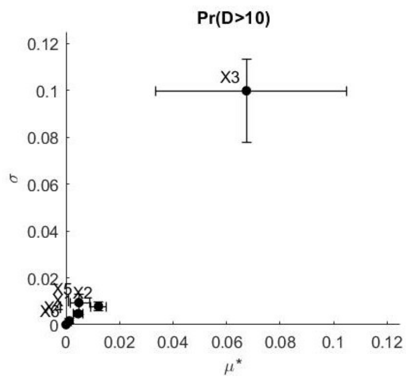

Figure 6.8: Streamlined approach results of the Morris Elementary Effect (EE) screening of MACCS input parameters (from Table 6.3). The error bars show the 95% confidence intervals

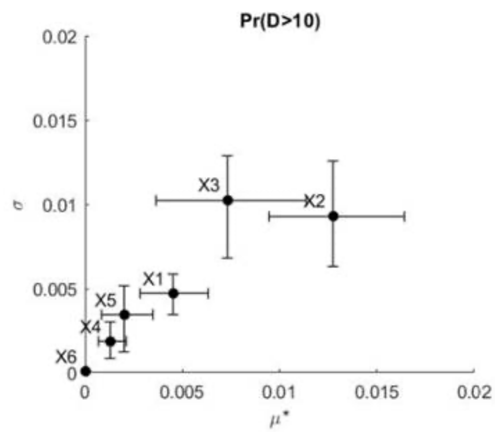

Figure 6.9: Streamlined approach results of the Morris Elementary Effect (EE) screening of MACCS input parameters with the lower bound of X3 (Evacuation Speed) being set as 5 mph. The error bars show the 95% confidence intervals

2. Implement the PDTM modules (A.1 and A.2 in Figure 6.5) on a set of NPPs to generate a model-based population departure time distribution, and then apply the validated model for Sequoyah NPP; using 14 NPPs shown in Table 6.4 ($k = 1, \dots, 14$), the PDTM was built and validated. Sub-steps A.1.1 to A.1.7 in Figure 6.6 were applied using CDC SVI (CDC et al., 2018) and U.S. 2010 Census data, leveraging the task analysis and PSFs identified in Section 6.2.1.1, and using Eqs. 6.1 through 6.7. Table 6.4 shows the NPPs included in the study for the building subset ($k = 1, \dots, 7$) (A.1.11 in Figure 6.6), and the validation subset ($k = 8, \dots 14$) (A.2.1 in Figure 6.6), including the ETE study ML number (available in NRC ADAMS), analyst of the ETE study, total population reported in the ETE study, and departure time window survey results (i.e., 0-20 min, 20-40 min, 40-60 min, 60-90 min, 90+ min) (from A.4 in Figure 6.6).

Table 6.4: NPPs included in the case study for building and validating the PDTM

k	Subset	ML Number	NPP	0-20 min	20-40 min	40-60 min	60-90 min	90+ min
1	Building	ML101110357	Fermi	0.45	0.29	0.14	0.07	0.05
2	Building	ML12088A203	Indian Point	0.40	0.33	0.14	0.09	0.04
3	Building	ML12348A223	Clinton	0.33	0.43	0.13	0.05	0.05
4	Building	ML12348A382	Limerick	0.31	0.44	0.15	0.08	0.02
5	Building	ML12348A384	Dresden	0.31	0.46	0.14	0.05	0.03
6	Building	ML12349A294	Quad Cities	0.28	0.45	0.15	0.09	0.03
7	Building	ML13298A792	Virgil C. Summer	0.39	0.27	0.18	0.09	0.07
8	Validation	ML12048B369	South Texas Project	0.13	0.21	0.16	0.19	0.31
9	Validation	ML12355A267	Three Mile Island	0.22	0.44	0.17	0.13	0.05
10	Validation	ML12348A219	Braidwood	0.34	0.40	0.15	0.07	0.03
11	Validation	ML12348A221	Byron	0.27	0.45	0.18	0.05	0.05
12	Validation	ML12348A385	LaSalle	0.33	0.43	0.14	0.06	0.04
13	Validation	ML12355A240	Peach Bottom	0.26	0.42	0.20	0.09	0.03
14	Validation	ML13254A121	Oyster Creek	0.28	0.41	0.19	0.09	0.03

Using the development subset (see Table 6.4), sub-steps A.1.12 to A.1.18 in Figure 6.6 are applied to develop PE ranges for the time windows. As discussed in Section 6.3.1, Model 2 (M_2) is used to calculate the worst-case end state E_1 from Figure 6.4, using Eq. 6.6. The resulting PE ranges and their areas of overlap are included in Table 6.5. The areas of overlap are handled in the validation of the PDTM in the next sub-step.

Table 6.5: PDTM-generated Population Error (PE) ranges from the development subset (running sub-steps A.1.1 to A.1.18 from Figure 6.6)

Time Window	Lower Bound	Upper Bound
0-20 min	0	3.19E-08
Overlap between 20-40 min	3.20E-08	3.09E-07
20-40 min	3.10E-07	1.11E-06
Overlap between 40-60 min	1.12E-06	4.91E-06
40-60 min	4.92E-06	7.26E-06
Overlap between 60-90 min	7.27E-06	3.36E-05
60-90 min	3.37E-05	4.43E-05
Overlap between 90-90+ min	4.44E-05	2.06E-04
90+ min	2.07E-04	1

Using the validation subset (see Table 6.4), sub-steps A.2.2 to A.2.6 in Figure 6.6 are applied (using departure time survey data from Table 6.4) to test the goodness-of-fit using chi-squared for each NPP in the validation subset, shown in Table 6.6.

Table 6.6: Validation subset NPP goodness-of-fit test results

Validation Subset NPP	Chi-Square p-value
South Texas Project	0.533
Three Mile Island	0.829
Braidwood	0.651
Byron	0.589
LaSalle	0.829
Peach Bottom	0.921
Oyster Creek	0.138
Average	0.641

The validated PDTM was run for Sequoyah, resulting in the predicted time windows in Table 6.7. The PDTM results are used as the PMF departure time distribution in the transportation model.

Table 6.7. PDTM results for the Sequoyah NPP

Time Windows	0-20min	20-40 min	40-60 min	60-90 min	90+ min
PDTM Result	0.20	0.36	0.28	0.09	0.06

<u>3. Run the transportation model using the PDTM distribution to generate an average evacuation speed distribution;</u> the MATSim Evacuation module and Graphical User Interface (GUI) (see Section 6.3.2) is used as the transportation model (B from Figure 6.5). For more information on the MATSim Evacuation extension, see (Lämmel et al., 2016). Total population (B.2 from Figure 6.5) for the Sequoyah EPZ (97,726) was estimated using SecPop 4.3.0 (NRC, 2018). Open Street Map[9] data was used for the road network (B.3 from Figure 6.5) and was acquired using Java Open Street Map[10] before being converted to a MATSim input file. The evacuation area (B.4 from Figure 6.5) is the 10-mile EPZ of the Sequoyah NPP. Several assumptions are made in setting up the evacuation simulation; (1) population location is uniformly (randomly) distributed within the 10-mile EPZ, (2) persons per vehicle is considered to be 2.11 (i.e., from the Sequoyah ETE study (ARCADIS, 2013)), (3) "destinations" are set at the intersection of

[9] Open Street Map contributors. (2015). *Planet dump [Data file from 12/3/2019] Retrieved from https://planet.openstreetmap.org*.
[10] https://josm.openstreetmap.de/

the EPZ boundary and major roads (i.e., assuming that vehicles will travel outside of the EPZ to shelters or their intended destinations) where evacuation time is only measured until a vehicle leaves the EPZ, and (4) the number of agent re-planning (optimization) iterations is set to a default value of 10. In this case study, the transportation model was run based on default settings and under normal road network conditions (i.e., not considering damage due to a seismic event). Travel time and travel distance of each vehicle is divided to find the evacuation speed. The average speed of all vehicles is counted and fit to a cumulative frequency distribution. The average evacuation speed distribution serves as the input parameter of "ESPEED" in MACCS (B.5 to C.1 in Figure 6.5).

4. Run MACCS using SOARCA 2017 inputs, the PDTM distribution, and average evacuation speed distribution; MACCS inputs for source term and dose calculation are based on SOARCA Realization 554. In the MACCS calculation, the duration of source term was set up to 20 hours to avoid errors that occur when distributions are set for evacuation parameters. The PDTM departure time distribution and transportation model-based evacuation speeds were used as inputs in the evacuation module. Because a distribution was provided for evacuation speed, a speed multiplier was not set. To account for the integration of the evacuation speed outputs from the transportation model (B.5 in Figure 6.5) and the PDTM departure time distribution outputs (A in Figure 6.5), one general cohort is used to represent the entire population in the EPZ, considering uncertainty from the distributed input parameters for evacuation speed and departure time. Because one cohort was used, one notification delay time of 165 minutes (from SOARCA 2017) was used. Considerations for other cohort groups such as schools and special facilities can also be evaluated using model-based approaches and will be included in future research.

5. Interpret MACCS outputs using the output analyzer (D.1 in Figure 6.5);
The integrated methodological framework results in a probability of 1.64E-05 that 1.61 people evacuating the EPZ will receive a dose in exceedance of the EPA PAG (10 mSv) for the early phase. The results indicate that the population will receive a dose between 1 to 10 mSv with a probability of 1.59E-4. While the estimated risk in this case study would only affect 0.001% of the population, it indicates that for the modeled scenario, a reduction of risk could be achievable. The results of this case study indicate that the probability of the population receiving a dose greater than 10 mSv is low, and therefore the protective action may be acceptable. Through the integration of the PDTM, sensitivity analysis of social factors can be evaluated to determine which types of social investment may contribute to a further reduction of risk. Additionally, in future research, the methodological framework will be connected to long-term consequence models to provide a more realistic estimation of risk.

6.5. CONCLUSIONS & FUTURE WORK

This paper is part of a line of research by some of the authors of this paper on the advancement of socio-technical risk analysis for explicitly incorporating organizational/social factors into Level 3 PRA (Pence et al., 2018). The advancement towards explicit, or model-based incorporation of social factors can be considered from two perspectives: (i) internal (on the right side of the spectrum in Figure 6.1), and (b) external (the middle of the spectrum in Figure 6.1). Internal incorporation implies the development of advanced modeling and simulation to quantify the effects of underlying factors on the parameters in Level 3 PRA. This paper continues this line of research toward an “explicit-internal” incorporation of social factors into Level 3 PRA (i.e., an advancement toward the right side of the spectrum in Figure 6.1).

A macro-level theoretical causal framework for socio-technical risk analysis of severe nuclear accidents is expanded in Section 6.2. One element of the causal framework (i.e., population protective action performance) is further expanded in Section 6.2.1.1, where an HRA-based theoretical representation of Population Error (PE) is introduced for pre-evacuation departure performance. Without explicit consideration of social factors, it would be hard to analyze their effects on the population departure time to impove emergency response. While the long-term goal of this research is to operationalize the full scope of the macro-level theoretical causal framework introduced in Section 6.2, the methodological developments of this paper focus on the population protective action performance. Section 6.3 introduced a methodological framework for (A) building and validating the HRA-based Population Departure Time Model (PDTM), and (B) integrating it with the transportation evacuation model to generate model-based ETEs and evacuation speed estimates as inputs to (C) MACCS. This integrated methodology makes an advancement toward the explicit incorporation of social factors into Level 3 through the explicit incorporation of social factors into departure time and evacuation speed estimations. The integrated methodology can help (i) create a more realistic estimation of risk from MACCS by contributing to a more realistic representation of population evacuation performance and (ii) provide the opportunity to conduct importance ranking of the social factors, influencing departure time and evacuation speed, with respect to their impacts on risk. The results provide location-specific insights that can be useful in improving the RERP for areas where higher PE potential exists for the departure stage of an evacuation.

In Section 6.4, the integrated methodology is applied in a case study using results from the 2017 Sequoyah SOARCA study.

The case study in Section 6.4 conducted a streamlined screening approach to justify the development of the PDTM and transportation model. developed and validated the PDTM using data for 14 NPPs, ran the PDTM for the Sequoyah NPP, and implemented the methodological framework from Section 6.3 using MACCS parameters from the 2017 SOARCA study. The PDTM results were used as an input in a transportation model to generate an average evacuation speed distribution. The PDTM results and average evacuation speed distribution were used as inputs to MACCS in addition to SOARCA 2017 parameters to generate risk results. The estimated risk in this study, or the probability of population dose receiving 10 mSv within four days, was estimated at 1.64E-5. The case study provides location-specific insights that can be useful in improving the RERP for areas where higher PE potential exists during the departure stage of an evacuation.

Despite progress that has been made for Level 3 PRA, there are still several gaps to address; for example, the need to "explicitly" consider and analyze (i) unanticipated socio-technical factors influencing the communication of the Offsite Response Organization (ORO) (NAS, 2014), and (ii) the influence of social and psychological factors on the performance of an evacuating population, for example, as highlighted in (Pence et al., 2018). The incorporation of social factors into Level 3 PRA is a complex multidisciplinary research area. This paper does not explicitly consider the content and messaging of the ORO notification, or the ORO actions following the notification (e.g., (CastroSilva & Medeiros, 2015)). Although this paper provides a scientific contribution in the development of theoretical and methodological frameworks for developing model-based approaches to incorporate social and psychological factors influencing the performance of an evacuating population in PRA, many critical challenges remain, requiring future research. Some of these challenges may include: (i) the consideration of other cohort groups such as schools and special facilities using model-based approaches, (ii) evaluating other HRA methods to evaluate the accuracy of the PE prediction model, (iii) developing more detailed scenarios (i.e., daytime and special events) of departure time estimates to have more realistic simulations of mechanisms influencing population performance, (iv) expanding the theoretical framework to consider the influence of social media and social networks on the population's task of orienting and interpreting risk in the aftermath of a severe NPP accident given conflicting information, (v) developing model-based approaches for the delay of onsite notification to the ORO, and therefore delay in the population receiving the warning, and (vi) connecting the methodological framework to long-term consequence models to provide a more realistic estimation of risk, (vii) expanding scenarios to consider multi-unit NPP accidents, overlapping EPZs of NPPs in the same region (i.e., inter-state and regional transportation network dependencies), and the influence of population protective action performance on ORO performance (i.e., shadow evacuees impacting travel times of ORO sharing the transportation network). Forthcoming publications by the authors will provide further advancement of the theoretical framework and associated methodologies for operationalizing its elements.

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CHAPTER 7: METHODOLOGY TO EVALUATE THE MONETARY BENEFIT OF PROBABILISTIC RISK ASSESSMENT BY MODELING THE NET VALUE OF RISK-INFORMED APPLICATIONS AT NUCLEAR POWER PLANTS*

ABSTRACT

Probabilistic Risk Assessment (PRA) used in Nuclear Power Plants serves as a pillar of the U.S. Nuclear Regulatory Commission's Risk-Informed Regulatory framework and is required for new reactor licenses to satisfy regulatory safety compliance. The benefits of PRA are not only experienced in terms of safety, but also from the monetary value derived from Risk-Informed Performance-Based Applications (RIPBAs), where risk estimated from PRA is utilized in decision making to expand the safe operational envelope of plants, leading to either an increase in profits or a reduction in costs. This paper introduces a methodology to evaluate this monetary value by the systematic causal modeling of the net value of RIPBAs and demonstrates the methodology for one of the RIPBAs, called Risk-Managed Technical Specifications (RMTS). The key steps of this methodology are: (i) Cost-Benefit Analysis to formulate the net value of PRA based on the net value of RIPBAs, (ii) Causal modeling to systematically model the operational scenarios leading to costs and benefits associated with RIPBAs, (iii) Uncertainty analysis, and (iv) Sensitivity analysis and validation. The results of this research could help decision makers with evaluating investment strategies in PRA that go 'beyond-compliance' to maximize industry profit while maintaining regulatory safety goals.

7.1. INTRODUCTION

Risk assessment insights are used by decision-makers in their evaluations of the potential outcomes of scenarios and for the mitigation of those that are deemed undesirable. In this paper, 'risk' in high-consequence industries such as nuclear, space, aviation, healthcare, chemical processing, transportation, oil and gas, etc., refers to 'system risk'. Commercial nuclear power plants have robust protective systems, leading to sparse datasets for catastrophic failure such as core damage. A central risk assessment technique used for these industries is Probabilistic Risk Assessment (PRA) (NRC, 1975), a systematic methodology for quantifying the emerging risk from the interactions of equipment failure and human error. PRA is a key pillar of safety policy setting and regulation for the U.S. Nuclear Regulatory Commission's (NRC's) Risk-Informed Regulatory (RIR) Framework (NRC, 2011a), and following its

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lead, a growing number of U.S. governmental agencies have begun using, or are evaluating the possibility of using PRA for decision making and policy setting.

In classical PRA, fault trees and event trees are commonly used to model the causal relationships among system states, components, and human actions that could generate scenarios leading to a specific end state (NRC, 1983). Over the past four decades, classical PRA has improved both theoretically and methodologically. An important advancement has been the ability to go beyond individual-level human error and to explicitly incorporate the underlying social and organizational root causes of failure, such as training quality or organizational culture, into technical system PRA scenarios (Alvarenga et al., 2014; Embrey, 1992). To further this advancement, the Socio-Technical Risk Analysis (SoTeRiA) framework (Mohaghegh, 2007, 2009; Mohaghegh et al., 2009; Mohaghegh & Mosleh, 2009) was developed. SoTeRiA generates a theoretical causal integration for both the social aspects (Safety Culture; Node 8 in Figure 7.1) and the structural features (Safety Practices; Node 7 in Figure 7.1) of organizations with technical System Risk (Node 1 in Figure 7.1). The development of SoTeRiA was based on a multi-level organizational effectiveness theory (Ostroff et al., 2003). It considers the "Financial Outcome" (Node 11 in Figure 7.1) and "System Risk (PRA)" (Node 1 in Figure 7.1), as two competing outcomes of organizational performance. While SoTeRiA has been operationalized in the aviation (Mohaghegh, 2010a, 2010b; Mohaghegh et al., 2009) and nuclear industries (Pence et al., 2015; Pence et al., 2014), the relationship between "Financial Outcome" (Node 11 in Figure 7.1) and "System Risk (PRA)" (Node 1 in Figure 7.1) has not yet been modeled in detail. Developing this relationship requires theorizing and quantifying all the direct and indirect causal mechanisms between Node 1 and 11 and is the long-term goal of the research demonstrated in this paper. For the short term, however, this research focuses on evaluating the monetary benefit that PRA, a well-known safety-oriented technique, can generate for NPPs through Risk-Informed Performance-Based Applications (RIPBAs).

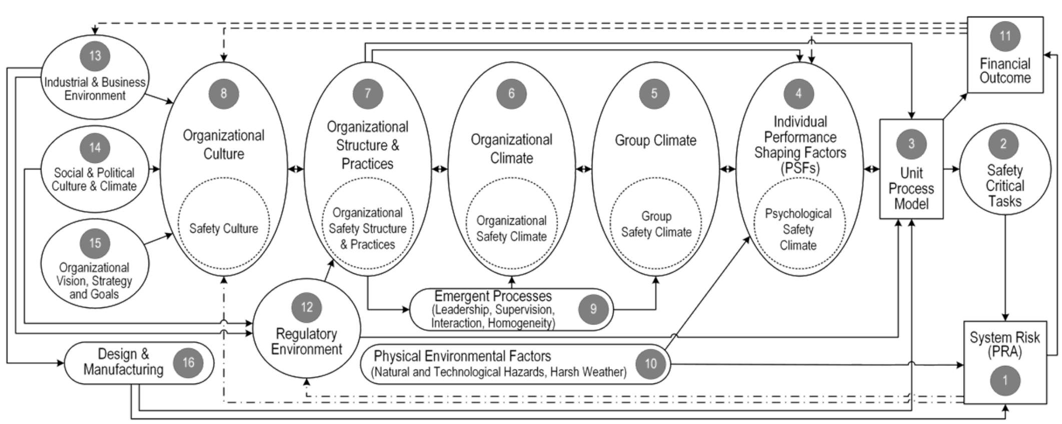

Figure 7.1: Socio-Technical Risk Analysis (SoTeRiA) Theoretical Framework

Although the connection between financial outcome and safety has long been of interest to managers, business scholars, economists, and policy makers (Clarke & Varma, 1999), the economic aspects of PRA are only beginning to be investigated by academia. In practice, however, the monetary advantages of PRA are being experienced in the nuclear industry, where through several RIPBAs, risk estimated from PRA is utilized in decision making to expand the operational envelope of plants, leading to either an increase in profits or a reduction in costs. Liming and Kee et al. have used data-driven Cost-Benefit Analysis (CBA) to estimate the costs of maintenance by leveraging information from empirical data of RIPBAs (Kee et al., 2004; Liming, 2015; Liming & Wakefield, 1996). Despite these research efforts and the widespread use and successes of PRA in nuclear regulatory decision making and safety applications for industry, the net value of PRA has not yet been justified by a model-based approach utilizing systematic causal modeling.

Without a justified representation of the 'market value' of PRA, there are few incentives for companies to go 'beyond-compliance' and to make investments in RIPBAs. To provide industry with a reason to go beyond the minimum PRA requirements for demonstrating compliance with regulatory safety goals, this research focuses on the development of a model-based methodology to evaluate the monetary benefit of PRA through the systematic causal modeling of the net value of RIPBAs, considering the associated uncertainties. Sections 7.1.1 and 7.1.2 provide a brief background on RIR, and RIPBAs, specifically Risk-Managed Technical Specifications (RMTS). Section 7.2 demonstrates a methodology to evaluate the monetary benefit of PRA. Although the key steps of this methodology are applicable to all RIPBAs, they are explained through their implementation for Risk-Managed Technical Specifications (RMTS) in this paper.

7.1.1. Background on Risk-Informed Regulation

Initially, the NRC took a prescriptive and deterministic approach to rulemaking and regulation, relying on conservative safety margin, defense-in-depth, and design parameters for the evaluation of severe accident sequences. The evolution of PRA began in the 1940s and focused on early reactor safety approaches and continued into the 1970s when the Reactor Safety Study (NRC, 1975) was issued in the aftermath of the Three Mile Island accident. In 1988, a PRA-based Individual Plant Examination (IPE) was introduced as part of a severe accident policy (NRC, 1988). In an IPE, PRA was used to gain knowledge regarding the scenarios and behaviors in severe accidents, obtain a quantitative estimation of the overall probabilities of core damage and fission product release, and learn how to use this information to help reduce the overall probabilities by modifying hardware and procedures (OIG, 2006). The issuance of NUREG-1150 (NRC, 1990b) and the PRA Policy Statement, from 1990 to 1995, gave more legitimacy to the use of PRA in the regulation of the nuclear industry. In 1998, the NRC published Regulatory Guide

1.174 to formally develop a framework for RIR to support regulatory decision making using PRA information and deterministic criteria rooted in the defense-in-depth philosophy (NRC, 2011a). In parallel, the adoption of the Maintenance Rule and an increased focus on the measurement of the effectiveness of maintenance activities for components and systems identified by the results of PRA resulted in fewer prescriptions in maintenance processes (Modarres, 2009). In the nuclear RIR framework, cost was not explicitly addressed, however, implicit considerations of cost through public exposure as dollar per person-rem and offsite property damage, are used in the justification of safety enhancements and licensing actions (NRC, 1984, 1997) in three NRC guidance documents including NUREG/BR-0058 (NRC, 2004b), NUREG/BR-0184 (NRC, 1997), and NUREG-1409 (NRC, 1990a). In 2012, NUREG 2150 proposed an update to the regulatory framework, highlighting potential uses of CBA in more regulatory activities (Apostolakis et al., 2012). The proposed additions include; performing CBA for design-enhancement considerations by analyzing a larger set of accident scenarios, and using CBA in deliberation for determining policy or economic extent of exercising regulatory authority (Apostolakis et al., 2012). These recommendations did not include the cumulative benefit of RIPBAs in the CBA associated with PRA. The research initiated in this paper aims to more comprehensively consider the monetary value of PRA to support the regulatory framework and to help utilities realize the financial benefits of using PRA, thus encouraging greater investment in RIPBAs.

7.1.2. Background on Risk-Informed Performance-Based Applications

RIPBAs leverage the significant investment that is made in developing and maintaining PRA to fully utilize risk information and performance data in operational decision making to create cost savings for NPPs (Liming, 2015). RIPBAs can support decision-making for improving operational flexibility, efficiency, and strengthening regulatory-plant cooperation. A list of programs, applications and activities that use PRA to promote the efficient functioning of NPPs (Liming, 2015) include; Risk-Informed Asset Management (RIAM) (Liming & Kee, 2002), Risk-Informed Business Modeling (Liming & Grantom, 2000), On-Line Maintenance (Kee et al., 2002), Safety-Assured Maintenance Scheduling and Evaluation (Erguina, 2004), Risk-Informed Project Prioritization (Koc et al., 2009), Risk-Informed Surveillance Frequency Control (RISFC) (Gaertner et al., 2008), Risk-Informed Graded Quality Assurance (Holmberg, 2002), Risk-Informed In-Service Inspection (RI-ISI) (Corak, 2003; Mitman, 1999; Vinod et al., 2003), Risk-Informed Containment Integrated and Local Leak Rate Testing (Petti et al., 2008), Risk-Informed Fire Protection (RIFP) (Barry, 2002), Risk-Informed Plant Security Management (RISM) (Suzuki et al., 2011), Risk-Informed Resolution of Generic Safety Issue 191 (GSI-191) (Fleming et al., 2011; Mohaghegh et al., 2013; Morton et al., 2014; Sande et al., 2012), and the RMTS program (Gaertner et al., 2006; Kee et al., 2008; NEI, 2006). Section 7.1.2.1 provides a more detailed background on RMTS, which is the focus of this paper.

7.1.2.1. Background on Risk-Managed Technical Specifications

The RMTS program is one of the RIPBAs for evaluating and managing Technical Specifications (TS), a set of parameters that control the maintenance, surveillance, and repair of NPP Systems, Structures, and Components (SSCs) by defining the critical minimum functional capabilities or performance levels of equipment required for plant safety. These functional capabilities are called the Limiting Conditions for Operation (LCO) (Hess, 2009; NRC, 1992, 1995a, 2015). When the LCO are not met, safety regulations require the licensee to shut down the reactor or to follow other types of remedial actions that are commensurate with the provisions of TS. Since, initially, the regulation of LCO did not indicate any explicit timing, each licensee developed a set of time limits and specific actions when an LCO is not met. These time limits are termed the Allowable Outage Time (AOT) or Completion Time (CT). Due to the lack of standardization among plants in developing TS, the NRC established a standard or conventional TS for different reactor types in commercial service in the U.S. (NRC, 2012). Despite the plant-specific nature of the standard TS, they were developed using conservative engineering judgments (Hess, 2009; NRC, 2015). In 1995, the NRC issued a final policy statement on the use of PRA methods that utilize risk information in the specification of performance monitoring and maintenance programs applied to plant SSCs (NRC, 1995b). In 1998, and under the supervision of the Nuclear Energy Institute (NEI), the U.S. nuclear industry formed a Risk-Informed Technical Specifications Task Force (RITSTF), to identify useful risk-informed applications and develop implementation guidelines that would be acceptable to regulatory authorities. The most ambitious of these applications was RMTS (Kee et al., 2008), to specify the requirements necessary for identifying configuration-specific TSs for AOTs, and to risk-inform the plant TS. As a result of these efforts, a final RMTS methodology was published in EPRI report 1013485 (Schnider et al., 2006), which was incorporated into NEI guidance document 06-09, Risk-Informed Technical Specifications Initiative 4b: Risk-Managed Technical Specifications Guidelines (NEI, 2006). NEI 06-09 was submitted to the NRC and was approved for use at U.S. NPPs.

In 2007, RMTS was implemented at a commercial NPP in the U.S. with the purpose of providing a risk-informed approach to assign the amount of time allowed for certain equipment, within the scope of TS, to be out of service (Yilmaz et al., 2011). In RMTS, the magnitude of the Instantaneous Core Damage Probability and Instantaneous Large Early Release Probability, estimated from PRA and associated with the real-time plant configurations, is compared to specified risk thresholds in order to calculate an appropriate Risk-Informed Completion Time (RICT) to extend the prescriptive CT, or the Front-Stop (FS) (Gaertner et al., 2006). Furthermore, the RMTS program requires the development and implementation of compensatory Risk Management Actions (RMA) to mitigate the additional risks incurred due to the inoperability of TS (Gaertner et al., 2006). NEI 06-09 (NEI, 2006) specifies two configuration-specific action times that must be calculated in order to implement RMTS:

(a) Risk-Management Action Time (RMAT), which is defined as the time from discovery of a condition requiring entry into a TS action, until the threshold of 10^{-6} = Instantaneous Core Damage Frequency; or 10^{-7} = Instantaneous Large Early Release Frequency is reached. Applicable RMAs must be taken no later than the computed RMATs.

(b) The RICT, which is defined as the time interval from the discovery of a condition requiring entry into TS, until the threshold of 10^{-5} = Instantaneous Core Damage Probability or 10^{-6} = Instantaneous Large Early Release Probability is reached, or 30 days, whichever is shorter. To provide a conservative administrative limit to the RICT, an upper limit of 30 days, called the Back-Stop, is provided.

For more detailed background regarding RMTS, we refer the readers to RG 1.174 (NRC, 2011a) and RG 1.177 (NRC, 2011b), which are updated regulatory documents regarding the development of RMTS, taken from NRC's Regulatory Guides and Standard Review Plan sections focused on risk-informed applications.

7.2. METHODOLOGY TO EVALUATE THE MONETARY BENEFIT OF PROBABILISTIC RISK ASSESSMENT: DEMONSTRATION VIA MODELING THE NET VALUE OF RISK-MANAGED TECHNICAL SPECIFICATIONS

To satisfy regulatory safety goals, a basic-level of PRA usage is common in U.S. NPPs and now required for new reactor licenses (NRC, 2007). The methodology demonstrated in this section evaluates what the monetary benefits, as well as the safety regulatory compliance values, of PRA would be if NPPs would use the risk estimated from PRA, through RIPBAs, in operational decision making. This methodology provides a model-based approach to evaluate the monetary benefit of PRA by causal modeling of the net value of RIPBAs. The key steps of this methodology include:

- Step 1. CBA to formulate the net value of PRA based on the net value of RIPBAs;
- Step 2. Causal modeling to systematically model the operational scenarios considering technical, organizational, and regulatory causal factors leading to costs and benefits associated with the net value of RIPBAs;
- Step 3. Uncertainty analysis to consider parameter uncertainties and to generate probabilistic estimates of the net value of RIPBAs;

- Step 4. Sensitivity analysis and validation to rank the criticality of factors and to support model validation.

These methodological steps are applicable for all RIPBAs; however, they are explained in the following sub-sections through their implementation for RMTS.

7.2.1. Cost-Benefit Analysis

Based on the principles of CBA (Arrow et al., 1997; Kopp et al., 1997; Shapiro, 2011; Zerbe Jr et al., 2010), the Net Value ($\mathrm{NV}_{(\cdot)}$) of PRA in year t ($\mathrm{NV}_{\mathrm{PRA\_t}}$) and its Present Value (PV) are formulated by Eqs. 7.1 and 7.2, respectively:

$$NV_{PRA\_t} = \sum_{i=1}^{N} B_{i\_k\_t}^{o} + B_{PRA\_t}^{r} + \sum_{i=1}^{N} B_{i\_k\_t}^{r} - \sum_{i=1}^{N} C_{i\_k\_t}^{a} - C_{PRA}^{b}\,, \tag{7.1}$$

$$PV\big(NV_{(\cdot)}\big) = \sum_{t=1}^{n}\big(NV_{(\cdot)} \times (1+r)^{-t}\big), \tag{7.2}$$

where;

- $\mathrm{B}_{\mathrm{i\_k\_t}}^{\mathrm{o}}$ is the operational monetary benefit from using a RIPBA of type (i) in year t, when it is used k times in year t at the NPP;
- $\mathrm{B}_{\mathrm{PRA\_t}}^{\mathrm{r}}$ is the monetary benefit from avoiding rare events/severe accidents by having a basic-level PRA (without having any RIPBAs) in year t;
- $\mathrm{B}_{\mathrm{i\_k\_t}}^{\mathrm{r}}$ is the monetary benefit from avoiding rare events/severe accidents due to the contribution of a RIPBA of type (i) in the change in risk in year t, when the application is used k times in year t;
- $\mathrm{C}_{\mathrm{i\_k\_t}}^{\mathrm{a}}$ is the cost of developing and maintaining a RIPBA of type (i) in year t, when the application is used k times in year t;
- $\mathrm{C}_{\mathrm{PRA}}^{\mathrm{b}}$ is the annual cost[†] of developing and maintaining the basic-level PRA usage at a given NPP;
- "n" represents the number of years until the end of the NPP license life;
- "t" is the year index, and t=1,2, …,n;
- "r" is the annual rate of return, and;
- "i" is the index for types of RIPBAs at a nuclear power plant, and i=(1, 2, …, N).

The annual cost of developing and maintaining basic-level PRA usage ($\mathrm{C}_{\mathrm{PRA}}^{\mathrm{b}}$) can be extracted from the financial data of NPPs. The main conceptual difference between $\mathrm{B}_{\mathrm{PRA\_t}}^{\mathrm{r}}$ and the other two

[†] This refers to the average annual costs considering the initial costs in developing PRA and yearly maintenance costs.

monetary benefit terms ($B^{o}_{i\_k\_t}$ and $B^{r}_{i\_k\_t}$) in Eq. 7.1 is that $B^{r}_{PRA\_t}$ is the monetary benefit from a basic-level PRA usage (i.e., for a plant without any RIPBA), which is common in U.S. NPPs and now required for new reactor licenses (NRC, 2007) to satisfy regulatory safety compliance, while $B^{o}_{i\_k\_t}$ and $B^{r}_{i\_k\_t}$ are the monetary benefits from RIPBAs, which are beyond basic-level PRA compliance, and where the plant can implement them to enhance the value of PRA. The commonality between $B^{r}_{PRA\_t}$ and $B^{r}_{i\_k\_t}$ is that both relate to the monetary benefits of avoiding costs associated with catastrophic failures. $B^{r}_{PRA\_t}$ is related to the contribution of a basic-level PRA to accident prevention and $B^{r}_{i\_k\_t}$ relates to the amount of change in risk, and therefore, in a reduction of the cost of catastrophic accidents associated with RIPBAs. When implementing the RIPBA, if there is no change in the risk of the plant, i.e., no change from the basic risk of the plant without any RIPBAs, $B^{r}_{i\_k\_t}$ is "zero". Due to changes in some operating conditions by using RIPBAs (compared to conditions without RIPBAs), there may be changes in risk, leading to a positive or negative value of $B^{r}_{i\_k\_t}$.

Estimating the monetary benefit of PRA as a result of avoiding rare events/severe accidents ($B^{r}_{PRA\_t}$) has some challenges, similar to the ones that studies using CBA have highlighted in other contexts (Sunstein, 2009), due to uncertainties in estimating the probability of "rare" events and also due to uncertainties in evaluating the long-term consequences of severe accidents. The frequency of a rare/severe catastrophic event is represented by the Large Early Release Frequency (LERF) estimated from PRA, therefore, $B^{r}_{PRA\_t}$ can be estimated as a function of LERF and an average value from existing short- and long-term cost estimates of severe nuclear accidents. NUREG/BR-0184 explored average estimates for short- and long-term costs, using Murphy's and Holter's estimates for low, best, and high (10,000 per person-rem; 20,000 per person-rem; and 30,000 per person-rem; respectively) (Murphy & Holter, 1982). Murphy and Holter took into account the following elements in their estimates: (i) a cost of \$2,000 per person-rem conversion value, (ii) a \$1.1E+9 (in 1993 dollars) base value cost considering cleanup and decontamination, (iii) years required to return site to pre-accident state, and (iv) real discount rate (NRC, 1997). Cleanup costs ranged from \$3.1E+8 (lower bound) to \$1.1E+9 (upper bound), while short-term onsite damage costs started at \$2.3E+10, continuing at a discounted rate (NRC, 1997). These estimates of exposure rates and costs are partially based on the Price-Anderson Act, which helps determine liability insurance estimates from public or property damage claims. The NRC's CBA guidelines are being updated to reflect new determinations, probabilities and uncertainties in existing policies (Apostolakis et al., 2012), while additional research is being conducted to estimate the cost of severe accidents (Pascucci-Cahen & Patrick, 2012; Silva & Okamoto, 2016).

The operational benefit ($B^{o}_{i\_k\_t}$) of an RIPBA is a function of (i) increase in revenue due to avoiding the revenue loss that a plant without the RIPBA would have, but could be avoided, if the plant had the RIPBA, and (ii) operational cost-savings due to avoiding the costs that a plant without the RIPBA would have, but could be avoided, if the plant had the RIPBA. For example, as explained in Section 7.1.2.1., RMTS is an RIPBA that quantitatively assesses the risk of taking plant equipment out of service prior to performing maintenance, where a RICT is used instead of relying on the prescribed Allowed Outage Time (AOT) (Kee et al., 2008). The possibility of a longer outage period, by utilizing RICT, provides operational flexibility, and therefore; (i) increases production (revenue) by avoiding unnecessary shut downs, which a plant without RMTS would have due to passing the prescribed AOT, while maintaining safety requirements, and (ii) avoids some additional costs such as outage and regulatory costs (Kee et al., 2008; NEI, 2006). Another example of a RIPBA is the risk-informed resolution of Generic Safety Issue 191 (Kee et al., 2016; Mohaghegh et al., 2013), where, by using risk information, the NPP avoided changing the insulation around the reactor coolant system, i.e., avoided having to be limited to standard options for insulation, which reflected increased operational flexibility. While still satisfying the safety requirements of the NRC, the costs associated with changing the insulation were avoided (Kee et al., 2016).

The rest of this paper focuses on explaining the next steps of the method through its implementation for RMTS. Adopting the cost and benefit terms associated with RIPBAs in Eq. 7.1, including the first, third and fourth terms on the right side of Eq. 7.1, and assuming the net value constant (averaged) with respect to time, the net value of RMTS can be estimated based on Eq. 7.3. Utilizing Eq. 7.2 and assuming the net value constant (averaged) with respect to time, the present value RMTS can be estimated from Eq. 7.4.

$$NV_{RMTS\_k} = B^{o}_{RMTS\_k} + B^{r}_{RMTS\_k} - C^{a}_{RMTS\_k} \quad (7.3)$$

$$PV\left(NV_{RMTS\_k}\right) = NV_{RMTS\_k} \times \left(\frac{1-(1+r)^{-n}}{r}\right) \quad (7.4)$$

where NV_{PRMTS_k} stands for the annual net value of RMTS, $B^{o}_{RMTS\_k}$ is the annual operational monetary benefit from using RMTS, $B^{r}_{RMTS\_k}$ is the annual monetary benefit from avoiding rare events/severe accidents due to the contribution of RMTS in the change in risk, and $C^{a}_{RMTS\_k}$ is the annual cost of developing and supporting RMTS. All terms in Eqs. 7.3 and 7.4 are based on the consideration that RMTS is used “K” times, on average, per year. The next step of the method is focused on modeling and quantifying the terms in Eq. 7.3.

7.2.2. Causal Modeling for Net Value of Risk-Informed Performance Based Applications

In this research, causal modeling techniques are utilized to model the influencing factors affecting cost and benefit terms in the net value of RIPBAs, and in this case, the net value of RMTS in Eq. 7.3. Integrating causal modeling with CBA allows for (a) more accurate consideration of uncertainties, (b) sensitivity analysis to analyze the effects of change in the underlying causal factors associated with the monetary value, and (c) evaluation of the effects of dependencies due to shared causal factors (i.e., technical, organizational and regulatory factors) among multiple RIPBAs and between two performance outcomes of profit and safety.

In this research, a causal model (Figure 7.2) is developed to visualize the interrelationships among the causal factors influencing the cost and benefit terms of RMTS (formulated in Eq. 7.3). As stated in Section 7.2.1., the annual operational benefit of RMTS in this research is estimated by the amount of costs and revenue losses in a “plant without RMTS” that may be avoided if the plant uses RMTS, while the annual costs of RMTS are estimated based on a “plant with RMTS”, and therefore, at the lowest level of the causal model (Figure 7.2), operational conditions of the plant “with” and “without” RMTS are separated. Because of the changes in some operational conditions, the plant using RMTS may lead to a change in risk, as Figure 7.2 shows, while satisfying regulatory risk/safety requirements. Part of the causal model (presented in Figure 7.2) is quantified in this research utilizing Decision Tree (DT) (Magee, 1964) (Figure 7.3). The scope of DT is also highlighted by the module with the dotted outline in Figure 7.2. Future research will focus on quantifying other parts of Figure 7.2 to analyze and balance the effects of RMTS on both safety/risk and monetary value in a unified causal modeling framework.

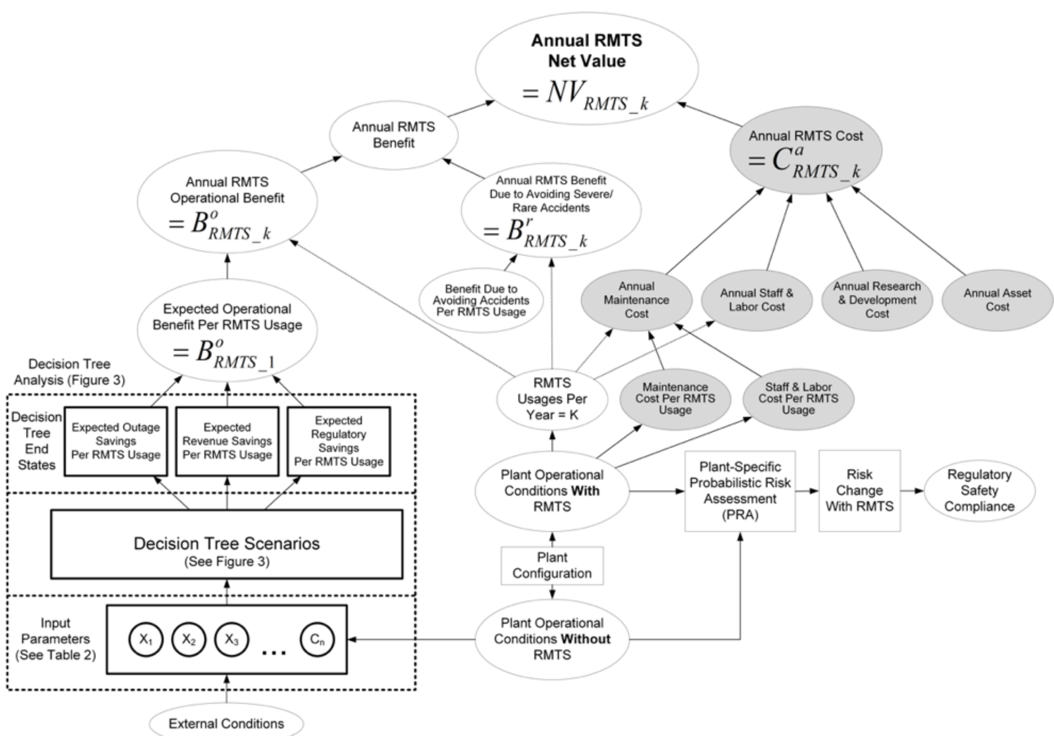

Figure 7.2: Causal Modeling of the Net Value of Risk-Managed Technical Specifications and the Interactions with PRA

The target node of the causal model in Figure 7.2 is the net value of RMTS, which refers to NV_{RMTS_k} in Eq. 7.3. The next layer of this causal model consists of the cost ($C^{a}_{RMTS\_k}$) and benefit ($B^{o}_{RMTS\_k}$ and $B^{r}_{RMTS\_k}$) terms as reflected in Eq. 7.3. The next supporting causal layers are developed based on the theoretical and operational information of RMTS. As Figure 7.2 shows, the cost of RMTS relates to (a) maintenance, (b) staff and labor, (c) research and development, and (d) assets. The 'maintenance cost' is associated with supporting the RMTS software. The staff and labor costs relate to the administrative costs associated with running the risk calculations from PRA and reviewing PRA model updates that are needed for the RMTS program. The first two cost categories (a and b) increase based on the number of "RMTS Usages Per Year", which refers to index "K" in Eq. 7.3, while the other two (c and d) are the initial costs of establishing RMTS, which are distributed over the life of the plant to find annual costs. At this stage of the research, due to lack of adequate information, the "cost side" factors (grey nodes) in Figure 7.2 are not quantified in detailed layers of causality, and instead, the annual cost of developing and maintaining RMTS ($C^{a}_{RMTS\_k}$) is used as a lump sum and is based on information from industry experts.

On the benefit side (white nodes) of Figure 7.2, the causal term $B^{r}_{RMTS\_k}$ refers to the benefit of RMTS by its contribution to the reduction of risk, and therefore, to the avoidance of rare events/severe accidents. As explained in Section 7.2.1., $B^{r}_{i\_k\_t}$ can be positive, negative or zero, depending on the nature of the RIPBA, and the change in the operating conditions of the plant due to the RIPBA. Applying RMTS allows for online maintenance of inoperable SSCs within the scope of TS, therefore, risk has the potential to increase, resulting in a negative value for $B^{r}_{RMTS\_k}$. There are, however, several aspects that may lead to reduction or no change in risk due to RMTS. Implementation of RMTS requires the employment of compensatory RMAs at specific times, according to RICT and RMAT thresholds, to mitigate additional risk incurred due to the inoperability of TS. Both the conventional TS thresholds and the thresholds for RICT and RMAT are established deterministically and in accordance with the defense-in-depth philosophy (NEI, 2006); therefore, the change in the value of risk due to the application of RMTS may represent a fairly small number when RMTS applications are compared to cases of similar TS following standard or conventional TS requirements. In addition, a longer period of maintenance in RMTS can increase the overall quality of maintenance, and therefore, can increase component reliability. However, the maintenance quality is not "explicitly" incorporated in plant PRA, and the estimated risk of the plant may not adequately reflect the effects of maintenance quality (Mohaghegh, 2007, 2010b). Therefore, at this stage of the research, $B^{r}_{RMTS\_k}$ is not considered.

In Figure 7.2, RMTS Operational Benefit ($B^{o}_{RMTS\_k}$) is decomposed into three causal factors:

(i) Revenue Savings: Avoiding loss of revenue due to shut down (mid-cycle outage) required by TS;

(ii) Regulatory Savings: Avoiding the cost of developing and filing a Notice of Enforcement Discretion (NOED);

(iii) Outage Savings: Avoiding extended outage costs (in addition to avoiding the loss of revenue during the extended outage).

As explained in Section 7.1.2.1., RMTS allows the NPP maintenance staff to exceed the FS or prescribed AOT and makes more time available to perform maintenance with the plant at-power without a significant increase in risk. This results in the prevention of unnecessary plant shutdowns that occur due to low-risk, in-service failures, thereby creating Revenue Savings (Belyi et al., 2009). Through the use of RMTS, an extra operational envelope and maintenance flexibility are justifiable to the regulator, hence, the second category of RMTS operational benefits relate to Regulatory Savings that include the reduction of support costs for licensing, engineering, and risk management needed to prepare an NOED for the NRC (NRC, 2013). The third category of RMTS operational benefits relate to the reduction of costs during the plant extended outage, in addition to the avoidance of loss of power during the extended outage. Because the plant has normal staffing levels that may be set to meet "unexpected" maintenance (e.g., emergent or upset conditions), during power operation, such staff can address maintenance during regular working hours that otherwise would be on overtime during an outage or require longer outage duration. These Outage Savings increase when the number of maintenance extended outages that come close to exceeding the FS in the TS could be planned more effectively using RMTS. In such cases, the plant would benefit by having the capacity for more deliberate problem solving, and if needed, RMTS could provide staff with more time for maintenance activities (Yilmaz et al., 2011).

As the module with the dotted outline in Figure 7.2 shows, DT analysis is used to quantify causal relationships associated with Operational Benefit per RMTS usage ($B^{o}_{RMTS\_1}$). DT was chosen because detailed information regarding the mechanisms of causality is available to generate the scenarios leading to costs and losses of revenue. Figure 7.3 shows the DT that depicts operational scenarios, including cost scenarios associated with Regulatory cost and related to Outage cost, and Revenue loss scenarios due to mid-cycle shutdowns for a plant without RMTS. The summation of the end states of the DT, covering all the potential costs and revenue losses (with consideration of the probability of each scenario) that can be avoided if RMTS is used once, provides an estimate of the expected operational benefit per RMTS usage ($B^{o}_{RMTS\_1}$). As Figure 7.2 indicates, the annual Operational Benefit of RMTS ($B^{o}_{RMTS\_k}$) is a function of the number of "RMTS Usages Per Year=K" for a plant with RMTS and the value of expected Operational Benefit per RMTS usage ($B^{o}_{RMTS\_1}$), estimated from the DT.

Figure 7.3: A Decision Tree to Model Operational Benefits of Risk-Managed Technical Specifications (RMTS)

The two main scenarios in the DT (Figure 7.3) are: (1) Emergent Maintenance, and (2) Planned Maintenance. The top branch (Emergent Maintenance) includes paths where maintenance can or cannot be completed before the FS is exceeded, occurring either in peak season, from June 1 to September 30, or off-peak season. When the time exceeds the FS, an NOED must be submitted to the NRC to obtain approval and avoid a shutdown. The distinction of peak or off-peak season is important to the success of NOED approval. Taking the plant off-line during a high electrical load may lead to grid instability. In the case where the NOED is not granted, the cost of preparation of the NOED, plus the impact of lost revenue, would be incurred. If the NOED is granted, the plant may continue to operate and only the cost of the NOED application would be incurred. The plant also has the option of shutting down, and in this case, there would not be any cost of the NOED application, but the impact of the lost revenue would be realized.

In the Planned Maintenance branch of the DT (Figure 7.3), the plant would enter a maintenance activity (e.g., surveillance of a planned equipment upgrade) with the assumption that maintenance would be completed within the FS. As shown in Figure 7.3, an unexpected issue may arise during the planned activity that extends the time for completion beyond the FS, resulting in the same decision branches that were developed for the Emergent Maintenance branch previously described. Alternatively, the maintenance may be completed within the FS, but due to expediting the activity to achieve completion within the FS, it may increase the likelihood of emergent maintenance sometime after finishing the Planned Maintenance. In other words, rushing Planned Maintenance may lead to lower quality maintenance and that may lead to an increase in the likelihood of emergent maintenance. Again, in this case, similar decision branches described for Emergent Maintenance would result. However, if repairs work well for the duration of the operating cycle, then no additional costs would result. On the other hand, some maintenance may need to be deferred to the outage, resulting in outage costs that are incurred for the extension of the outage plus the revenue lost due to the outage extension. Not all such costs may be directly attributable to the deferred maintenance as it is possible that emergent conditions during the outage may result in an extended outage duration thereby "shadowing" or sharing the cost for the extended duration.

Eqs. 7.5 through 7.10 formulate $B^{o}_{RMTS\_1}$ based on Figure 7.3. Utilizing the scenarios in the DT, $B^{o}_{RMTS\_1}$ is the summation of the expected monetary loss for each scenario "i" (Y_i), in a plant without RMTS, that could potentially be avoided if the plant had RMTS, and used RMTS in each scenario i=1, 2, 3…, 22. In other words, Y_i, is the expected operational benefit associated with scenario "i" and in a plant with RMTS.

$$B^{o}_{RMTS\_1} = Y = \sum_{i=1}^{i=22} Y_i \qquad (7.5)$$

Equations that are placed at the end states of scenarios in Figure 7.3, formulate Y_i for each scenario. Y_i can be estimated from the multiplication of the conditional probability of each scenario and the dollar loss associated with each scenario. Table 7.1 provides the description of the input variables related to the DT in Figure 7.3. In scenarios #7, 20, and 22, using RMTS would not add savings, lower costs, or avoid revenue losses, and so there would not be any RMTS operational benefit associated with these scenarios.

$$Y_7 = Y_{20} = Y_{22} = 0 \qquad (7.6)$$

In the cases of scenarios #1, 4, 8, 11, 14, and 17, using RMTS could lead to Regulatory Savings by avoiding the NOED cost. The expected operational benefit (Y_i) associated with each of these scenarios is the multiplication of the cost of NOED (C) and the conditional probability of each of the scenarios. Eq. 7.7 formulates the expected operational benefit related to scenario #1. Similarly, the operational benefits from scenarios # 4, 8, 11, 14, and 17 can be estimated from the equations that are presented at the end states of the associated scenarios in Figure 7.3.

$$Y_1 = X_1 * X_2 * X_{14} * X_3 * X_4 * C \qquad (7.7)$$

In the case of scenarios #3, 6, 10, 13, 16, and 19, if the plant were to use RMTS, it would lead to Revenue Savings by avoiding revenue loss. To estimate the avoided revenue loss, we consider that if a reactor is required to shut down due to TS, it would be a specific mid-cycle outage duration (X_{11}) associated with each of these scenarios. If the average net electrical production of the fleet is considered as P, the production loss associated with a TS shutdown would be "($X_{11} * P$)". Assuming an average net revenue from electricity sales as X_{13}, the expected revenue loss for a shutdown in scenarios #3, 6, 10, 13, 16, and 19 would be the multiplication of "($X_{13} * X_{11} * P$)" and the conditional probability of each of these scenarios. Eq. 7.8 formulates the expected operational benefit related to scenario #3. Similarly, the operational benefits from scenarios # 6, 10, 13, 16, and 19 can be estimated from the equations that are presented at the end states of the associated scenarios in Figure 7.3.

$$Y_3 = X_1 * X_2 * X_{14} * (1 - X_3) * (X_{13} * X_{11} * P) \qquad (7.8)$$

In the case of scenarios # 2, 5, 9, 12, 15, and 18, if the plant were to use RMTS, it would lead to both Regulatory Savings and Revenue Savings by avoiding the cost of the NOED and the lost revenue. Eq. 7.9 formulates the expected operational benefit related to scenario #2. Similarly, the operational benefits from scenarios # 5, 9, 12, 15, and 18 can be estimated from the equations that are presented at the end states of the associated scenarios in Figure 7.3.

$$Y_2 = X_1 * X_2 * X_{14} * X_3 * (1 - X_4) * [C + (X_{13} * X_{11} * P)] \qquad (7.9)$$

In scenario #21, if the plant would use RMTS, it would lead to Revenue Savings and Outage Savings by avoiding both revenue loss and the cost of extended outage. The expected revenue loss for this scenario can be estimated by the multiplication of "$(X_{13} * X_{12} * P)$" and the conditional probability of this scenario. It should be noted that the duration of extended outage (X_{12}) is different (usually smaller) than the mid-cycle outage duration (X_{11}). The expected cost of an outage is estimated by multiplying the average cost of the outage per hour (C_o), the duration of extended outage (X_{12}), and the conditional probability of this scenario. To estimate the expected operational benefit of RMTS for scenario #21, the summation of expected avoided revenue loss and expected avoided cost of the outage is multiplied by a shadowing percentage (S). Shadowing percentage is considered because only a specific percentage of outage duration is related directly to the deferred maintenance. Eq. 7.10 formulates the expected operational benefit related to scenario #2.

$$Y_{21} = (1 - X_1) * (1 - X_7) * (1 - X_8) * X_{10} * [S * ((X_{13} * X_{12} * P) + (C_o * X_{12}))] \quad (7.\ 10)$$

Table 7.1: Description of Input Variables for Figure 7.3 and for Eqs. 7.3 to 7.10

Parameter	Description	Point Estimates	Distributions
X_1	Conditional probability of emergent maintenance, given a maintenance ‡	-	Uniform (0.025, 0.075)
X_2	Conditional probability of passing Front-Stop, given emergent maintenance	-	Uniform (0.009, 0.011)
X_3	Conditional probability of filing the NOED, given peak season and when Front-Stop is passed in an emergent maintenance (or a planned maintenance)	-	Uniform (0.985, 0.995)
X_4	Conditional probability of NOED approval, given peak season and when Front-Stop is passed in an emergent maintenance (or a planned maintenance)	-	Uniform (0.985, 0.995)
X_5	Conditional probability of filing NOED, given off season and when Front-Stop is passed in an emergent maintenance (or a planned maintenance)	-	Uniform (0.54, 0.66)
X_6	Conditional probability of NOED approval, given off season and when Front-Stop is passed in an emergent maintenance (or a planned maintenance)	-	Uniform (0.2, 0.6)
X_7	Conditional probability of passing the Front-Stop in planned maintenance	-	Uniform (0.005, 0.015)

‡ This probability excludes the emergent maintenance generated due to rushed planned maintenance.

Table 7.1 (cont.)

Parameter	Description	Point Estimates	Distributions
X_8	Conditional probability of occurrence of emergent maintenance, following a rushed planned maintenance, and when Front-Stop is not passed[§]	-	Uniform (0.009, 0.011)
X_9	Conditional probability of passing Front-Stop, given occurrence of emergent maintenance, following a rushed planned maintenance, and when Front-Stop is not passed	-	Uniform (0.855, 0.945)
X_{10}	Conditional probability of extended outage, given no increase in emergent maintenance and when Front-Stop is not passed in a planned maintenance	-	Uniform (0.01, 0.03)
X_{11}	Mid-cycle outage duration (hour)	-	Triangular (0, 96, 48)
X_{12}	Extended outage duration (hour)	-	Uniform (12, 36)
X_{13}	Electricity price ($/MW-hour)	-	14.0 + Gamma (4.63, 3.35)[**]
X_{14}	Probability of peak season	-	Uniform (0.425, 0.575)
S	Average shadowing percentage	0.35	-
C_o	Average outage cost per hour ($/hour)	25,000	-
P	Average net electrical production (MW)	900	-
C	Average cost of filing NOED ($)	10,000	-
K	Average RMTS Usages Per Year	10	-
n	Number of years until the end of the NPP license life	20	-
r	Interest Rate	0.07	-

7.2.3. Uncertainty Analysis

To find the probabilistic monetary value of PRA, uncertainty analysis is required for all the terms in Eq. 7.1. In this paper, however, the methodology is explained through the estimation of the probabilistic monetary value of RMTS, which is one of the RIPBAs in Eq. 7.1. To estimate the probabilistic monetary value of RMTS, uncertainty analysis is required for the terms in Eq. 7.3. As stated in Section 7.2.2, in this research, among the three terms in Eq. 7.3, $B^r_{RMTS\_k}$ has not been considered, and $C^a_{RMTS\_k}$ is considered only as an average value point estimate with no consideration of uncertainty. This section is focused on the probabilistic estimation of the third term in Eq. 7.3, the annual RMTS Operational Benefit ($B^o_{RMTS\_k}$), utilizing the DT model (Figure 7.3), explained in Section 7.2.2. In this

[§] This probability is suggested by an industry expert considering the reduced percentage of emergent maintenance in the plant with RMTS, compared with the one without RMTS.
[**] U.S. Energy Information Administration: https://www.eia.gov/electricity/wholesale/

study, the number of "RMTS Usages Per Year" is considered as an average value (a point estimate of K=10, rather than a distribution), based on information from plant experts, therefore, uncertainty analysis is focused on the expected Operational Benefit Per RMTS ($B^o_{RMTS\_1}$) utilizing Eqs. 7.5 to 7.10 (as well as the associated equations presented at the end states of each scenario in Figure 7.3). At this stage of the research, an approximate value of $B^o_{RMTS\_k}$ is estimated by the multiplication of "K" and ($B^o_{RMTS\_1}$).

The uncertainty analysis process in this research covers two key elements: (i) Uncertainty characterization that relates to developing probability distributions for the input variables of Eqs. 7.5 to 25, and (ii) Uncertainty propagation in Eqs. 7.5 to 7.10 (as well as the associated equations presented at the end states of each scenario in Figure 7.3) to develop a distribution for $B^o_{RMTS\_1}$. Table 7.1 provides the distributions considered for the input variables in this research. The ranges and distributions of input parameters are derived from information provided by plant experts. Because of limited information, a uniform distribution is utilized for most of the input parameters with upper and lower bounds being set to the maximum and minimum values based on expert opinion. In the case of mid-cycle outage duration (X_{11}), the triangular distribution is used based on the plant expert's suggestion. Gamma distribution is also fitted (utilizing Kolmogorov-Smirnov goodness-of-fit test and outlier analyzer) to electricity price data from the U.S. Energy Information Administration (see Table 7.1) to develop the distribution of X_{13} (EIA, 2017).

Regarding uncertainty propagation, Monte Carlo simulation is conducted to propagate input parameter uncertainties through Eqs. 7.5 to 7.10 (as well as the associated equations presented at the end states of each scenario in Figure 7.3) to develop the uncertainty distribution for the expected Operational Benefit per RMTS ($B^o_{RMTS\_1}$). Table 7.2 provides the expected values and 95% Confidence Intervals for $B^o_{RMTS\_1}$ and $B^o_{RMTS\_k}$ (considering K=10). Figure 7.4 shows a histogram for the distribution of $B^o_{RMTS\_1}$ that has a short right tail, meaning its value is rarely larger than \$50,000.

As Table 7.2 highlights, the expected value of $B^o_{RMTS\_1}$ is estimated as \$17,386. Using this number in Eq. 7.3, and assuming "$B^r_{RMTS\_k} = 0$" and considering the annual cost of RMTS ($C^a_{RMTS\_k}$) equal to \$35,000*, the annual net value of RMTS (NV_{RMTS_k}) is estimated as \$138,860. Utilizing this value in Eq. 7.4 and considering interest rate/year (r) equal to 0.07 as recommended by NUREG/BR-0184 (NRC, 1997), and a 20-year remaining-life license (n), the PV of RMTS is estimated at \$1,470,000. Table 7.2 also provides a net benefit-cost ratio of 3.97, serving as a useful way to summarize the economics of the RMTS application.

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* Based on information from industry experts and considering that RMTS has a one-time initial investment with recurring operating costs, observed as an aggregated annual value.

Table 7.2: Probabilistic Monetary Value of RMTS

Variable	Value
Expected Operational Benefit Per RMTS: $B^{o}_{RMTS\_1}$	\$17,386.00
$B^{o}_{RMTS\_1}$ Standard Deviation	\$6,397.40
$B^{o}_{RMTS\_1}$ Lower CI Boundary	\$17,382.00
$B^{o}_{RMTS\_1}$ Upper CI Boundary	\$17,390.00
RMTS Annual Cost: $C^{a}_{RMTS\_k}$	\$35,000.00
RMTS Annual Operational Benefit: $B^{o}_{RMTS\_k}$	\$170,386.00
RMTS Annual Net Value: NV_{RMTS_k}	\$138,860.00
PV of RMTS Annual Net Value: $PV\left(NV_{RMTS\_k}\right)$	\$1,470,000.00
RMTS Net-Earning-to-Cost Ratio	3.97

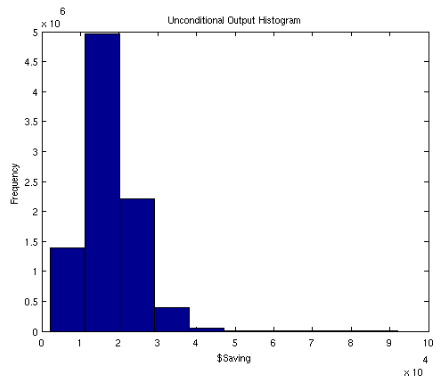

Figure 7.4: Distribution of the Expected Operational Benefit Per RMTS Usage ($\mathrm{B}^{\mathrm{o}}_{\mathrm{RMTS\_1}}$)

7.2.4. Sensitivity Analysis and Validation

In PRA, verification is typically used more than validation. Verification covers a process of independent oversight with a critical review of models and methodologies following regulatory standards (NRC, 2009). To achieve partial verification, the method and the case study demonstrated in this paper have been reviewed by academic and industry experts of RMTS. Partial empirical validation, using NPP financial records, is also included in this research. NPPs that use RIPBAs present the operational benefit of PRA, labeled risk savings, within the scope of their accounting statements issued at the end of each fiscal period. For example, Table 7.3 shows an average value of \$704,773 in the plant's risk savings per year from 2008 to 2013. Based on the opinions of industry experts, the operational benefit from the RMTS application is approximately 25% of the annual risk savings of a plant. The operational benefit of RMTS, therefore, according to the NPP fiscal reports and expert opinion, is approximately \$176,193, which is reasonably close to the expected RMTS annual operational benefit estimated using the methodology of this research, \$170,386, as listed in Table 7.2.

Table 7.3: NPP Reported Risk Savings

Year	Historical Recurring Totals	Historical One-Time Totals
2008	\$10,400	-
2009	\$87,680	-
2010	\$125,400	-
2011	\$149,800	\$2,594,185
2012	\$175,400	\$73,800
2013	\$182,400	\$124,800
Total	\$731,080	\$2,792,785

Total Historical Savings (2008-2013)	Average Savings Per Year
\$3,523,685	\$704,773

In this research, Global Sensitivity Analysis (GSA) is also conducted to analyze the effects of change in the causal factors associated with $B^{o}_{RMTS\_1}$. GSA provides a means to evaluate the contribution of each input parameter to the total uncertainty associated with the model output (Sakurahara et al., 2014). Instead of a local (one-way) sensitivity analysis, GSA is applied to take the following three aspects into consideration when ranking the causal factors: (i) uncertainty associated with the input parameters, (ii) nonlinearity and interactions among input parameters within the model, and (iii) uncertainty associated with the model output. In GSA, the sensitivity indicator S_i^{CDF} (Liu & Homma, 2010) is used to rank the input parameters according to their impact on the Cumulative Distribution Function (CDF) of the model output. Assuming the model output "Y" in Eq. 7.5, as a function of its input parameters X= (X_1, X_2,…, X_{14}), and using the Monte Carlo method, the input parameters are randomly sampled from their distributions provided in Table 7.1, producing the unconditional model output. This is followed by quantification of the empirical CDF of Y, denoted as F_Y. To estimate the conditional output, a two-loop Monte Carlo method is utilized. In each simulation, input parameter X_i is randomly sampled from its distribution, determining the random value of X_i^* (first Monte Carlo loop), while the other input parameters are being randomly sampled from their distributions (second Monte Carlo loop), producing the CDF for the conditional output denoted as $F_{Y|X_i}(Y)$. Next, by integrating the absolute difference between F_Y and $F_{Y|X_i}(Y)$, the area closed by F_Y and $F_{Y|X_i}(Y)$ is measured. This is denoted by $A(X_i)$ and is described in Eq. 7.11.

$$A(X_i) = \int | F_{Y|X_i}(y) - F_Y(y)|dy \quad (7.11)$$

Random samples of X_i^* are obtained and $A(X_i)$ is replicated; Eq. 7.12 demonstrates the expected difference between F_Y and $F_{Y|X_i}(Y)$, where $f_{x_i}(X_i)$ denotes the marginal density function of input parameter X_i.

$$E[A(X_i)] = \int f_{x_i}(X_i)A(X_i)dx_i \qquad (7.12)$$

The moment-independent, and CDF-based sensitivity indicator S_i^{CDF} is derived from Eq. 7.13, where $E(Y)$ is the expected value of the unconditional model output Y.

$$S_i^{(CDF)} = \frac{E[A(X_i)]}{|E(Y)|} \qquad (7.13)$$

Using the two-loop GSA framework, CDF-based sensitivity indicators are produced for input parameters of the model. Table 7.4 reports on the sensitivity indicators associated with input parameters (X_1, X_2,…,X_{14}). As shown in Table 7.4, GSA indicates that input parameters X_{11} (Mid-cycle outage duration), X_{10} (Conditional probability of extended outage, when Front-Stop is not passed in a planned maintenance), X_{12} (Extended outage duration) and X_{13} (Electricity price) are ranked as the most important contributors to the uncertainty of the model output.

Table 7.4. Sensitivity Indicators for Input Parameters of the Expected Operational Benefit Per RMTS ($B^o_{RMTS\_1}$)

Ranking	**S_i**	**X_i**
1	1.847E-01	X_{11}
2	1.172E-01	X_{10}
3	1.172E-01	X_{12}
4	1.006E-01	X_{13}
5	0.671E-01	X_7
6	0.405E-01	X_6
7	0.376E-01	X_{14}
8	0.127E-01	X_8
9	0.102E-01	X_1
10	0.091E-01	X_5
11	0.075E-01	X_9

Table 7.4 (cont.)

12	0.047E-01	X_4
13	0.047E-01	X_3
14	0.045E-01	X_2

7.3. DISCUSSION

The results of GSA can be used to check the accountability of DT model results for the Operational Benefits of RMTS. It should be noted that an underlying assumption in developing the DT for RMTS considers all potential costs and revenue losses that the NPP would incur in the absence of RMTS, and with a level of uncertainty, links them to the Operational Benefit of the application. On the other hand, the objective of the RMTS application is to risk-inform the Completion Time (CT) for several critical Systems, Structures, and Components (SSCs). Therefore, one could conclude that reducing the mid-cycle outage duration, X_{11}, is the goal of the RMTS application, making this input parameter the most important contributor to the variation of the RMTS output, and this is confirmed by the results of GSA.

The next step of this research should focus on conducting more accurate data analysis of NPP and NRC databases so that more objective data, in addition to expert opinion, can be used for the input parameters (Table 7.1) of the model. Distributions of input parameters will then be obtained by conducting a more structured statistical analysis, such as Bayesian inference for integrating all available information to estimate the parameters, and a goodness-of-fit test to decide if the developed probability distributions are acceptable. This would allow for a more precise development of uncertainty distributions for these parameters. As Table 7.1 shows, some of the input parameters are considered as point estimates rather than as distributions. For example, the interest rate/year (r) is considered equal to 0.07 along with a 20-year remaining-life license (n); however, future work should evaluate the effects of uncertainties in these parameters.

At this stage of the research, ($B^{r}_{RMTS\_k}$), i.e., the annual monetary benefit of RMTS from avoiding rare/severe accidents due to the contribution of RMTS in changing risk, is not quantified. Future research is needed to develop a causal model depicting the influences of the operational conditions of the plant (with RMTS) on the probabilities of the events in PRA, and ultimately, on the system risk estimated from PRA in order to have a more realistic estimate of the change in risk due to RMTS.

$B^{r}_{PRA\_t}$ is not the focus of the current paper, but the authors have started a line of research to explore the effects of regulation and catastrophic failure in terms of population response, and are expanding their framework to include NPP investors' point of view (Bui et al., 2016; Bui et al., 2017; Kee et al., 2017). Future work will dedicate research on more in-depth consideration of diverse types of uncertainties in estimating the monetary benefit of PRA as a result of avoiding rare events/severe accidents ($B^{r}_{PRA\_t}$).

Future research will also focus on quantifying other modules of the causal model in Figure 7.2. Bayesian Belief Network (BBN) (Pearl, 1988) can be a candidate causal modeling technique to facilitate further expansion of causal layers in Figure 7.2, for example: (i) Causal modeling of the annual cost of developing and maintaining RMTS ($C^{a}_{RMTS\_k}$), rather than considering a lump sum average value that is used in this paper; (ii) Causal modeling of the relationships between operational conditions of the plant with RMTS and the number of "RMTS Usages/Year =K" so that uncertainties and dependencies can be better considered. In this paper, a constant value of "K=10" is assumed; and (iii) Causal modeling of the underlying socio-technical causal mechanisms (i.e., technical, organizational, and regulatory factors), in association with the operational conditions of the plant, that influence the input parameters of the DT (Figure 7.3).

7.4. CONCLUSION

The methodology demonstrated in this research evaluates the monetary benefits of PRA by developing causal models of the net value of Risk-Informed Performance-Based Applications (RIPBAs). This methodology evaluates the monetary benefit, in addition to safety benefits, that PRA could bring to NPPs if they would utilize the risk estimated from PRA through RIPBAs to expand the operating envelope and improve operational flexibility and efficiency while maintaining safety performance or regulatory compliance, thereby strengthening regulatory-plant cooperation. The key steps of this methodology include: (i) Cost-Benefit Analysis (CBA) to formulate the net value of PRA based on the net value of RIPBAs, (ii) causal modeling to systematically model the operational scenarios considering technical, organizational and regulatory causal factors leading to costs and benefits associated with the net value of RIPBAs, (iii) uncertainty analysis to consider parameter uncertainties and to generate a probabilistic estimate of the net value of RIPBAs, and (iv) sensitivity analysis and validation. This paper demonstrates the feasibility of the methodology via its implementation for Risk-Managed Technical Specifications (RMTS), which is one of the RIPBAs used in NPPs. Based on the results, the benefit of investment in RMTS is justified from a net-positive perspective. The results of sensitivity analysis indicate that X_{11} (Mid-cycle outage duration), X_{10} (Conditional probability of extended outage, when Front-Stop is not passed in a planned maintenance), and X_{12} (Extended outage duration) are the most important input parameters, and therefore, require further data collection to increase the accuracy of the results and observations.

Although a solely data-driven approach**,** which refers to using the average monetary benefit of each application from the NPP data over several years, may provide an estimate for the monetary value of existing RIPBAs of NPPs, it cannot provide resolution on the causality of how the cost and benefit scenarios are associated with each application. Therefore, this research uses a model-based approach that integrates causal modeling with CBA, and offers the following advantages: **(1)** it allows for more accurate consideration of uncertainties in technical, organizational and regulatory factors, leading to more accurate assessment of the monetary benefit of RIPBAs and PRA, **(2)** it allows sensitivity analysis to be conducted to rank the criticality of influencing factors and to analyze the effects of change in the underlying causal factors associated with the monetary value, **(3)** it sets the stage for future research on the modeling, evaluation, and design of new RIPBAs that can balance changes in risk and the monetary gain from RIPBAs in NPPs, **(4)** it enables future research on the quantification of the effects of RIPBAs on both monetary benefits and safety (i.e., the risk estimated from PRA) in a unified modeling environment, as shown in the causal model developed in Figure 7.2, which facilitates the evaluation of dependencies due to shared technical, organizational, and regulatory causal factors among multiple RIPBAs, and between the two organizational performance outcomes of profit and safety.

The goal of demonstrating the benefit of PRA to an organization's bottom line and safety performance is supplemented by a long-term road map for delineating the market value of PRA to support wider industry adoption. A possible benefit of PRA in the heavily-regulated commercial nuclear power domain is to help show where regulatory initiatives may be unjustified based on the risk reduction against the cost of the initiative; and risk assessment can be used to show where greater benefit may be realized at less cost to the regulated industry. Although such assessments are not applicable for eliminating regulation (NRC, 2011a), they are useful for prioritizing expenditures and for making efficient use of existing resources based on safety benefit, for example under 10 CFR 50.69 (NRC, 2004a).

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CHAPTER 8: CONCLUSIONS

This dissertation is the product of my multidisciplinary and collaborative research activities as a graduate research assistant in the Socio-Technical Risk Analysis (SoTeRiA) Research Laboratory[1] in the Department of Nuclear, Plasma, and Radiological Engineering (NPRE) at the University of Illinois at Urbana-Champaign (UIUC). Figure 8.1 shows a roadmap of research activities discussed in this dissertation. The ideal goals of explicit incorporation of organizational/social factors into PRA are to; (a) make risk assessments more accurate in order to avoid underestimating or overestimating risk, and (b) improve risk management and prevention strategies by identifying and ranking critical organizational/social factors based on their influences on the technical system risk (i.e., sensitivity analysis and risk importance ranking; viii in Figure 8.1) and by evaluating their monetary impacts through Risk-Informed Performance-Based Applications (RIPBAs) (i.e., understanding the costs and benefits of RIPBAs with consideration of organizational/social factors; vii.a in Figure 8.1). Therefore, building a theoretical framework equipped with reliable modeling techniques and data analytics to quantify the influence of organizational/social performance on risk scenarios is important for improving realism in PRA and is the motivation for this research (i in Figure 8.1). This dissertation addressed the incorporation of organizational/social factors from two levels of analysis: (1) the meso-level (organizational) in Level 1 PRA (ii to iv in Figure 8.1), and (2) the macro-level (social) in Level 3 PRA (v to vi in Figure 8.1).

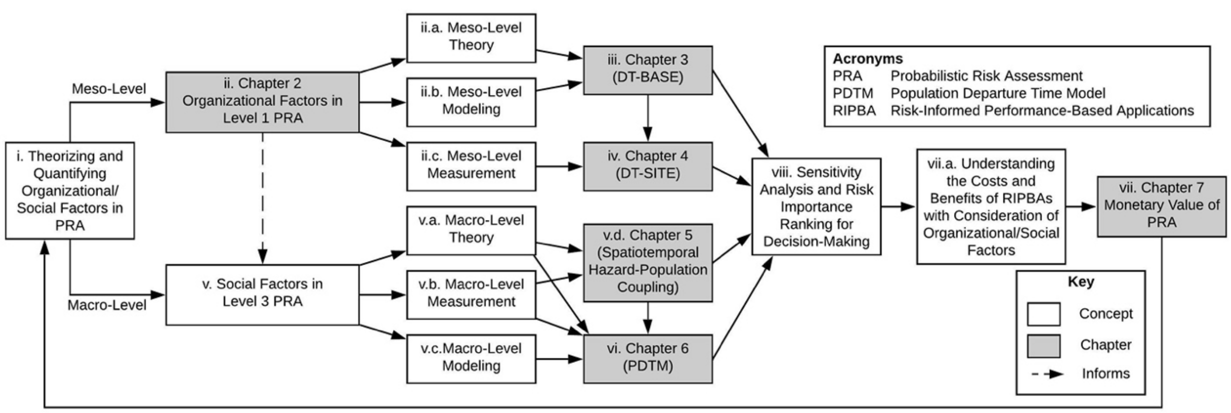

Figure 8.1: Research Roadmap

Chapter 2, a published journal paper (Pence & Mohaghegh, 2020), focused on the incorporation of organizational factors in Level 1 PRA (ii in Figure 8.1), a topic of debate since the 1980s, and conducted a comprehensive review and categorization of existing research at the meso-level analysis (i.e.,

[1] https://soteria.npre.illinois.edu/

one Nuclear Power Plant (NPP)), to summarize the current state-of-the-art and remaining challenges of meso-level theories (ii.a in Figure 8.1), meso-level modeling (ii.b in Figure 8.1), and meso-level measurement (ii.c in Figure 8.1) for the incorporation of organizational factors in Level 1 PRA. To address some of the critical challenges associated with theory, modeling, and measurement, the Data-Theoretic approach was developed in Chapter 3, a published journal article (Pence, Sakurahara, Zhu, Mohaghegh, Ertem, Ostroff, & Kee, 2019), which emphasized theory-building and causal modeling in the DT-BASE module (iii in Figure 8.1). Chapter 4, a published journal article (Pence, Farshadmanesh, Kim, Blake, & Mohaghegh, 2020), focused on the DT-SITE module (iv in Figure 8.1), which leveraged the results from Chapter 3 to advance meso-level measurement using data analytics.

Compared to the incorporation of organizational factors in Level 1 PRA, the incorporation of social factors into Level 3 PRA (v in Figure 8.1) is in its infancy. Therefore, lessons learned from the incorporation of organizational factors in Level 1 PRA (i.e., Chapters 2, 3, and 4) can be leveraged to inform the line of research for incorporating social factors in Level 3 PRA (i.e., represented by the dashed arrow between ii and v in Figure 8.1). Because research on the incorporation of social factors in Level 3 PRA is limited, my research aimed to establish a basis for macro-level theory (v.a in Figure 8.1), macro-level measurement (v.b in Figure 8.1), and macro-level modeling (v.c in Figure 8.1) approaches. Chapter 5, a published journal article (Pence, Miller, Sakurahara, Whitacre, Reihani, Kee, & Mohaghegh, 2018), addressed the lack of explicitness of social factors in Level 3 PRA, initiated a macro-level socio-technical risk analysis theory for emergency response applications and offered a methodology for adapting the concept of social vulnerability, commonly used in natural hazard research, in the context of a severe NPP accident. Chapter 6, a manuscript to be submitted to a journal of risk analysis in May 2020, further expanded the macro-level theoretical causal framework for socio-technical risk analysis of severe nuclear accidents and leveraging concepts from meso-level research for Level 1 PRA, adapted a Human Reliability Analysis (HRA)-based theoretical representation of Population Error (PE) in the development of a Population Departure Time Model (PDTM) for Level 3 PRA (vi in Figure 8.1). A methodological framework was developed to integrate the PDTM with a transportation model and Level 3 PRA for evaluating population radiation exposure.

An advantage of explicitly incorporating organizational/social factors into PRA is that sensitivity and importance measure analyses can be used to obtain the ranking of organizational/social risk-contributing factors based on their contribution to human/population errors and system risk (viii in Figure 8.1). While sensitivity and importance measure analyses can be used to improve risk management and prevention, without a justified representation of the 'market value' PRA, there are few incentives for companies to go 'beyond-compliance' and to make investments in PRA, for example, investing in the explicit incorporation of organizational/social factors (ii.a in Figure 8.1). Therefore, Chapter 7 introduced a methodology to evaluate the monetary value of PRA through the systematic causal modeling of the net value of RIPBAs and demonstrates the methodology for one RIPBA at an NPP called Risk-Managed Technical Specifications (RMTS) (vii in Figure 8.1).

Chapters 2 through 7 of this dissertation include conclusion sections that provide summaries of chapter contributions and detailed future research directions associated with the research activity published in each chapter. In a broader perspective, the methodological and theoretical development introduced in this dissertation provide support for modeling and quantifying the unprecedented, unimagined, and undesirable risk futures that may emerge in our world:

- The Data-Theoretic philosophy bridges the gap between an uncertain phenomenology and unstructured data, emphasizing the importance of theory-building to preserve causality (e.g., to enhance the capability of explainable artificial intelligence in risk applications). This research is one step toward the necessary level of comprehensiveness that is needed to understand the complexities of underlying organizational/social root causes of incidents and accidents. Continued advancement in the field of socio-technical risk analysis is critical for understanding how significant organizational/social factors act as contributors to incidents and accidents. Only through explicit model-based or mechanistic integration of organizational/social performance with PRA can we find and rank critical organizational/social root causes of failure, improve efforts to take effective corrective action, and avoid the possibility of underestimating risk. While this research was demonstrated in the context of NPPs, meso-level organizational causal models can be applied in the assessment of organizational performance in the oil and gas, space, aviation, and healthcare industries. The results of this line of research can help organizations develop best practices for maintaining safety, improving resilience in unprecedented circumstances, and increasing the reliability of socio-technical systems in high-consequence endeavors.
- Although the macro-level case studies in this dissertation focus on man-made NPP hazards, the logic of spatiotemporal hazard-population coupling can be adapted to support risk-informed emergency response for emergent socio-technical problems resulting from natural hazards, pandemics, terrorist attacks, and co-evolving multi-hazard scenarios. I hope that insight from this research can advance the way our institutions anticipate, assess, and mitigate global catastrophic risks, helping to usher in a new era, void of human-made accidents, where collaborative research between industry, academia, and regulatory agencies is leveraged to raise social responsibility for the protection of workers, the public, and the environment.

APPENDIX A: INTER-RATER RELIABILITY USING COHEN'S KAPPA

This appendix explains the calculation of inter-rater reliability using Cohen's kappa statistic. In the annotation process, annotators tag sentences as "related" or "not related" to the target node category. Cohen's kappa (k) measures agreement (i.e., the proportion of agreement after chance agreement is removed from consideration) between annotators using Eq. A.1:

$$k = \frac{p_o - p_c}{1 - p_c} = 1 - \frac{1 - p_o}{1 - p_c}, \qquad \text{(A.1)}$$

where p_o is the proportion of sentences where the annotators agreed, and p_c is the proportion of sentences where agreement is expected by chance. If annotators are in complete agreement, then $k = 1$. If there is no agreement, other than chance agreement (p_c), then $k = 0$. One target node category was considered in this paper (i.e., training-related in Chapter 4, Section 4.4). Therefore, two annotators reading each piece of data have the option to say "Yes" or "No," that the data is related to the target node category or not. Table A.1 provides an example from the case study in Chapter 4, Section 4.4, depicting one annotation result.

Table A.1. Example of Sentence-Level Annotation

LER	Sentence	Annotator A	Annotator B
4582006006	"Training on this condition will be conducted for the Operations and Licensing staffs."	Yes	Yes

The totals from the annotations (i.e., "Annotator A" and "Annotator B" columns in Table A.1) are used to calculate a matrix that includes the number of total agreement ("a" in Table A.1), total disagreement ("d" in Table A.1), and disagreement combinations between annotators ("b" [i.e., Yes/No] and "c" [i.e., No/Yes] in Table A.1).

Table A.2. Simple Example of Inter-Rater Reliability

		Annotator B	
		Yes	*No*
Annotator A	*Yes*	a	b
	No	c	d

To calculate p_o, considering the matrix in Table A.2, Eq. A.2 is used:

$$p_o = \frac{a+b}{a+b+c+d} \qquad \text{(A.2)}$$

Considering the matrix in Table A.2, Eq. A.3 is used to calculate chance probability that both annotators mark “Yes” at random (p_{Yes}) and Eq. A.4 calculates the chance probability that both annotators mark “No” at random (p_{No}):

$$p_{Yes} = \frac{a+b}{a+b+c+d} \times \frac{a+c}{a+b+c+d} \qquad \text{(A.3)}$$

$$p_{No} = \frac{c+d}{a+b+c+d} \times \frac{b+d}{a+b+c+d} \qquad \text{(A.4)}$$

The overall probability of random chance agreement (Yes or No) is calculated using Eq. A.5:

$$p_c = p_{Yes} + p_{No} \qquad \text{(A.5)}$$

Sources:

- *Cohen, J., 1960. A coefficient of agreement for nominal scales. Educational and psychological measurement 20, 37-46.*
- *Landis, J.R., Koch, G.G., 1977. The measurement of observer agreement for categorical data. biometrics, 159-174.*
- *McHugh, M.L., 2012. Interrater reliability: the kappa statistic. Biochemia medica 22, 276-282.*

APPENDIX B: CANCELLED LICENSEE EVENT REPORTS

The following LER numbers were removed from the dataset due to being canceled (C) [as of March 2019]:

3242007004, 3162000001, 4992010004, 4982014001, 4822011010, 4822011003, 4822011001, 4822009008, 4822009007, 4582007001, 4572010004, 4572010002, 4562011003, 4552010002, 4542011003, 4402014001, 4232004003, 4002004002, 3612010002, 3542012002, 3542011001, 3542004011, 3362006007, 3312012001, 3312007001, 3252013003, 3242014002, 3242013002, 3152014001, 3152012002, 3052009005, 3052007003, 3052005010, 2982014005, 2862013006, 2852013004, 2852012011, 2852012006, 2852011006, 2852011001, 2852009003, 2852006007, 2822014002, 2822014001, 2822012004, 2822010003, 2822009006, 2752014001, 2702011002, 2612015004, 2552011003, 2552010004, 2552007003, 2552005007, 2552005006, 2542005004, 2372005003, 2202004002, 3252008001 (Duplicate), 3342014003 (Duplicate).

APPENDIX C: EXCLUDED LICENSEE EVENT REPORTS

The ‘Cause’ Section of the following LERs could not be identified by the python code. 3132014002, 3092007001, 2852017001, 2852002001, 2822003002, 2802015002, 2692000007, 2662012004, 2662012002, 2472002003, 3252006005, 3252008001, 3612004003, 3612004004, 3612007005, 3612007007, 3612008001, 3612008002, 3612008005, 3612009004, 3622004003, 3622008001, 3622009001, 3642017003, 3642017004, 3952014004, 3952015001, 4162009003, 4832002011, 3822019002, 2982018003, 3482018001, 3952016003, 4582002001, 4582005003, 4582016007, 4582017004, 4582017006, 4572003001, 4582013001, 4582017001, 3952003005, 3952003006, 3952009003, 3952010003, 3952012003, 3952013001, 3952013002, 3952013003, 3952013004, 3952013005, 3952013006, 3952014001, 3952014002, 3952014003, 3952015002, 3952016002, 3952016005, 3952016006, 3952017001, 3952017002, 3952017003, 3952017004, 3952017005, 3952017006, 3952018001, 3972003002, 3972003004, 4582001002, 4402006001, 3972004007, 3522005001, 3332003001, 3352003001, 3012012001, 2892000001, 2892002002, 2932017003, 2982015003, 2472000001, 2472000002, 2472000003, 2472000004, 2472000005, 2472000006, 2472000007, 2472000008, 2472000009, 2472001001, 2472001002, 2472001003, 2472001004, 2472001005, 2472001006, 2472001007, 2472002001, 2472002002, 2472003003.

APPENDIX D: NUCLEAR POWER PLANT EVACUATION TIME ESTIMATE INFORMATION

Table D.1. Evacuation Time Estimate (ETE) Study Information

ML Number	Year	NPP	Code	Author
ML12088A203	2004	Indian Point	IDYNEV	KLD
ML101030980	2008	Victoria	PTV Vision	IEM
ML090300688	2008	Calvert Cliffs	IDYNEV	KLD
ML082830276	2008	River Bend	IDYNEV	KLD
ML101110357	2009	Fermi	IDYNEV	KLD
ML12048B369	2009	South Texas Project	IDYNEV	KLD
ML12202A109	2010	Comanche Peak	IDYNEV	KLD
ML123630620	2010	San Onofre	IDYNEV	KLD
ML12355A267	2011	Three Mile Island	PTV Vision	ARCADIS
ML12348A219	2012	Braidwood	PTV Vision	ARCADIS
ML12348A221	2012	Byron	PTV Vision	ARCADIS
ML12348A223	2012	Clinton	PTV Vision	ARCADIS
ML12348A382	2012	Limerick	PTV Vision	ARCADIS
ML12348A384	2012	Dresden	PTV Vision	ARCADIS
ML12348A385	2012	LaSalle	PTV Vision	ARCADIS
ML12349A294	2012	Quad Cities	PTV Vision	ARCADIS
ML12355A240	2012	Peach Bottom	PTV Vision	ARCADIS
ML12362A473/2	2012	Browns Ferry	PTV Vision	ARCADIS
ML13298A792	2012	Virgil C. Summer	DYNEV II	KLD
ML101110357	2012	Oconee	DYNEV II	KLD
ML13023A035	2012	Palisades	DYNEV II	KLD
ML13037A619	2012	Kewaunee	DYNEV II	KLD
ML103630183	2012	Turkey Point`	DYNEV II	KLD
ML13007A078	2012	Beaver Valley	DYNEV II	KLD
ML13004A003	2012	Nine Mile Point/James A. FitzPatrick	DYNEV II	KLD
ML13023A031	2012	Pilgrim	DYNEV II	KLD
ML12355A748	2012	Palo Verde	DYNEV II	KLD
ML13004A004	2012	R.E. Ginna	DYNEV II	KLD
ML13007A119	2012	Davis-Besse	DYNEV II	KLD
ML12363A209	2012	Diablo Canyon	DYNEV II	KLD

Table D.1 (cont.)

ML Number	Year	NPP	Code	Author
ML13023A070	2012	Grand Gulf	DYNEV II	KLD
ML13037A621	2012	North Anna	DYNEV II	KLD
ML13002A335	2012	Duane Arnold	DYNEV II	KLD
ML123630597	2012	Brukswick	DYNEV II	KLD
ML12363A173	2012	Prarie Island	DYNEV II	KLD
ML13037A635	2012	Surry	DYNEV II	KLD
ML12363A113	2012	St. Lucie	DYNEV II	KLD
ML12363A207	2012	Fort Calhoun	DYNEV II	KLD
ML12356A131	2012	Point Beach	DYNEV II	KLD
ML13007A115	2012	Perry	DYNEV II	KLD
ML13023A048	2012	Arkansas	DYNEV II	KLD
ML12362A100	2012	Crystal River	DYNEV II	KLD
ML13002A414	2012	Wolf Creek	DYNEV II	KLD
ML13023A072	2012	River Bend	DYNEV II	KLD
ML12356A204	2012	Columbia	DYNEV II	KLD
ML13023A028	2012	Vermont Yankee	DYNEV II	KLD
ML12356A170	2012	Monticello	DYNEV II	KLD
ML13037A623	2012	Millstone	DYNEV II	KLD
ML13003A135	2012	Susquehanna	DYNEV II	KLD
ML13052A677	2012	Salem-Hope Creek	DYNEV II	KLD
ML13002A366	2012	McGuire	DYNEV II	KLD
ML12363A239	2012	Seabrook	DYNEV II	KLD
ML12363A056	2012	Robinson	DYNEV II	KLD
ML13234A356	2013	Watts Bar	PTV Vision	ARCADIS
ML13246A050	2013	Sequoyah	PTV Vision	ARCADIS
ML13254A121	2013	Oyster Creek	PTV Vision	ARCADIS
ML12346A413	2013	Vogtle	PTV Vision	IEM
ML12346A411	2013	Joseph M. Farley	PTV Vision	IEM
ML12346A412	2013	Edwin I. Hatch	PTV Vision	IEM
ML13002A356	2013	Cooper	DYNEV II	KLD
ML13134A308	2013	Bell Bend	DYNEV II	KLD
ML16312A330	2016	Harris	DYNEV II	KLD
ML17102B193	2017	Duane Arnold	DYNEV II	KLD
ML18311A210	2018	Brunswick	DYNEV II	KLD

Table D.1 (cont.)

ML Number	Year	NPP	Code	Author
ML18289A782	2018	Catawba	DYNEV II	KLD