Causal Pathways Leading to Human Failure Events in Information-Gathering System Response Activities

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1. ABSTRACT

Human Failure Events (HFEs) are complex, multi-layer events culminating with a human-machine team's failure to complete a plant objective. HFEs can be further described by Crew Failure Modes (CFMs) which document specific ways the objective tasks may be unsuccessfully performed. In turn, these CFMs are affected by Performance Influencing Factors (PIFs), some of which exert a more direct influence than others. However, in current Human Reliability Analysis (HRA) methods, the multitudes of causal relationships between PIFs, CFMs, and HFEs are not explicitly modeled. This work seeks to fill that gap by developing structured causal models that document direct and indirect pathways from PIFs, through CFMs, and into HFEs. This work is intended to expand the current application of causal-based HRA modeling beyond control room environments to external environments under natural hazard scenarios.

A Bayesian network of information-gathering operator activities in response to a system demand is developed by following the causal mapping methodology defined in Zwirglmaier et al. (2017). The relationships in this structure are substantiated with existing psychological and organizational literature, thereby allowing for the identification of the main causal pathways leading to a particular CFM, and therefore an HFE. The work draws upon proximate causes of failure from the NRC's NUREG-2114, CFMs in the Phoenix HRA method, and PIFs from Groth's 2012 hierarchy. Capturing these causal pathways provides the foundation for an improved causal basis of HRA, which represents a promising strategy for enhancing the accuracy and technical basis of HRA. Future efforts will include validation of the structures, constructing similar models for decision-making and action HFEs, and quantification of the Bayesian network structures.

Keywords: Human Reliability Analysis, Bayesian Networks, Human Failure Events, Causal Pathways

2. INTRODUCTION

One of the main goals of human reliability analysis (HRA) in current practice is the identification of potential human failure events, or HFEs. HFEs arise from complex chains of causally related events, and represent the culmination of a human-machine team's failure to complete an objective [1]. This objective is comprised of multiple high-level cognitive or physical actions, called major crew functions (MCFs). MCFs are system-specific instantiations of macrocognitive functions, such as information gathering, decision-making, or action taking: this paper will examine the pathways by which information gathering failures occur.

A proportionally large share of accidents across various industries can be attributed to human error, or contexts conducive to human error [2]. HRA is a useful tool for characterizing this human error in a wide variety of domains so that it can be acknowledged and mitigated. There has been a need for cognitively

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realistic, yet quantifiable, models that account for the full range of contexts inherent to human operation [3]–[7]. While older models frequently lack this psychological realism, newer models may lack quantification schemes that are feasible in practice. Current research has sought to enhance this theoretical basis [8]–[10], but is yet incomplete in its lack of explicit acknowledgement of human error's causal chains.

Although most methods directly compute human error probabilities (HEPs) from multipliers derived from combinations of performance influencing factors (PIFs) relating to the event context, it is clear that there is more psychological depth to the HFE than models are capable of representing [1], [11]. Therefore, there is a present need for a cognitively based HRA method with a topography based in organizational and psychological literature [4]. It is important to fully describe all these pathways so that mitigation strategies can be applied in a targeted manner. By substantiating these pathways through the ways that PIFs exert their influence, model outputs will be rendered traceable back to theory.

3. BACKGROUND & LITERATURE REVIEW

3.1 Background

As shown in Fig. 1, HFEs do not occur in a vacuum: there are multiple contextual factors that tell the story through a causal chain. In recent literature, the HFE has been defined as the result of a failed function-level HRA variable (MCF, CFM) and the culmination of the human failure process. As stated above, the MCF is a high-level action taken by a human-machine team and a system-specific instantiation of a macrocognitive function [4], [12]. This could be tasks such as interpreting an alarm, deciding on a procedure to follow, or actually carrying out the procedure. Macrocognitive functions have been defined as a higher-level cognitive process as outlined by the Information-Decision-Action (IDA) framework [13]. Failure of an MCF can occur by various different crew failure modes (CFMs). For example, someone might fail to gain situational awareness because they misinterpreted data, or because they were looking at the incorrect data source.

Then, PIFs serve as the context during which the error occurs, and can be categorized into personal, task, situational, and organizational factors as shown in the hierarchy developed by Groth & Mosleh [14]. Some PIFs exert a more direct influence on CFMs and represent cognitive or physical causal pathways, similar to mechanisms of mechanical failure modes. There is a trade-off involved between constructing complete, psychologically substantiated models, and the ease of conducting an HRA. There are infinitely many cognitive pathways to a functional-level failure as there are infinite responses to a situation. However, only the most relevant and potentially risk-inducing pathways should be modeled, and a manageable subset of the most commonly documented mechanisms of failure should be used.

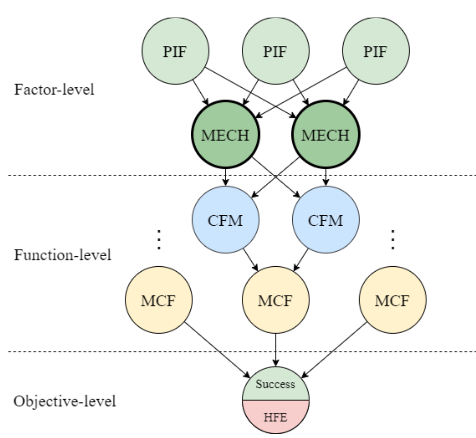

Figure 1: Sample BN of the components of a HFE, adapted from [1].

3.2 Literature Review

Bayesian networks (BNs) are a good candidate for developing HRA models because they provide a robust framework to address a number of shortcomings in existing HRA methods [15]. These shortcomings include oversimplifications of cognitive processes, lack of technical basis, and lack of causality. Furthermore, BNs allow for the expansion and adjustment of HRA models with the availability of more data. While the application of BNs in HRA has been limited, one comprehensive survey found a number of issues in their current use [16]. First, the authors found that the surveyed studies had an over-reliance on expert judgement to develop the BN structures. This resulted in limited emphasis on building traceable and credible models [17] due to the lack of documentation on how the expert interviews and questionnaires were structured. Second, the BNs are presented as complete works, without context and insights into the reasoning behind the nodes included as well as the causal connections between them [18]. Third, large variabilities exist between analysts in the definitions of BN nodes' states.

In order to tackle some of the limitations in HRA modeling, a method for simplifying qualitative BN models was developed by Zwirglmaier, Straub, and Groth [10]. Through this process, dependencies between the CFMs (from the IDHEAS [9] method) and their causal factors were identified. In another work, Groth, Smith and Moradi developed a hybrid algorithm fusing data from multiple sources, existing HRA models, and cognitive literature [4]. Both works serve to enhance the traceability and scientific basis of HRA methods and provide a foundation for the current research.

4. METHODS

4.1 Data

In this work, we utilized a combination of research works that focused on different aspects of third-generation human reliability analysis (HRA) modeling in order to develop the Bayesian networks (BNs) that present the causal structure of the information-gathering (I) phase failures. First, the documentation for a number of existing HRA methods were consulted to compare the phases and macrocognitive functions in their human response models. These methods include the:

- Information-Decision-Action in a Crew Context (IDAC) framework [19],
- Phoenix framework [20], [21] and the
- Integrated Human Event Analysis System (IDHEAS) [9].

The main resource used to define the scenario examined in this work was the NUREG/CR-7256 report titled "Effects of Environmental Conditions on Manual Actions for Flood Protection and Mitigation" [22]. The report provides an approach to decompose manual actions into tasks, subtasks, and specific actions, and further enumerates performance demands and presents a typology of these demands. Specifically, Section 6.3 of [22] provides three task decomposition examples that were achieved through group discussion and consensus building by a research team representing a wide array of expertise.

The performance influencing factors (PIFs) hierarchy detailed in [14] was used to construct the BNs. The hierarchy, shown in Table 1, includes 71 defined PIFs under a top level containing five categories: machine-based, person-based, team-based, organization-based, and situation/stressor-based. The hierarchy is particularly appropriate for this work as it provides a mechanism for integrating information from multiple sources. This division scheme allows the PIFs to be defined with respect to the appropriate category of the socio-technical system. In turn, this allows the analyst to identify the root cause of the human error and supports strengthening the causal basis of HRA. The Phoenix framework is a set of modeling tools that enables an analyst to conduct a more extensive analysis for the conditions that can lead to a human or crew failure. The modeling tools in this framework are an integrated set of crew response trees (CRTs), fault trees (FTs), and Bayesian belief networks (BBNs).

Table 1: Proposed PIFs classification, adapted from [14].

Organization-based	Team-based	Person-based	Situation/stressor-based	Machine-based
Training program	Communication	Attention	External environment	HSI
Availability	Availability	To task	Conditioning events	Input
Quality	Quality	To surroundings	Task load	Output
Corrective action program	Direct supervision	Physical & psychological abilities	Time load	System response
Availability	Leadership	Alertness	Other loads	
Quality	Team coordination	Fatigue	Non-task	
Other programs	Team cohesion	Impairment	Passive information	
Availability	Role awareness	Sensory limits	Task complexity	
Quality		Physical attributes	Cognitive	
Safety culture		Other	Execution	
Management activities		Knowledge/experience	Stress	
Staffing		Skills	Perceived situation	
Scheduling		Bias	Severity	
Workplace adequacy		Familiarity with situation	Urgency	
Resources		Morale/motivation/attitude	Perceived decision	
Procedures			Responsibility	
Availability			Impact	
Quality			Personal	
Tools			Plant	
Availability			Society	
Quality				
Necessary information				
Availability				
Quality				

Literature concerning the psychological and organizational factors leading to error was used to develop the theoretical basis of this work. In particular, Endsley's work on situational awareness described the effects of many person-based PIFs, such as stress, human-system interface, and loads, as well as several error mechanisms, including bias and attention [23]. Endsley poses a general model of situational awareness and reviews sources documenting the pathways by which information synthesis errors may occur. Letsky et al's macrocognitive model of team collaboration was instrumental in developing the relevant organizational- and team-based factors [24]. Additional literature used in the substantiation of this Bayesian network is documented in Table 2 below.

Table 2: Literature consulted for psychological and organizational factors leading to human error

Ref on BN	Ref Number	Citation	Area of BN
a)	[25]	Broadbent, D. (1958).	Sensory limits
b)	[23]	Endsley, M. R. (1995).	Person-based PIFs, attention, bias, knowledge, training
c)	[26]	Eriksen, C.W., & St. James, J.D. (1986).	Sensory limits, attention
d)	[27]	Jones, D. G., & Endsley, M. R. (1996)	Loads
e)	[28]	Klein, G. A. (1993).	Person-based PIFs for misinterpretation
f)	[29]	Klein, G., & Moon, B. (2006).	Discounting of data
g)	[24]	Letsky, M. P., Warner, N. W., Fiore, S. M., & Smith, C. A. P. (2008).	Collaboration and organization based PIFs
h)	[30]	Lipshitz, R. (1993).	Training, perceived impact
i)	[31]	Orasanu, J., & Martin, L. (1998).	Bias, knowledge, training, goal prioritization
j)	[32]	Roth, E.M. (1997).	Safety culture, knowledge and training for misinterpretation
k)	[33]	Wickens, C. D., Lee, J. D., Liu, Y. & Becker, S. E. G. (2004).	Stress, fatigue, knowledge, training, perceived impact

4.2 Approach

In previous work [34], we used the task decompositions from NUREG-7256 [22] to identify human failure events (HFEs) that may occur in external actions aimed at mitigating nuclear power plant flooding hazards and develop fault tree models with the appropriate crew failure modes (CFMs). Building on that, our method in this work was to use the definitions for the nine information gathering CFMs from the Phoenix framework documentation [20] to determine the possible mechanisms by which a failure may occur. Then, we utilized the PIFs hierarchy [14] to identify the applicable PIFs to each CFM. Next, we consulted a set of draft Bayesian networks (BNs) developed at Sandia National Laboratories (Groth & Hendrickson [35]) to construct a set of BNs for seven of the I-phase CFMs by adding arcs that illustrate the causal relationships among the PIFs. The final step was to substantiate these relationships through psychological literature (detailed in Table 2 above) to solidify the causal basis of these BN models.

5. RESULTS

The full Bayesian Network structure is shown in Fig. 2 below. Each arc in the structure is substantiated in existing psychological literature as described above, and the source is indicated on the arc. Some of the structures are logically derived, such as the definitional nature of Time Load, Task Load, and Non-Task Load comprising All Loads.

In this work, we identified five key causal clusters that are readily apparent in the structure. Each corresponds to a mechanistic PIF, and are shown through the darker green nodes and their connections in Figure 2. These clusters are prioritization, bias, attention, procedural, and team coordination/efficacy. These are not deterministic in their causation: they are probabilistic, increasing the probability of occurrence of a CFM. Thus, multiple clusters can contribute to a particular CFM, with differing degrees of influence on the causation of that CFM.

The first cluster, prioritization, directly causes two CFMs (I1 and I3). Prioritization errors are directly caused by three PIFs (perceived situation severity and urgency, perceived decision responsibility and impact, and safety culture). These errors are also indirectly caused by loads (task, non-task, time) which in turn can be compounded by three other PIFs: human-system interaction, task complexity, and staffing. Prioritization can also be caused by the presence of bias, which is another mechanistic PIF that we identified.

The second cluster, bias, directly causes five CFMs (I1, I2, I3, I4 and I9). Bias errors were found to be directly caused by four PIFs (perceived situation severity and urgency, perceived decision responsibility and impact, training availability and quality, and familiarity). These errors are also indirectly caused by high loads. Through familiarity, bias errors were found to be indirectly caused by two more PIFs: training availability and quality, and knowledge/experience. In addition to prioritization errors, bias is a mechanism that may cause attention errors.

The third cluster, attention, directly causes eight CFMs (all except I2), the most among the five clusters. Attention errors were found to be directly caused by four PIFs: sensory limits, stress, loads, and alertness and fatigue. These errors are also indirectly caused by task complexity (through sensory limits), loads (through stress) as well as the causes of loads enumerated above. The mechanistic PIF of Attention was found to be connected to the most PIFs and CFMs out of all of the mechanistic PIFs, indicating that it may be one of the most common mechanisms for information-gathering failures.

The fourth cluster, procedural error, directly causes four CFMs (I3, I5, and I8). Procedural errors were found to be directly caused by four PIFs: procedure availability and quality, knowledge/experience, loads, and safety culture. These errors are also indirectly caused by training program availability and quality (through knowledge/experience).

The fifth cluster, team coordination efficacy, directly causes three CFMs (I1, I7 and I9). These errors were found to be directly caused by four PIFs: staffing, knowledge/experience, communication availability and quality, and team cohesion. Team coordination efficacy errors are also indirectly caused by the following PIFs: safety culture (through staffing); training availability and quality (through knowledge); staffing, supervision, role awareness and knowledge/experience (through team cohesion).

In the preceding paragraphs we discuss direct and some of the indirect causal influences on the CFMs and clusters. However, all clusters are also affected by influences that propagate in from further-out PIFs. For example, staffing can be considered one of these higher-level influences because it affects the overall load (All Loads), which may induce stress on the operator. Supervision is another higher-level influence as it impacts an operator's role awareness, which may affect the overall team cohesion. This inherently captures a wide range of additional indirect factors that meaningfully influence multiple CFMs resulting in structures with a strong, complete causal basis. This multi-layered result captures the dependencies between individual and mechanistic PIFs, whereas other existing models do not consider the interactions between the different HRA variables.

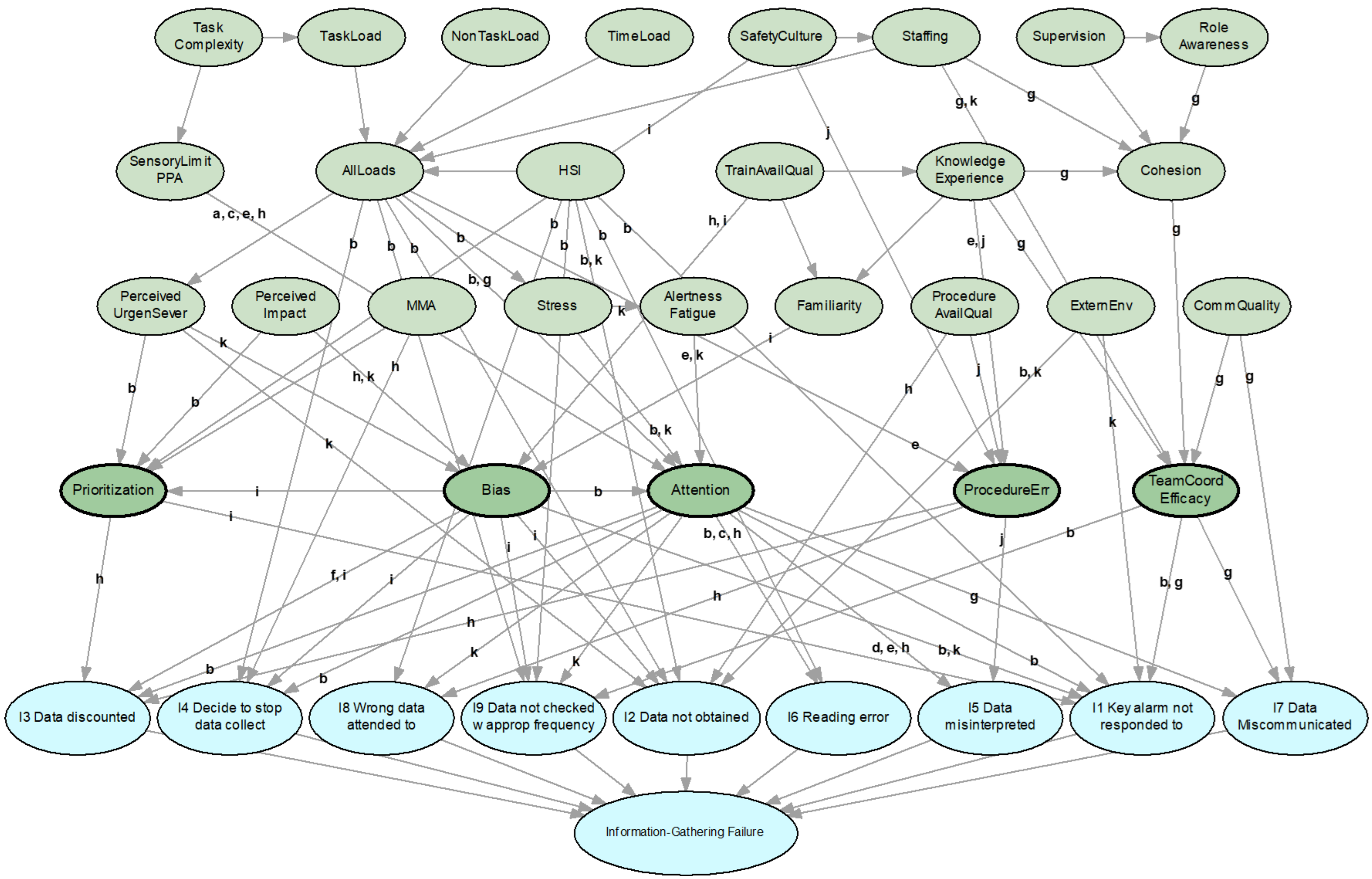

Figure 2: Full cognitive literature-substantiated Bayesian network (BN) structure for the Phoenix method I-phase CFMs.

6. DISCUSSION

The development of this Bayesian network for the Phoenix method's Information gathering phase represents an opportunity to apply this method to the external actions domain [36]. In addition, it is a step forward in enhancing the causal basis of HRA by adding theoretical foundations to the connecting arcs and causal relationships between variables. We uncovered that a wealth of psychological/cognitive literature, while well-known to human factors professionals, had not been previously utilized in HRA to build a BN's causal connections. This is an improvement upon current models which rely primarily on expert opinions and judgements. With further development, especially in model quantification, we hope to form the foundation of a new, causally-based HRA method that is domain-agnostic. Several important insights were gained during this process.

We identified a set of five PIFs that act as cognitive mechanisms through which CFMs may occur. These are similar to mechanisms of mechanical failure such as fractures from fatigue or overstress of a material. For example, the CFM I4 ("Decide to stop collecting data") is influenced by two mechanistic PIFs: the lack of attention, and bias. In turn, these mechanistic PIFs can be influenced by one or more layers of PIFs, depending on logically derived relationships and the documentation found in cognitive literature. These layers of PIF influences are detailed in Section 4 above. A more comprehensive discussion of these mechanisms and their place in HRA will be presented in another paper at this conference [37].

Another insight that we noticed was that CFM I7 ("Data Miscommunicated") was originally thought not to fit with the rest of the I-phase CFMs. However, the PIFs used were relevant to multiple other CFMs and mechanistic PIFs, so modeling these team-based attributes was important to the completeness of the I-phase BN model. Based on this, we concluded that it may not be necessary to develop a whole Coordination Phase BN [34], [38].

Furthermore, the mechanism of Team Coordination Efficacy was found to be the one with one of the most complex causal origins. While the other mechanisms model a single operator's internal cognitive processes, any mechanism relating to coordination or team performance models multiple operators' internal and external cognitive processes. These processes are not only affected by person-, situation-, organization-, and machine-based PIFs, but also team-based PIFs.

7. CONCLUSION

In this work, we developed a Bayesian network for the nine Information-phase CFMs of the Phoenix method substantiated with 13 cognitive literature sources. This model will lead to a more valid, justifiable human error probability (HEP) estimation by eliminating the uncertainties of the origins of the causal relationships. Rather than assuming a given task is particularly prone to failure, a root cause can be identified so that an effective and targeted mitigation strategy can be developed. Our future work in this area will involve creating BNs for the Decision and Action macrocognitive functions and their associated CFMs. For this, we anticipate being able to reuse many of the current structures identified in this BN model. After completing the models, we will implement a quantification scheme to estimate HEP values for representative HFEs from each of the Information-Decision-Action phases to validate our approach.

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