Why Do Human-Machine Teams Fail: Investigating Failure Mechanisms in Human Reliability Analysis

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ABSTRACT

Human Reliability Analysis (HRA), whether qualitative or quantitative, typically focuses on the *how* of "human failure." For instance, the possible *modes* (Crew Failure Modes – CFMs) of failure define how a Major Crew Function (MCF) can be unsuccessfully performed by a crew of operators. The CFMs are typically associated with various Performance Influencing Factors (PIFs) that change the probability of occurrence (and thus, the probability of failing the MCF). However, the cognitive and/or physical pathways that result in a specific CFM (i.e., the question of *why* a failure occurs) are not often explicitly included in HRA methods. Even in Bayesian network (BN) models, these failure pathways are found implicitly (if at all) in the encoded causal relationships between the lower-level PIFs and higher-level CFMs. Our work posits that failure *mechanisms* may be revealed by cognitive-physical patterns underlying the presence of identified failure modes, i.e., specific sets of PIFs and/or subtasks (crew activity primitives – CAPs) specify failure mechanisms that can result in the failure mode. Our research reviews previous works that cover failure mechanisms in HRA and identifies possible failure mechanisms in tasks related to information gathering. We then extrapolate this finding to propose a definition for the failure mechanism in HRA and a preliminary procedure for identifying and modeling failure mechanisms in BN models.

Key Words: Human Reliability, Failure Mechanisms, Human Failure, Bayesian Networks

1 INTRODUCTION: HRA CONSTRUCTS

Human reliability analysis (HRA) is the field charged with understanding, modeling, and ultimately quantifying the reliability of human operators/technicians, typically in the context of complex engineering system operations (e.g., nuclear power plants). However, humans do not exist or operate in a vacuum, but rather as human-machine teams in a complex and inter-dependent context that will impact their error probability [1], [2]. To obtain reliable estimates of the human error probability (HEP), analysts must understand both the constructs that impact human reliability and the relationships that exist between them. There are many different constructs that can be included in HRA models, but typically include at a minimum the *performance influencing factors* (PIFs), *crew failure modes* (CFMs), *major crew functions* (MCFs), and *human failure events* (HFEs) [2], [3]. However, these constructs do not necessarily fully characterize the performance of human-machine teams. There is another aspect of reliability in component and system

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reliability analysis that, we propose, is useful for understanding human-machine team performance: the *failure mechanism*.

In this paper, we propose the *crew failure mechanism* as a logical expansion to the theoretical basis of HRA that can explicate the cognitive and physical processes that serve as proximate causes to failure modes. Whereas the crew failure mode captures the modality (i.e., the *how*) of function failure, the crew failure mechanism explains the underlying processes in the physical or cognitive context that can result in specific failure modes (i.e., capturing the *why*). The crew failure mechanism can also add traceability and detail to HRA modeling efforts, and further the understanding of how and why human-machine teams fail. More pragmatically, the addition of the crew failure mechanism into the hierarchical taxonomy of HRA constructs ([3]) can simplify modeling efforts, particularly when using Bayesian networks (BNs).

The present work was motivated by a recognition that PIFs can form logical groups that align with understandable cognitive and/or physical processes/patterns such as *attention*, *bias*, *prioritization*, and *coordination*. These processes, in turn, can produce certain failure modes – such as *attention process failures* resulting in reading errors. The addition of this level of detail to existing HRA will allow for a better understanding of why human-machine teams are failing and expose possible mitigation strategies to further reduce "human error" in complex systems operation.

The remainder of this paper is structured as follows. Section 2 describes background information on HRA modeling constructs and BNs for HRA. Section 3 details the motivation and approach for identifying and defining the crew failure mechanism as a construct for HRA. Section 4 summarizes the principal result of this work, a standard definition for the crew failure mechanism for implementation in HRA. Section 5 provides a high-level process for identifying and modeling crew failure mechanisms, with examples taken from existing HRA data and models. Section 6 concludes with a discussion of the results and their impact for HRA, as well as proposed future directions for expanding this work.

2 BACKGROUND: HRA CONSTRUCTS AND BAYESIAN NETWORKS

There are multiple ways to perform an HRA, but in general the 'scenario', that is, the event and the crew's response, is typically discretized and modeled by a number of constructs. The ultimate goal of the HRA is *both* a quantitative representation of the human-machine team reliability (i.e., the human error probability, HEP) and a qualitative understanding of *how* and *why* failures might occur. Paglioni and Groth [2] comprehensively defined the modeling constructs used for HRA, which are briefly summarized below. These constructs are used in model-based applications (e.g., fault trees and Bayesian networks, BNs) to develop a richer picture of the human-machine team (HMT) performance in the scenario, and ultimately arrive at an informed value of the HEP.

2.1 HRA Constructs

There are many causal constructs that can be incorporated into HRA modeling applications. The constructs represent the discrete elements of a scenario or event to which the HMT responds, including the functions, failure modes, and contextual factors that affect performance. Typical HRA constructs include the following [2], [3]:

- *Human Failure Event (HFE)*: The highest-level failures considered in a model, composed of at least one failed MCF.
- *Major Crew Function (MCF)*: high-level actions of the HMT under study.
- *Crew Failure Mode (CFM)*: The failure pathways that result in (define) a failed MCF.
- *Performance Influencing Factor (PIF)*: The "situational" (e.g., task, personal, organizational, or environmental) characteristics that describe the operational context.

These constructs can be represented on a semi-hierarchical Bayesian Network (BN) structure that illustrates the causal dependencies that can exist between the constructs, as shown in Figure 1. Each level in Figure 1 represents a distinct element of the scenario (e.g., objective, function, task, and factor), each of which may be represented at differing levels of abstraction, although the semi-hierarchical structure will hold.

In the semi-hierarchical BN structure ([3]), the HFE can be decomposed into its requisite MCFs, the functions that must be accomplished in order to *avoid* the HFE. The MCFs are further delineated into the CFMs which define how the MCF is failed [4]. The CFMs are causally related to the PIFs, which act to change the probabilities of various CFMs occurring.

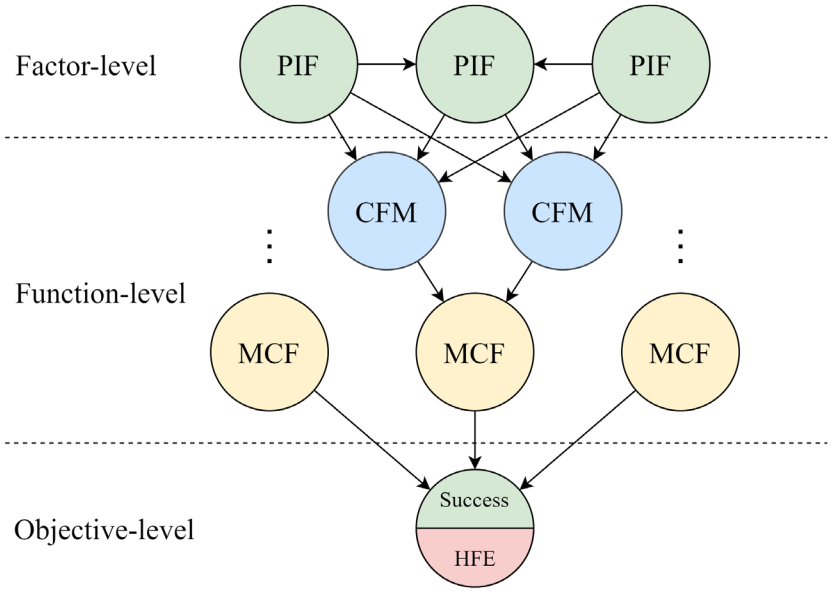

Figure 1. Semi-hierarchical HRA BN structure. Adapted from [3].

We propose that there is an important construct missing, at least explicitly, from existing taxonomies of causal constructs in HRA: the failure *mechanism*. Some previous HRA studies, e.g., [5], identified mechanisms, but these are more analogous to macrocognitive functions ([6]) or HFEs than to true causal mechanisms. For example, the failure mechanisms in [5] are encapsulated as CFMs, not mechanisms, in Phoenix [7]. This points to the incomplete and inconsistent interpretation of the failure mechanism as a construct in HRA. The crew failure mechanism requires a robust definition to facilitate its consistent use in HRA.

2.2 Bayesian Networks

The HFE, as discussed previously, represents the highest-level failure considered in an HRA, and is further delineated into one or more MCFs, the failure of any of which may define the HFE. Figure 1 shows the relationship between the HFE and its components in a semi-hierarchical structure composed in a BN architecture. BNs are a useful modeling structure for HRA because they can visualize the dependencies between the HRA constructs and facilitate the quantification of the probabilities based on the encoded dependency structure [2].

Bayesian networks consist nominally of two parts: the graph and the conditional probability tables (CPTs) [8]. The graph itself is composed of nodes that represent the HRA constructs (PIF, CFM, MCF, HFE in Figure 1) and directed arcs that represent the dependencies between the nodes. The graph is *directed*, meaning that the dependencies have a directionality – the direction of causality – and *acyclic*, meaning that the graph does not support feedback loops. Nodes on the graph can be classified as either *parent* or *child* nodes – parent nodes feed into the children nodes (e.g., the MCFs are parents to the Objective-level node

in Figure 1). Each node is quantified with either a CPT in the discrete space (i.e., in HRA) or conditional probability distribution in the continuous space.

For HRA applications, the BNs are typically composed in the discrete space. The BN structure visualizes the dependencies between various HRA constructs, as shown in Figure 1. This makes the BNs especially useful for understanding the causal structure of an HRA scenario, and allows analysts to gain additional insights into *how* the observed "human error" was produced. The CPTs in the BN allow for data-driven quantification of the dependencies, as further presented in [9]. For the present work, however, the BN structure, rather than the quantification, is of more interest.

Using BNs to explicate the causal structure of a specific CFM in an HRA scenario (Figure 2), further presented in [10], showed that the PIFs formed logical groups. This led to the recognition that failure mechanisms were visible in the causal structure of the scenario.

3 MOTIVATION

The failure mechanism has typically been eschewed by previous and current HRA methodologies, which focus on the failure modes (i.e., *how* the failure manifests) and the failures themselves (i.e., *which* functions were failed). One exception is NUREG-1921 ([5]), which defines "mechanisms" in the context of the cause-based decision tree method (CBDT). This method is used to assess cognitive HEPs for procedure-directed actions. However, the mechanisms described therein are more analogous to the crew failure modes (CFMs) in cognitive-based HRA methods such as IDHEAS, IDAC, and Phoenix. For example, the failure mechanism 'Relevant step in procedure missed' is analogous to Phoenix's D4 CFM 'Procedure step omitted'. Another example is the 'Data misread or miscommunicated' which is analogous to Phoenix's I7 CFM 'Information miscommunicated'.

This discrepancy between how failure mechanisms in an HRA context are defined shows the need for a standardized definition explaining their role as a construct. In mechanical equipment, a failure mode is defined as "a symptom, condition, or fashion in which hardware fails including a loss of function, premature function, out of tolerance condition, or a leak." These failure modes can occur by a variety of mechanisms, which are physical, chemical, thermodynamic or other processes, including corrosion, wear, and thermal shock among others [11]. Drawing upon this, a definition for human failure mechanism should explicitly acknowledge the causality of how a certain failure occurs. A standard definition would be useful for HRA from both qualitative and quantitative perspectives. Qualitatively, it would enhance the scientific accuracy of HRA models by adding a layer describing the failure process, i.e. how a set of PIFs influences a CFM. Quantitatively, it would serve as a point of sensitivity analysis to identify the set of PIFs that significantly influence a HEP and therefore would be most important to address to mitigate a resulting CFM and HFE.

4 RESULT: DEFINITION FOR THE HUMAN FAILURE MECHANISM

The human failure mechanism is therefore a construct that can explicit useful causal information for the study of human failure events in HRA. However, incorporating the human failure mechanism as a modeling construct in HRA requires an accurate lexicographical and mathematical understanding, i.e., what the human failure mechanism is (as a construct) and how it can be modeled and quantified in HRA. Therefore, this section provides a definition of the human failure mechanism as an HRA construct, to augment the lexicographical dictionary created in [2].

We propose that the human failure mechanism is a distinct concept from the HFE and the CFM in HRA. Whereas the HFE defines the top-level failure itself, and the CFM defines a possible *mode*, i.e. typology, of the HFE, the failure mechanism characterizes the underlying reasons that a CFM is observed. For example, a HFE might be "fail to collect data," which can be defined by the CFMs "data not checked with appropriate frequency" or "incorrect data attended to." The CFM therefore defines *how* the data was

not collected, but there is an opportunity to further explore *why* the data was not checked with appropriate frequency. For example, the CFM "data not checked with appropriate frequency" might occur because of issues related to "attention," "team coordination," or "bias." However, in the current HRA construct taxonomies (shown in Figure 1), the reason(s) for the CFM is not explicitly presented. Figure 2 shows how

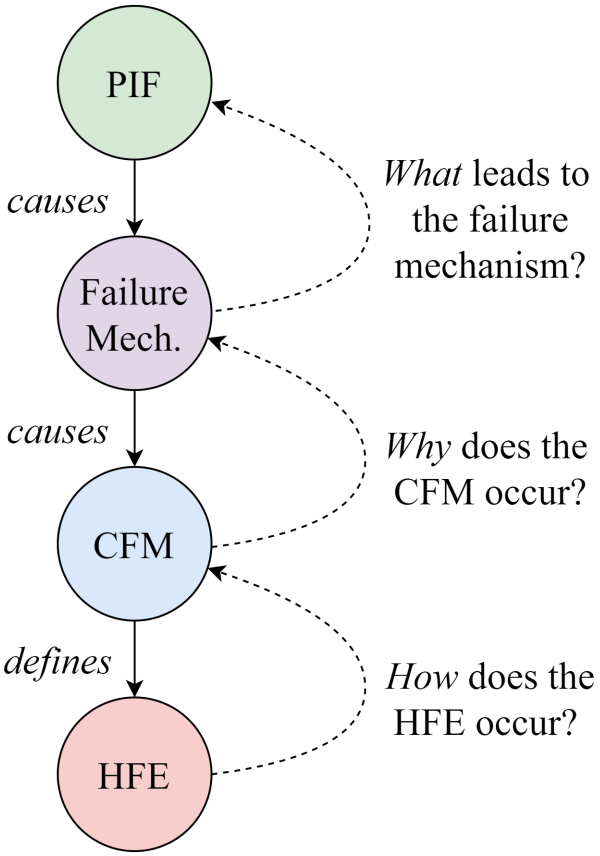

Figure 2. The relationship between existing HRA causal constructs and the proposed failure mechanism construct.

the PIF, failure mechanism, CFM, and HFE are related, as well as the questions each can answer about the other.

As Figure 2 shows, the failure mechanism is caused by groups of PIFs to form a construct that defines *why* an observed CFM occurs, which in turn defines the failure of an objective (i.e., the HFE). The failure mechanism itself can therefore be further explored to identify the PIFs that lead to the occurrence of the failure mechanism. The failure mechanism, as an HRA construct, provides more causal information that can be used for analyzing HFEs and developing mitigation actions.

The failure mechanism for HRA can be defined analogously to the concept of a failure mechanism in component reliability, which is viewed as a stressor-induced physical processes that weaken the capabilities of an item [11]. For HRA purposes, "stressors" may be considered as a broader concept than in hardware reliability. An HRA stressor (in the general sense, not to be confused with the personal-level "stressor" PIF from [12]) can be any PIF that negatively affects performance. A failure mechanism in HRA is therefore the catalyzing context to the observed failure mode [13].

The failure mechanism can be formally defined for HRA as follows:

The failure mechanism is the catalyzing context of a crew failure mode (CFM) that describes the cognitive and/or physical process that resulted in the failure mode. The failure mechanism is a causal component of the decomposed HFE that is part of the causal pathways leading from the PIFs to the CFMs.

In HRA, as in component reliability, there are multiple ways by which a failure mode might be initiated, which are the failure mechanisms. For example, a component might fail by fracture (failure mode) which could be caused by overstress or fatigue (failure mechanisms). Understanding whether a fracture occurred due to overstress or fatigue is a useful causal insight for the mechanical system. Similarly, understanding whether "data not checked with appropriate frequency" is due to "attention," "team coordination," or "bias" is a useful causal insight for HRA.

5 MODELING FAILURE MECHANISMS

Modeling crew failure mechanisms is crucial to ensuring scientific completeness in identifying causal pathways leading to HFEs. Failure mechanisms, as an intermediate HRA variable, enhance model interpretability and simplicity.

5.1 Modeling Basis and Example

In concurrent work also presented at this conference [10], a BN model of these failure pathways leading to an information-gathering failure explores specific processes in further depth. This model builds on the IDAC framework [14] and the Phoenix HRA method [7] to enumerate the relevant contexts and processes through which a crew might fail to gather information. Each causal arc in the BN is substantiated through psychological literature or logical relationships. Although the intent of this work was to identify documented causal connections leading to Phoenix CFMs, it became clear during modeling that there are separate error contexts through which the failure modes arise.

While developing the model architecture, separate clusters of PIFs repeatedly emerged. Similar to the three causal paths identified in [15], each cluster represents a different psychological or physical mechanism. The lowest layer of PIFs directly leading into each CFM acts as a kind of pinch point to combine the effects of the secondary and tertiary layers of PIFs. For example, Attention can degrade due to fatigue, sensory overload, stress, or work overload. In turn, lack of attention can manifest in a wide variety of failure modes. In this sense, Attention is a failure mechanism, since it is not possible to observe directly, but it results in the observable failure modes.

One of the BN models in which these mechanisms were particularly apparent was the network structure for Phoenix CFM I9, "Data not checked with appropriate frequency". The structure for I9 is shown below in Figure 3. There are several different ways that an operator might fail to check data at the correct frequency. A crew with poor team coordination might not properly communicate team roles, resulting in unclear data collection duties and lapses in observation [16]. An individual member on the team may experience lapses in attention, which might be drawn away by external factors or by internal psychological limits [17]. Finally, they might be biased against a certain source of data due to premature closure during situational assessment [18]. The bias mechanism is unique because although it may cause the CFM directly, it can also result in a biased reallocation of attentional resources that in turn causes the CFM. In addition to these three mechanisms, poor human-system interface (HSI) or overloading may result in the operator being physically unable to check data frequently enough.

Different clusters of contextual factors affect each mechanism. Coordination efficacy is primarily affected by PIFs relating to organizational- and team-based factors, while attention and bias are primarily affected by person- and situation/stressor-based factors. There is some overlap between these clusters: for example, poor staffing may result in poor coordination, or it may also result in higher workload and stress levels for the operator. Accordingly, while CFMs (and failure modes in hardware) are mutually exclusive, failure mechanisms are neither mutually exclusive nor independent. However, it can be observed that there

are multiple, separate contexts by which the CFM might be brought about, with each error context corresponding to a failure mechanism.

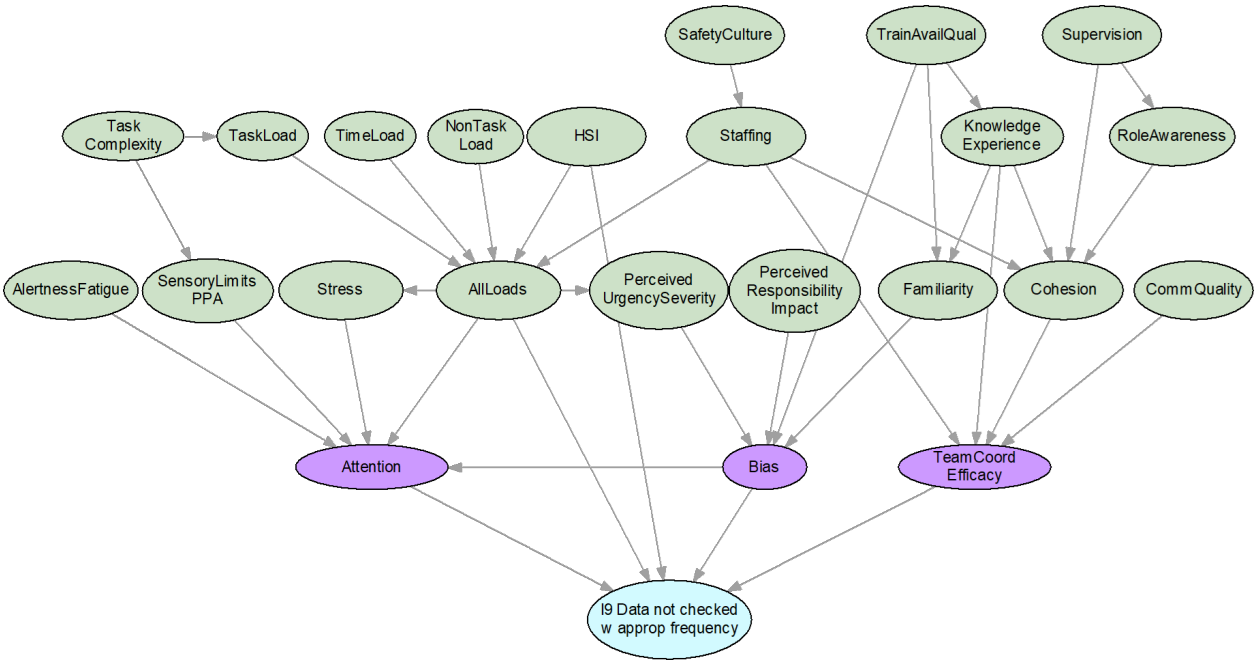

Figure 3. BN structure for CFM I9, with PIFs shown in the upper layers in green, failure mechanisms in purple, and the CFM in blue. Adapted from [10].

5.2 Identification Procedure

A preliminary procedure has been developed for identifying these mechanisms using the causal structure of Bayesian networks. Initially, this was done by inspection. In the Phoenix method's CFM definitions [19] as well as the Groth 2012 PIF hierarchy and definitions [12], certain connections between PIFs and CFMs were already identified. Other constructions were apparent immediately, such as the logical connections between *training availability and quality*, *familiarity*, and *knowledge/experience*. These patterns repeatedly emerged for multiple CFMs, reflecting their nature as cognitive and physical causal pathways.

Through further examination, three main shared characteristics among the mechanisms emerge. By checking a causal BN node against these characteristics, it should be possible to identify whether or not it is a mechanism.

1. First, it **must be a direct cause of a CFM**. If it only exerts influence indirectly through other nodes, this means that the mechanism can be better described by the downstream effects of this node. For example, *familiarity* is not a human failure mechanism as shown in Figure 3, because it does not have a direct arc leading to the CFM. Instead, it acts through the mechanism of *bias*. In a Bayesian framework, this means that a potential mechanism must have an arc leading directly to a CFM node.
2. The node **must be an effect of at least two separate, distinct PIFs**. Mechanisms are brought about by contextual factors. Inherent aspects of the scenario are PIFs but not mechanisms, because they are not caused by any other aspects of the task, operators, or organization. Some PIFs are direct causes of CFMs, such as *HSI* in Figure 3. Poor HSI is an effect of the way the system is designed, which is a human factors issue and outside the scope of the current HRA purview. Crucially, failure

mechanisms represent a compound error context that is affected by multiple contextual factors. In the Bayesian framework, this means that the node must have at least two parent nodes that are PIFs. Furthermore, the node should not be a definitional representation of the PIF parents, such as *All Loads* in Figure 3. High mental and physical loading conditions have the same overloading effect (i.e., there is too much for the operator to do in too short of a time period), so this node was introduced during modeling as a simplification to aggregate the effects of the load-causing PIFs.

3. Finally, **it is likely to be modeled as a previously identified PIF**. The majority of human failure mechanisms found in [10] were identified as high-level PIFs in Groth's 2012 hierarchy [12]. High-level PIFs are typically complex phenomena stemming from other contextual factors with a high likelihood of leading to CFMs, and are thus failure mechanisms. For example, "Attention" in Figure 3 is a failure mechanism stemming from contextual factors including "Stress," "Load," and "Fatigue," that is also a high-level personal PIF in [12]. Internal cognitive mechanisms that are impossible to identify as an external observer, and thus excluded from PIFs used in HRA, may also serve as failure mechanisms.

6 CONCLUSIONS AND FUTURE WORK

This paper briefly reviewed previous conceptualizations of the "failure mechanism" in HRA and discussed the inconsistency with which the concept has been included in HRA literature and methods. To rectify this gap in the literature, we proposed a robust definition of the crew failure mechanism as the catalyzing context for a CFM that describes the cognitive and/or physical processes leading to the failure mode. Furthermore, we describe a method for modeling and identifying failure mechanisms in BN-based HRA using the framework presented in more detail in [10].

Incorporating the failure mechanism as a construct for HRA may appear to add model complexity. However, leveraging advances in computing techniques and incorporating BN modeling practices such as node reduction can facilitate handling the more complex models. Additionally, the discrete nature of HRA constructs means that BN modeling does not require computationally intense simulation techniques to quantify the model [9].

Including the failure mechanism as an HRA construct provides increased scientific accuracy and model *completeness* to the resulting HRA model. Understanding the underlying processes (cognitive and/or physical) that result in observed failure modes allows analysts to analyze the HMT performance with more detail and thereby develop more effective error-mitigating strategies. Accordingly, the enhanced scientific clarity serves to *reduce* the complexity of the model by providing more understandable results.

Future work in this area will focus on modeling additional error typologies, such as are present in Action and Decision-making functions. This will help to refine the process for identifying and modeling the failure mechanisms in HRA.

7 ACKNOWLEDGMENTS

This research was supported in part by the U.S. Nuclear Regulatory Commission grant number 31310020M0002. Any opinions, conclusions, or recommendations expressed in this paper belong to the authors alone and do not necessarily represent the views or opinions of the sponsoring agency.

This material is based upon work supported under a Department of Energy, Office of Nuclear Energy, University Nuclear Leadership Program Graduate Fellowship. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the Department of Energy Office of Nuclear Energy.

The authors would like to thank the A. James and Alice B. Clark Foundation for their support through the Clark Doctoral Fellows program at the University of Maryland.

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