Causal Pathways Leading to Decision and Action Human Failure Events: Structures and Validation

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Abstract: Human failure events (HFEs) in complex engineering systems are the culmination of multiple layers of interconnected variables describing the conditions leading up to failure. These variables include performance influencing factors (PIFs), human failure mechanisms, and crew failure modes (CFMs). In previous work, we presented an approach that leverages the Phoenix human reliability analysis (HRA) method, Groth and Mosleh's 2012 PIF hierarchy, and Zwirglmaier et al.'s causal mapping methodology to develop a Bayesian network (BN) model for information-gathering macrocognitive function activities. The BN documents direct and indirect causal pathways from PIFs through mechanisms, CFMs, and into HFEs.

In this work, we develop two new BN models for two cognitive phases of the Phoenix method, decision-making and action execution. We substantiated all arcs in the BNs with a variety of literature sources originally drawn from the U.S. NRC's *Cognitive Basis for HRA*. To ensure the models' comprehensiveness and correctness, we conducted a validation session with several international experts having a combined 92 years of research experience in HRA. The experts suggested narrative resources to validate our model arcs, and we made the necessary changes according to their recommendations. We used 5 event narratives from the ATHEANA method to further validate some CFMs and their causal structures. Promising results were obtained, with causal factors driving the events corresponding well to causal chains in the models. Future work will involve synthesizing several available data sources to support eventual parameterization of the Bayesian networks for human error probability (HEP) quantification. These models enable HRA analysts to identify root causes for HFEs and develop effective, targeted mitigation strategies to prevent their occurrence. They will lead to more valid, justifiable HEP estimates by better modeling the causal relationships among variables.

Keywords: human reliability analysis, Bayesian networks, probabilistic risk assessment, nuclear power

1. INTRODUCTION & BACKGROUND

In human reliability analysis (HRA) practice, one of the main goals is the identification of potential human failure events (HFEs). These HFEs arise from complex chains of causally related events and represent the culmination of a human-machine team's failure to complete an objective, which is comprised of multiple high-level cognitive or physical actions [1], [2]. These cognitive or physical actions are called major crew functions (MCFs) [1], and represent system-specific instantiations of macrocognitive functions, such as information-gathering, decision-making, or action execution. These functions, also referred to as cognitive phases, are standardized in the Information-Decision-Action in Crew Context (IDAC) framework [3].

Most HRA methods, such as SPAR-H [4] and CREAM [5], compute human error probabilities (HEPs) from multipliers derived from combinations of Performance Influencing Factors (PIFs) that characterize the event context. However, it is necessary to acknowledge the complex causal chains leading to human error. There is a present need for models that capture this complexity while also providing user-friendly quantification capabilities. Thus, cognitively-based HRA methods with a topographical basis in psychological and organizational literature are needed to accomplish this [6]. Since HRA was developed as an offshoot of probabilistic risk assessment (PRA), obtaining a number for the HEP is an important result, but having a robust qualitative technical foundation is critical so that the HEP values can be meaningful. In previous work, this approach was leveraged to develop a Bayesian network (BN) model for the information-gathering crew failure modes (CFMs) enumerated in the Phoenix HRA method [7].

Decision-making is one of the more intricate macrocognitive functions carried out by teams in complex engineering systems. For a decision-making error to occur, it is assumed that the crew have correctly gathered and understood information relating to system status, but have insufficient awareness of the broader situation [8]. This is due to the fact that crews can make incorrect decisions in a number of ways, with many unobservable cognitive processes going into response selection. Several HRA methods refer to all cognitive activities as decision-making, which may introduce ambiguity or bias through lack of specificity, and some methods ignore cognition activities after the crew's initial diagnosis is completed [9]. While these simplifications may reduce the complexity of the analysis, they compromise the accuracy of the results as decision-making tasks present distinct opportunities for human failure.

Action execution is typically the last macrocognitive function to be modeled, and arguably the most crucial phase of operations. Even if the operator has perfect situational awareness and correct goals, an error during action execution will result in an HFE without recovery. Unlike the information-gathering and decision-making phases, there are relatively few ways that action failures may manifest. In HRA models, action errors are modeled as either flat probabilities for given task types [10] or as modified probabilities given a set of PIFs [4], [11]. However, neither modeling choice paints a complete picture of the causes of human errors in action execution. Furthermore, action errors are typically modeled as either errors of omission or errors of commission. One major gap in current HRA practice is the lacking treatment of errors of commission, as it is difficult to list them exhaustively [12].

In this work, we develop rigorous, literature-based, and substantiated BN models for decision-making and action execution. This work, combined with previous work [7], is intended to match the three cognitive phases of the IDAC framework [3]. Overall, this approach serves to enhance the traceability and scientific basis of HRA methods.

2. METHODS AND DATA: MODEL DEVELOPMENT

In this work, we synthesized several research studies that focused on different aspects of third-generation HRA modeling in order to develop the BNs. These networks present the causal structures leading to decision-making and action execution failures, building upon the method developed in [13]. 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 IDAC [3], Phoenix [8], and the Integrated Human Event Analysis System (IDHEAS) [14]. Detailed discussions of these methods can be found in their respective documentation. Also, the PIFs hierarchy developed by Groth & Mosleh [15] was used to construct the BNs. This hierarchy defines 71 PIFs belonging to five categories: machine-based, person-based, team-based, organization-based, and situation/stressor-based. This categorization and hierarchical structure allow the PIFs to be defined with respect to the appropriate category and specificity needs of the socio-technical system.

Another documentation consulted was a set of draft BNs for information-gathering failures developed at Sandia National Laboratories by Groth & Hendrickson [16]. To substantiate and solidify the basis of the causal relationships identified in the BNs, we used psychological and organizational literature sources extracted from NUREG-2114 "Cognitive Basis for Human Reliability Analysis" [17]. These sources further provided a starting point to identify additional scholarly sources. Finally, the dependency idioms defined by Paglioni & Groth [1] served as a basis for some the BN causal relationships. The synthesis of these sources to form the final models is illustrated in Figure 1.

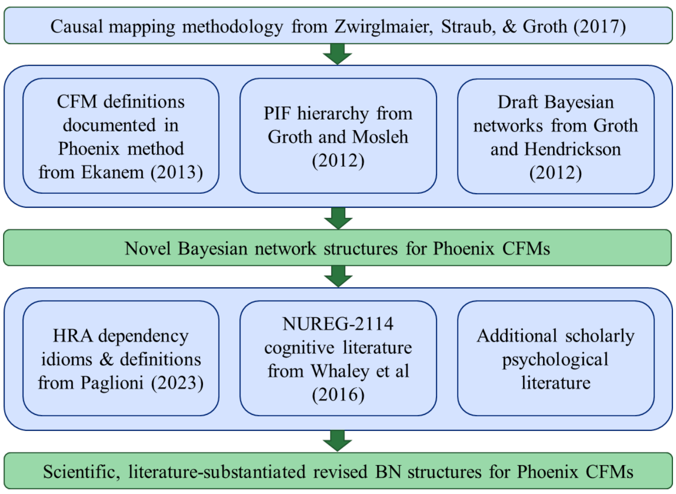

Figure 1: Synthesis of sources used in the development of human performance BNs.

In previous work in characterizing human failure events during external hazard mitigation, it was posited that there are two additional relevant CFMs for the decision and action phases [18]. These CFMs are D8*: Premature Termination of Actions and A4*: No Action Taken. Significant literature support was found for the existence of both failure modes, including [19], [20]. Both CFMs have been incorporated into the models alongside all of the pre-existing Phoenix method's CFMs.

3. RESULT: STRUCTURE AND SUBSTANTIATION OF DECISION-MAKING MODELS

The full Bayesian network structure for the decision-making models is shown in Figure 2. A source substantiating each arc in psychological literature is indicated on the arc, with letters corresponding to the sources enumerated in Table 1. Some of the structures are substantiated through the presence of construction or definitional idioms from [1] rather than through literature sources from the US NRC's Cognitive Basis for HRA [17]. For example, poor procedure quality deterministically defines the manifestation of CFM D2: Procedure Misinterpreted, as the crew is almost certain to misinterpret poorly constructed procedures.

There are five key causal clusters apparent in the structure of the decision-making human performance model. Each cluster corresponds to a mechanistic PIF, denoted by nodes in darker green with thicker borders. These clusters are **Perceived Severity**, **Skills**, **Bias**, **Prioritization**, and **Mental Model**. These clusters are probabilistic in their causation of error, increasing the probability of occurrence of the CFMs. Multiple mechanisms can contribute to the likelihood of a particular CFM with differing degrees of influence.

In addition to the mechanisms which lead to the decision-making CFMs, there is the presence of an "Information Failure" node. This encodes the potential for information-gathering failures to manifest as decision-making HFEs due to the sequential nature of the tasks. Although faulty or delayed information is the result of an information-gathering human failure event, the actual failure is likely to transpire as a "State Misdiagnosed" (CFM D1) or as "Delayed Action" (CFM D6). If the crew takes incorrect data as fact, their situational awareness is degraded, leading to an incorrect assessment of the plant state. With delays in gathering information, or conflicting data, the crew may decide to delay acting on their current knowledge of the system.

3.1 Decision-Making Failure Mechanisms

The first mechanism cluster, **perceived severity**, directly causes two CFMs (D1 and D8*). Incorrectly perceived severity is directly caused by three PIFs (perceived decision weight, overloading, and task complexity). The only indirect causes of the mechanism are the PIFs comprising loads to the operator, including time load, task load, non-task load, and task complexity.

The second mechanism cluster, **skills**, also directly causes two CFMs (D2 and D7). Skill errors are directly caused by six PIFs (personal and physical abilities (PPA), training, familiarity, knowledge and experience, use of information, and stress). Skill errors may also be indirectly caused by issues with morale, motivation, and attitude causing poor information use, overloading which causes stress, and poor safety culture which may lead to a poor training program.

The third mechanism cluster, **bias**, directly causes only one CFM (D4). Bias errors are directly caused by five PIFs (procedure quality, perceived decision weight, familiarity, knowledge and experience, and perceived urgency). Bias errors may also be caused indirectly by overloading which causes high perceived urgency, or by issues with safety culture that lead to a lack of quality procedures or training.

The fourth mechanism cluster, **prioritization**, directly causes two CFMs (D4 and D5). Prioritization errors may also be caused by the mechanism of bias. It is caused by four PIFs: perceived decision weight, safety culture, perceived urgency, and morale, motivation, and attitude. Similar to bias errors, prioritization errors are also caused by overloading caused by various demands to the operator, as well as the PIFs that cause bias errors through the paths previously identified.

The fifth mechanism cluster, **mental model**, directly causes a majority of the CFMs (D1, D3, D5, D6, D7, and D8*). Poor mental models may be caused by six PIFs: training, familiarity, knowledge and experience, overloading, communication quality, and information use. Similar to previous mechanisms, poor mental models may be indirectly caused by issues with morale, motivation, and attitude causing poor information use behaviors, highly complex tasks causing communication problems, safety culture leading to a lack of training program, and the demands to the operator that comprise overloading.

The network shown in Figure 2 captures the direct causal influences on CFMs and mechanisms as well as the indirect influences that propagate through secondary and tertiary contextual factors. This captures a wide range of factors that meaningfully influence human failure, documented through a strong, complete causal basis. Additionally, the resultant model captures the dependencies between PIFs, mechanisms, and CFMs, which represents a novel consideration of the interactions between different HRA variables.

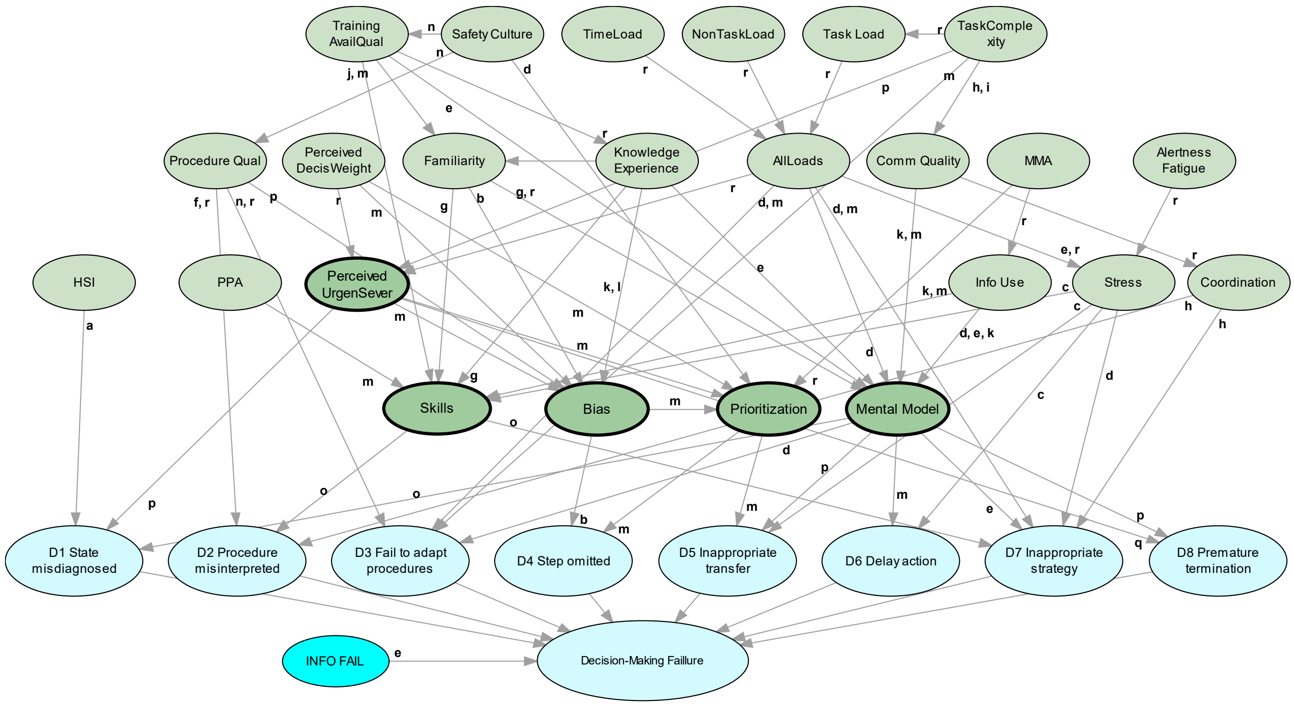

Figure 2: Full cognitive literature-substantiated BN structure for the Phoenix method's decision-making phase CFMs.

Table 1: References used to substantiate Decision-making network model arcs.

Ref on BN	Ref #	Citation	Area of BN
a)	[21]	Nystad E., Kaarstad, M., & McDonald, R. (2019).	Human-system interface
b)	[22]	Tversky, A. & Kahneman, D. (1974).	Familiarity and bias
c)	[23]	Siddle, B. (2008).	Stress
d)	[24]	Orasanu, J. & Martin, L. (1998).	Factors relating to mental model, overloading
e)	[25]	Endsley, M. (1995).	Effects of knowledge base and information
f)	[26]	Massaiu, S. & Holmgren, L. (2014).	Procedure quality
g)	[27]	Lipshitz, R. (1993).	Knowledge base
h)	[28]	Braarud, P. & Johansson, B. (2010).	Complexity and coordination
i)	[29]	Letsky, M. et al. (2008).	Team communication
j)	[30]	Hildebrandt, M. & McDonald, R. (2020).	Training
k)	[31]	Andersen, E., Kozine, I., & Maier, A. (2019).	Knowledge, information, communication
l)	[32]	Lipshitz, R. & ben Shaul, O. (1997).	Knowledge base
m)	[33]	Endsley, M. & Jones, D. (2016).	Situation and stressor based PIFs, organizational PIFs, PPA, prioritization
n)	[34]	Reason, J. (2000).	Safety culture, procedures
o)	[35]	Greitzer, F. et al. (2010).	Mental model, skills
p)	[20]	Wickens, C. et al. (2004).	Perceived severity, complexity, mental model, procedures
q)	[36]	Wickens, C. et al. (2012).	Perceived severity
r)	[1]	Paglioni, V. & Groth, K. (2023).	Deterministic dependencies

4. RESULT: STRUCTURE AND SUBSTANTIATION OF ACTION EXECUTION MODELS

The full BN structure for the action execution models is shown in Figure 3. Like the decision-making network structure, a source substantiating each arc in psychological literature is indicated by a corresponding letter, enumerated in Table 2. Some of the structures are substantiated through the presence of definitional idioms from [1]. For example, if the necessary tools are not available to the operator, they will not be able to execute actions on time or at all. Therefore, one can say that a degraded state in the parent node of tool availability defines the presence of an adverse state in the child nodes of “Incorrect Timing” (CFM A1) or “No Action Taken” (CFM A4).

There are four key causal clusters apparent in the human performance model for action execution, denoted by the darker green nodes with thicker borders. These clusters are **Coordination**, **Procedure Error**, **Skills**, and **Attention**. It is important to note that attention here draws upon different mental resources than the attention relevant to information-gathering. Rather than devoting attention to detecting cues in the environment, attention in the action execution phase refers to the operator's ability to focus on carrying out the task at hand.

Similar to the decision-making network, a “Decision Failure” node acknowledges the sequential nature of how decisions must be made before actions can be initiated. Failures in decision making, or in the following of procedures, may manifest as an omission error or commission error during the action execution stage of operations. For example, if the plant state is misdiagnosed, the operator may not act until it is too late, or may not execute the correct action at all.

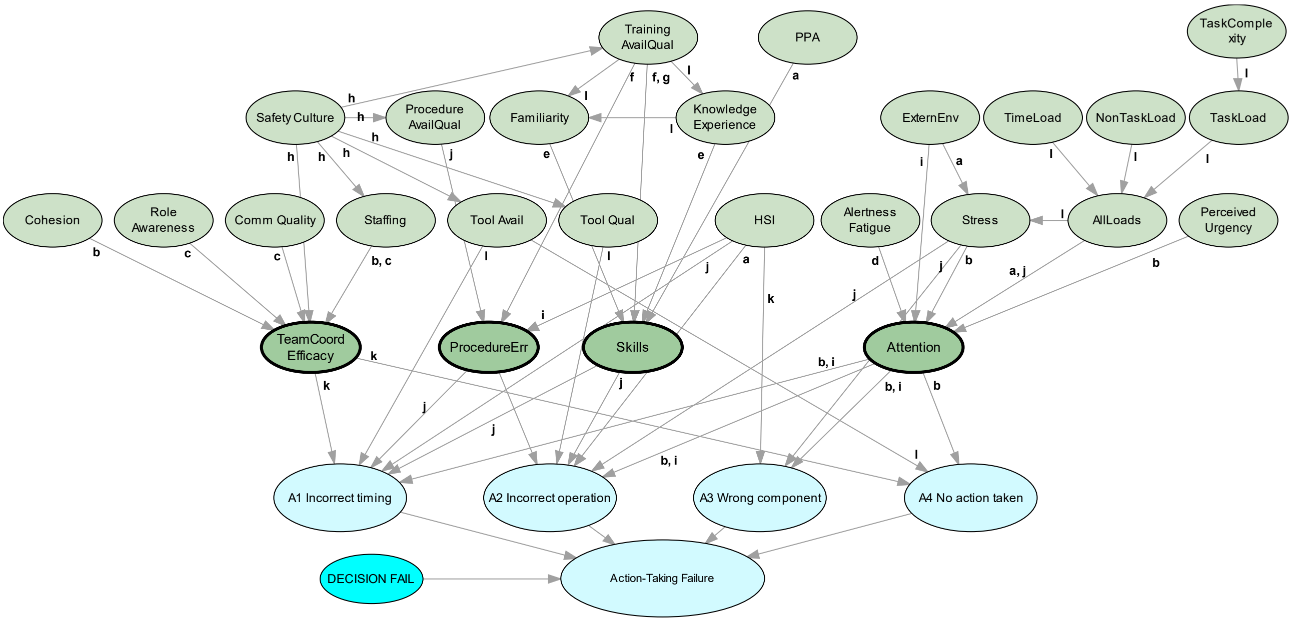

Figure 3: Full cognitive literature-substantiated BN structure for the Phoenix method's action execution phase CFMs.

Table 2: References used to substantiate Action Execution network model arcs.

Ref on BN	Ref #	Citation	Area of BN
a)	[37]	Proctor, R. & Van Zandt, T. (2017).	PPA, environment, loads, HSI
b)	[20]	Wickens, C. et al. (2004).	Attention, coordination
c)	[29]	Letsky, M. et al. (2008).	Coordination
d)	[38]	Hsieh, S., Tsai, C., & Tsai, L. (2009).	Fatigue
e)	[39]	Altmann, E. & Trafton, J. G. (2002).	Knowledge base
f)	[25]	Endsley, M. (1995).	Training
g)	[24]	Orasanu, J. & Martin, L. (1996).	Training
h)	[34]	Reason, J. (2000).	Safety culture
i)	[36]	Wickens, C. et al. (2012).	Attention, HSI, environment
j)	[40]	Huey, B. & Wickens, C. (1993).	Attention, procedure error, skills, task-related PIFs
k)	[41]	Poozhithara, J. et al. (2023).	Coordination
l)	[1]	Paglioni, V. & Groth, K. (2023).	Deterministic dependencies

4.1 Action Execution Failure Mechanisms

The first mechanism cluster, **coordination**, directly causes two CFMs (A1 and A4*). Coordination errors are directly caused by five PIFs (cohesion, role awareness, communication availability and quality, safety culture, and staffing). Poor safety culture may also indirectly cause the mechanism through poor staffing, but otherwise the mechanism is not related to any other factors.

The second mechanism cluster, **procedure error**, directly causes two CFMs (A1 and A2). Procedure error is directly caused by three PIFs (procedure quality, training, and human-system interface). Safety culture may indirectly cause this mechanism through issues with the training program.

The third mechanism cluster, **skills**, directly causes two CFMs (A1 and A2). Skill errors are directly caused by four PIFs (training, familiarity, knowledge and experience, and personal and physical abilities). Similar to procedure error, a poor safety culture may lead to a poor training program.

The fourth and last mechanism cluster, **attention**, directly causes all four of the CFMs. Attention errors are directly caused by five PIFs (external environmental conditions, fatigue, stress, overloading, and perceived urgency). Indirectly, fatigue may be caused by the operator being unfit for duty, and the external environment may cause stress to the operator. In addition, overloading can be caused by a mixture of factors, including high task load, non-task load, time load, task complexity, and complications introduced by environmental conditions.

5. RESULT: MULTI-VALIDATION OF MODELS

5.1 Expert Validation

Expert feedback sessions were held in December 2023 for an initial validation. The intent of this session was to determine their suitability for use prior to parameterization. We conducted two structured sessions with several eminent experts in the HRA field whose expertise totaled 92 years. Some persuasive arguments were made for the addition and removal of arcs from the network, and these changes were implemented.

The experts also suggested that we seek out operational experience narratives to validate the progression of the models' causal chains through real-world events. We were directed toward the Korean Institute for Nuclear Safety (KINS) OPIS database [42], as well as pre-analyzed narratives in the appendices of the ATHEANA method's technical basis [43]. The ATHEANA narratives were particularly useful towards the validation of several causal pathways leading to failure.

5.2 ATHEANA Narrative Validation

The technical basis of the US NRC's ATHEANA HRA method [43] contains a retrospective analysis of several selected nuclear power plant operational events that resulted in accidents or near-misses. Each event analysis contains a summary of the event, a timeline of the unsafe actions and recoveries, and the key mismatches between operators' mental models of the situation and the actual reality of the situation. Crucially, the analysis also characterizes the relevant performance shaping factors and categorizes the unsafe actions into failures of specific macrocognitive functions. This makes the narrative analyses particularly useful for validating the causal chains of PIFs that lead to crew failure modes as represented in our BN models. Five of the ATHEANA analyses were used in model validation, covering a wide variety of CFMs and their causes. Table 3 provides a summary of the events and the specific failure modes that arose during each.

Table 3: ATHEANA event narratives applied to model validation, and the respective CFMs covered.

Event Location and Year	Phoenix CFMs Observed
Three Mile Island, 1979	I3: Data Discounted, I8: Wrong Data Attended To, D7: Inappropriate Strategy
Crystal River, 1991	I2: Data Not Obtained, D1: State Misdiagnosed, D7: Inappropriate Strategy
North Anna, 1993	D5: Inappropriate Procedural Transfer, D7: Inappropriate Strategy
Wolf Creek, 1994	A1: Incorrect Timing of Action
Davis-Besse, 1985	A3: Action on Wrong Component, D6: Decision to Delay Action

The 1994 event at Wolf Creek occurred during a refueling outage while the reactor coolant system (RCS) was being monitored and maintenance work was being done on the residual heat removal (RHR) system [44]. Maintenance work was being done on an RHR valve in the A train leading to the steam injection system. Simultaneously, the RHR B train was being prepared for use, which necessitated manually opening another valve for recirculation to raise the boron concentration. A plant electrician requested that a control room operator close and then reopen the valve in the A train to complete a test procedure. While the A train valve was being closed, a nuclear station operator (NSO) was opening the B train valve out in the plant to ready it for use. Neither the electrician nor the NSO understood what would happen when both valves were opened at the same time. As soon as the control room operator reopened the valve in the A train, the reactor coolant was flowing rapidly through the pathway that had just opened.

The NSO heard the noises of loud water flow and reported this to the control room. They instructed the NSO to close the manual B train valve, while a different supervising operator in the control room realized the issue, isolated the path, and decided to close the A train valve. In the 66 seconds that both valves were open, 9,200 gallons of water flowed out of the RCS and into the refueling water storage tank. A retrospective analysis of plant dynamics found that if this blowdown had not been quickly isolated, the water could have fully drained in 3 minutes and the core could have been uncovered in 30 minutes [44].

According to ATHEANA's retrospective analysis of the scenario [43], the main negative influences on the event were: 1) that some operators had a poor mental model of the plant, 2) that the operators were stressed about meeting a compressed outage schedule, 3) that there was heavy reliance on the control room operators to identify issues, 4) that the control room operator did not perform a brief, review the procedure, or plant blueprints. Furthermore, the event occurred in the very early hours of the morning, at 4:00am. Several organizational factors were at play, including poor command and control from the supervising operator, poor communication, and poor planning.

In this narrative, the failure mode of CFM A1: Incorrect Timing is primarily caused by the mechanism of poor **team coordination**. Relevant PIFs include poor *team cohesion*, a lack of *role awareness*, poor *communication quality*, and a lacking *safety culture*. The crew did not act as a cohesive unit, and the operators both in the control room and out in the plant were not aware of their simultaneous roles during the outage activities. Adequate briefing communications were not performed prior to executions of actions. Lastly, deficiencies in safety culture resulted in rushing to complete the outage activities, encouraging the operators to cut corners.

In addition to coordination issues, it can also be observed that a lapse in executive **attention** from plant leadership gave rise to the error. Relevant PIFs leading to the attentional lapse include *alertness and fatigue*, *stress*, and *time loads* leading to *overloading*. Many of the narratives in ATHEANA occur during the wee hours of the morning, when the natural fluctuation of one's circadian rhythm is at a low point and alertness is low [20]. Because the plant staff was rushing to meet a compressed schedule, this led to high time pressure and undue stress to achieve all of the maintenance work before the deadline. The combination of these factors led to a lack of concentrated attention to the activities at hand.

The relevant CFM, failure mechanisms, and PIFs are highlighted here in Figure 4. Although not all of the PIFs identified in the BN model were observed to be in a degraded state during this event, the relevant PIFs that were observed constitute a set of sufficient error causes to bring about the CFM. These patterns of degraded PIFs validates the existence of human failure mechanisms [45] representing clusters of interrelated factors. When various organizational factors are suboptimal, coordination tends to be poor. Likewise, when various personal factors and task factors are in an adverse state, it is difficult to direct attention towards a task. In addition to the driving human failure mechanisms of the events at Wolf Creek, the analysis provided by ATHEANA validates the relevance of many of the model's PIFs to action timing errors. This exercise validates many modeling choices made in developing the BNs: both the structure of the modeled causal pathways and the specific PIFs which were incorporated.

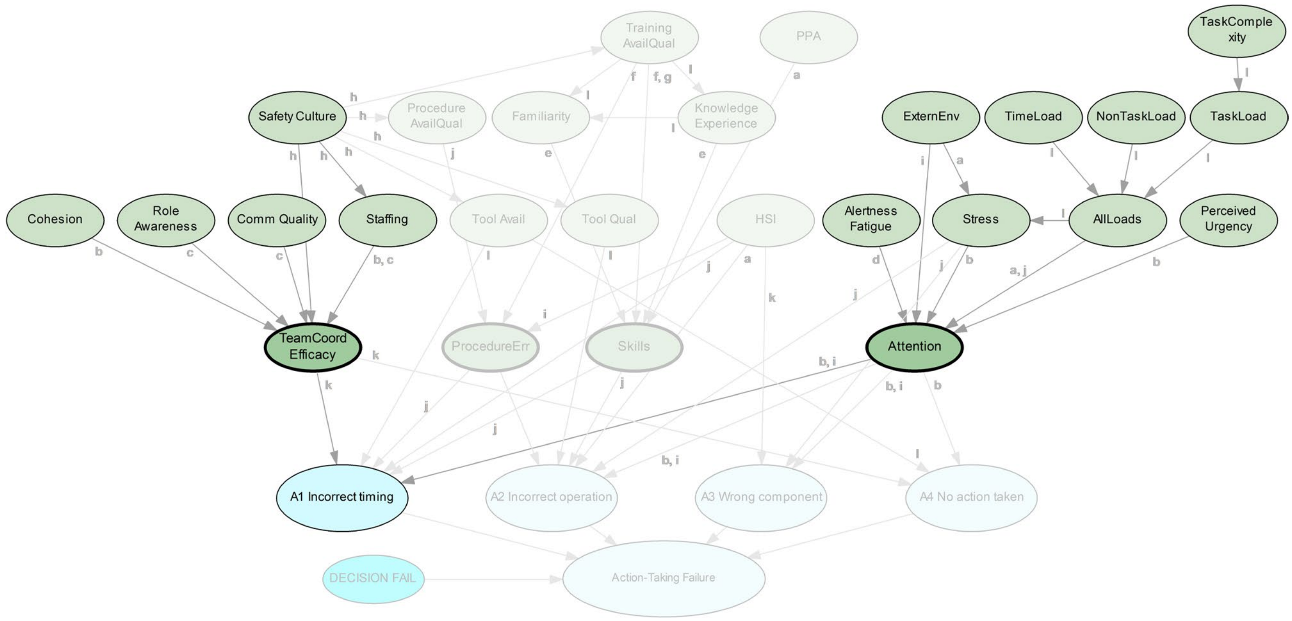

Figure 4: Partial Markov blanket of the CFM, highlighting the associated mechanisms of coordination and attention, and relevant PIFs validated by this narrative.

6. CONCLUSION AND FUTURE WORK

In this work, we developed two BN models for the decision-making and action execution phase CFMs of the Phoenix method substantiated by 23 unique cognitive literature sources. Through this approach, we identified key human failure mechanisms pertaining to both phases, as detailed in [45]. These human failure mechanisms act as qualitative and quantitative pinch points, simplifying both our understanding of how human errors occur and the mathematical challenges of BN parameterization. We also observed these mechanisms to be accurate to reality when validating the models using five ATHEANA case studies [43], one of which is presented in Section 5. These models, along with the information-gathering model [7], will lead to a more valid, justifiable HEP estimation process by eliminating the uncertainties of the origins of the causal relationships. Also, they will allow for identification of root causes of human failures and aid the development of effective, targeted mitigation strategies.

Future work will focus on quantification of the models using a variety of data sources including simulator training data, operating experience, expert judgment, and existing HRA methods. Mapping of these data sources to the models' elements has already been completed. We determined that the data streams have complementary capabilities, and that we can leverage them to adequately cover each probability in the networks. A small proportion of nodes will be mathematically condensed or removed from the models during this parameterization process, however, the vast majority of relationships can be quantified with the available data. As the state of data quality advances, the models can be updated with more accurate estimates. Additional future work on these models can involve modeling recovery actions, implementing dynamic HRA capabilities, and developing a user interface for analysts' ease of use.

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