Bayesian belief network-based HRA dependency analysis: Methodology and case study

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Abstract: Dependency among human actions remains a critical source of uncertainty in Human Reliability Analysis (HRA), particularly in complex accident recovery scenarios such as station blackout, where operators must perform multiple time-ordered actions under escalating stress, workload, and resource constraints. Traditional HRA approaches typically treat dependency using predefined levels or adjustment multipliers applied after base human error probabilities (HEPs) are estimated. Such treatments often lack explicit causal representation and do not capture the dynamic evolution of performance influencing factors (PIFs) across sequential tasks. This paper proposes a dependency analysis methodology based on Bayesian Belief Networks (BBNs), a model-based method which can be integrated into other HRA framework. It enables explicit representation of causal and probabilistic relationships among Human failure events (HFEs) and PIFs. Sequential dependency, static causal dependency (shared PIFs across tasks) and dynamic causal dependency (state evolution of PIFs across recovery actions) are incorporated into the quantification process. This paper presents its integration within Phoenix HRA framework and demonstrates its application to operation of manual opening power operated relief valve (PORV) of a nuclear power plant.
The case study evaluates operator recovery actions under two modeling assumptions: (1) independence among tasks and (2) dependency-aware modeling incorporating PIF degradation over time (e.g., stress) as well as shared contextual influences (e.g., team effectiveness). Results show that dependency-aware modeling leads to reduced HEP for dependent HFE when preceding action succeed, and produces notable shifts in end-state probabilities compared to the independence assumption.
The study, inspired by Phoenix HRA, demonstrates that BBN provides a mechanism-based and traceable approach to dependency treatment and highlights the importance of integrating dependency analysis early in the HRA quantification process. This study also discusses how the proposed method supports probabilistic risk assessment applications by producing traceable dependency-aware HEPs and improving the justification of dependency assumptions in risk-informed decision-making.

1. Introduction

Human Reliability Analysis (HRA) supports Probabilistic Risk Assessment (PRA) by identifying and quantifying Human Failure Events (HFEs) that may contribute to accident progression. In nuclear power plant operations, HFEs are often embedded in accident sequences involving diagnosis, procedure use, decision-making, communication, and recovery actions. Because these actions may share operational context, cognitive demands, procedures, cues, or crew resources, the failure probability of one HFE may not be independent of another [1]. Human error dependency therefore remains an important issue in HRA and PRA [2].

Existing HRA methods have developed practical approaches for treating dependency among HFEs. Traditional methods, such as THERP and SPAR-H, typically use predefined dependency levels, screening rules, or adjustment factors to modify Human error probabilities (HEPs) [3,4]. These approaches are useful because they are simple and compatible with PRA implementation. However, dependency is often treated as a post-processing adjustment after individual HEPs have been estimated. As a result, the underlying mechanisms that produce dependency are not always explicitly modeled. For example, two HFEs may be dependent because they rely on the same procedure, the same indication source, the same interface condition, or the same crew understanding of plant status. In other cases, the failure of an upstream action may increase workload, stress, time pressure, or confusion, thereby changing the performance conditions for downstream actions. These mechanisms are difficult to represent using only dependency multipliers or qualitative dependency levels. Recent HRA methods, such as Phoenix HRA [5,6] and IDHEAS [7], provide a stronger basis for cognitive and causal modeling of human performance. Instead of representing HFEs only as high-level PRA basic events, these methods decompose human actions into more detailed constructs, such as functions, tasks, failure modes, and Performance Influencing Factors (PIFs). This modeling structure creates an opportunity to treat dependency not only as a statistical relationship between HFEs, but also as a causal propagation process through shared or changing PIF states.

Bayesian belief network (BBN) is a probabilistic graphical model that represents variables as nodes and causal or influential relationships as directed links [8]. Its main advantage is that it can combine qualitative causal structure with quantitative probabilistic inference. This makes it possible to update the probability of one variable when evidence is observed for another variable [9]. In the Phoenix HRA framework [5,6], BBNs are used to explicitly represent the relationships among HFEs, PIFs, and shared contextual factors, and propagate evidence from degraded PIF states to downstream HFEs. Dependency among HFEs may arise from the sequential nature of human actions [10]. In addition, such dependency can also be attributed to PIFs that influence the operational context, as well as to shared upstream contextual factors underlying those PIFs, such as organizational factors [11].

Inspired by this, we propose to leverage BBN to represent HFE dependencies and quantify their effects on HEPs. Evidences of upstream HFEs can be propagated to downstream HFEs through shared operational context, i.e., PIFs or other contextual factors. It provides a traceable and mechanism-based manner to present why dependency exists, which PIFs or contextual factors drive the dependency, and how the dependency changes the estimated HEPs.

This paper presents a BBN-based HRA dependency analysis method, and distinguishes three types of dependency between HFEs. The first is sequential dependency, in which PRA event tree or accident sequence logic determines whether a downstream HFE is demanded following the outcome of an upstream HFE. The second is static causal dependency, in which two or more HFEs are influenced by the same PIF instance or shared causal source, such as a common procedure, cue, interface condition, training basis, or system diagnosis. The third is dynamic causal dependency, in which the outcome of an upstream HFE changes the downstream operational context by updating PIF states over time, such as workload, stress, or available time. Sequential dependency is represented through PRA logic, while static and dynamic causal dependencies are represented in the BBN layer through PIFs and causal links. The dependency-aware HEPs are quantified by propagating evidence through the BBN. In this way, the proposed method avoids treating dependency as an arbitrary adjustment and instead links dependency quantification to explicit causal assumptions.

This method is integrated into Phoenix HRA framework, and demonstrated through a case study of operation of manual opening of power operated relief valve (PORV). The case study illustrates how HFEs and PIFs are modeled, how dependency relationships are identified and represented, and how dependency-aware HEPs are quantified. Results compare baseline HEPs with dependency-aware HEPs.

The main contribution of this paper is to provide a causally and probabilistically traceable method for HRA dependency quantification using BBN. The remainder of this paper is organized as follows. Section 2 presents the proposed dependency analysis method. Section 3 provides an overview of integrating the proposed method into Phoenix HRA. Section 4 presents the case study. Section 5 discusses the findings, and Section 6 concludes the paper.

2. Development of HRA Dependency Analysis Method

The purpose to quantify HRA dependency is to translate the dependent HFE combinations into updated HEPs that can be incorporated into PRA quantification.

First, dependence between HFEs is defined as three types: sequential, static causal, and dynamic causal dependence, as described in Section 2.1. Second, we propose to use PRA logic trees, e.g., event tree and fault tree, and BBN to formalize and quantify the HFE dependence, which provides a model-based and traceable causal probabilistic propagation paths.

2.1. Definition of dependency between HFEs

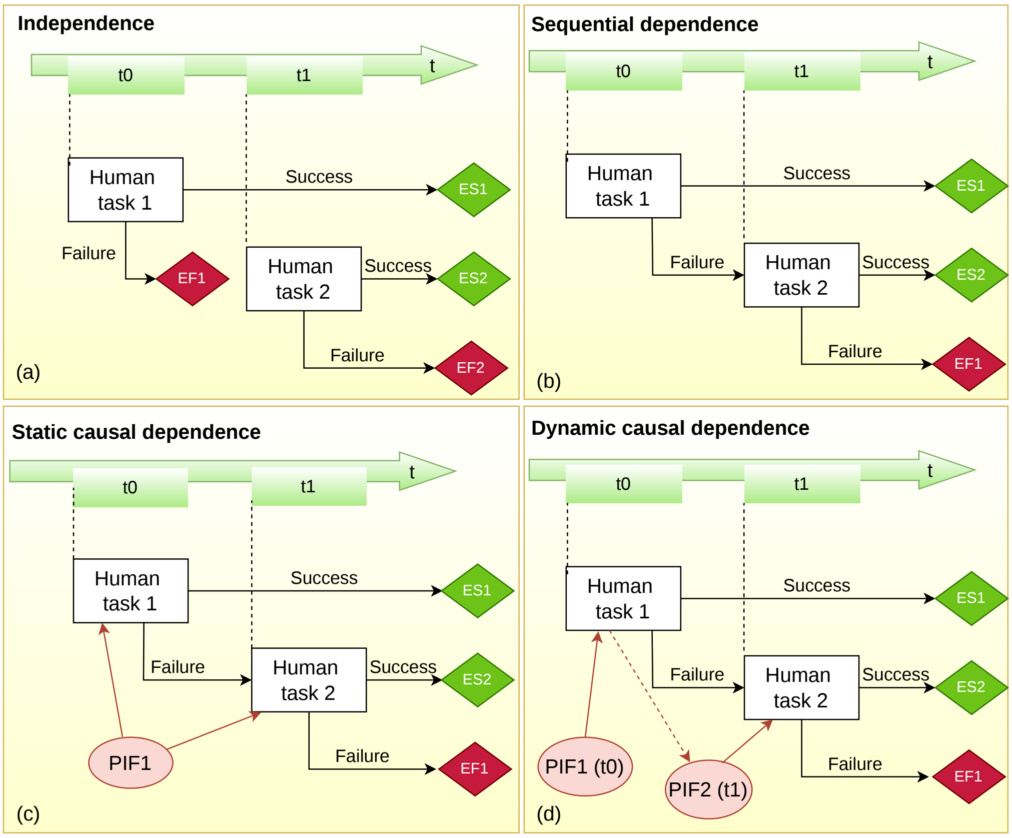

Figure 1 Overview of the dependence between HFEs

The independence case represents the baseline situation in which two HFEs are modeled as separate human actions without either sequence-based or causal dependence. As illustrated in Figure 1 (a), HFE A and HFE B are represented as distinct events.

Sequential dependence, occurs when the event tree logic places one HFE downstream of another. In this case, HFE B is reached only under a particular outcome of HFE A, such as the failure of HFE A. As illustrated in Figure 1(b), the failure path of HFE A leads to HFE B. Therefore, the failure end state associated with HFE B represents not only the failure of HFE B itself, but the joint path in which HFE A fails and HFE B is subsequently failed.

Static causal dependence, occurs when two or more HFEs are influenced by the same underlying PIF instance or common dependency source. Examples include the same procedure, the same indication source, the same interface feature, the same training deficiency, the same support-system condition, or the same environmental factor. As illustrated in Figure 1(c), PIF 1 affects both HFE A and HFE B. The PIF itself is not necessarily changed by the outcome of HFE A. Instead, observing the failure of HFE A provides evidence about the likely state of the shared PIF. This updated belief about the shared PIF then changes the assessed probability of failure for HFE B. For example, suppose HFE A and HFE B both rely on the same procedure. If HFE A fails, and that failure is associated with procedure use, the analyst has stronger evidence that the procedure may be degraded, confusing, incomplete, or difficult to apply. Since HFE B relies on the same procedure, the probability of failure for HFE B should be updated accordingly.

Dynamic causal dependence, occurs when the outcome of an upstream HFE changes the performance context for a downstream HFE by changing the state of one or more PIFs. This applies to PIFs that can evolve during the accident sequence, such as stress, workload, time pressure, fatigue, confusion, or situation awareness. As illustrated in Figure 1(d), HFE A is influenced by PIF 1 at an earlier point in the sequence. If HFE A fails, that failure changes the degradation probability of PIF 2 at a later point. PIF 2 then affects the probability of failure of HFE B. This is different from direct causal dependence. In static causal dependence, the previous failure provides evidence about a shared PIF. In dynamic causal dependence, the previous failure changes the degradation probability of the downstream PIF. For example, suppose the crew fails an initial diagnosis action. That failure may increase stress, workload, time pressure, or confusion for the next action. Therefore, the probability that stress is high during HFE B is no longer the original prior probability.

2.1. Quantification Methodology for HFE Dependency

2.1.1. PRA Tree to Quantify Sequential Dependency

It is proposed to quantify sequential dependency through the PRA logic trees, because this type of dependency occurs when the event tree or accident sequence determines that one HFE is encountered only after a previous HFE has succeeded or failed. As shown in Figure (b), HFE_B is only demanded after HFE_A fails, then the joint contribution of these events to the accident sequence is represented as equation (1), F denotes as failure:

$$P(Failure\ path) = P(HFE\_A = F) \cdot P(HFE\_B = F \mid HFE\_A = F) \qquad (1)$$

In the simplest case, the upstream HFE_A does not causally change the PIFs or context of the downstream HFE_B. It only determines whether the downstream HFE_B is demanded. Under this assumption, the conditional probability of HFE_B failure is equal to its baseline failure probability:

$$P(HFE\ B = F \mid HFE\ A = F) = P(HFE\ B = F) \qquad (2)$$

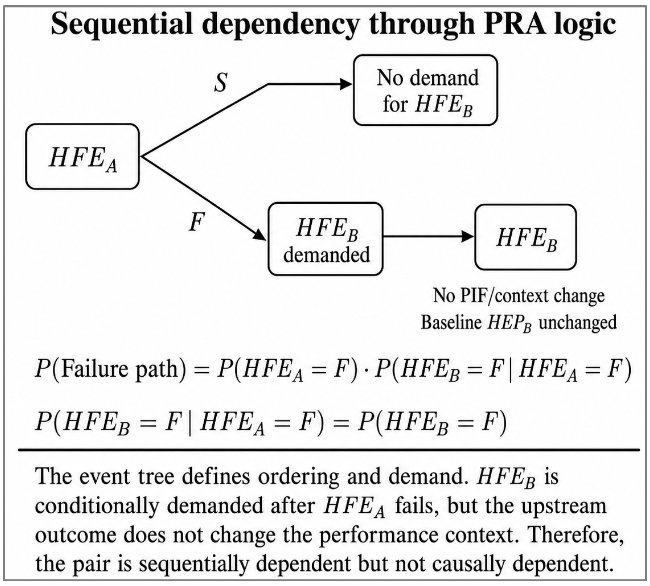

Figure 2 Formalize and quantify sequential dependency through PRA logic

In this case, event tree defines the ordering and demand condition, but the downstream HEP is not changed by the upstream outcome. Therefore, this pair of ordered HFEs is sequentially dependent but not causally dependent. Two HFEs may appear in the same accident progression, but unless the upstream HFE_A changes the performance context of the downstream HFE_B, the quantification remains a sequence-based multiplication of conditional events. However, if the failure of HFE_A changes the conditions under which HFE_B is performed, then sequential dependency should be combined with BBN-based causal dependency.

2.1.2. BBN to Quantify Static Causal Dependency

Static causal dependency is quantified when two or more HFEs are influenced by a shared PIF instance or common causal source. In this case, the dependency does not arise because one HFE directly causes another HFE to fail. Instead, the HFEs are statistically dependent because they share an upstream cause. The simplified BN structure can be represented as:

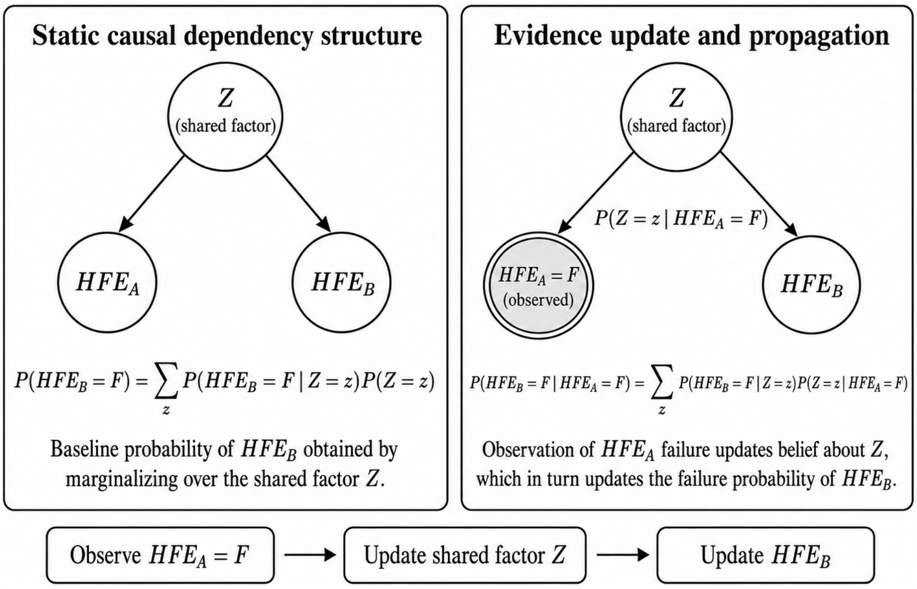

Figure 3 Formalize and quantify static causal dependency through BBN updating algorithm

Baseline probability of HFE_B is obtained by marginalizing over the possible states of (Z):

$$P(HFE_B = F) = \sum_z HFE_B = F \mid Z = z) P(Z = z) \tag{3}$$

When evidence is observed for HFE_A, such as (HFE_A = F), the BN updates the posterior belief about the shared factor:

$$updated\_P(Z = z) = P(Z = z \mid HFE_A = F) \tag{4}$$

This posterior distribution is then propagated to HFE_B:

$$P(HFE_B = F \mid HFE_A = F) = \sum_z (HFE_B = F \mid Z = z) P(Z = z \mid HFE_A = F) \tag{5}$$

These equations show the key mechanism of static causal dependency. The failure of HFE_A provides information about the likely state of the shared factor (Z). If HFE_A failed, and if that failure is strongly associated with a degraded procedure, high workload, poor cue availability, or another shared factor, then the posterior probability of the degraded state of (Z) increases. As a result, the failure probability of HFE_B is also updated. The quantification is therefore evidence-based: dependency is expressed through BN inference rather than through a predefined dependency factor.

2.1.3. BBN to Quantify Dynamic Causal Dependency

Dynamic causal dependency is quantified when the outcome of an upstream HFE changes the operational context or PIF degradation probability for a downstream HFE. Unlike static causal dependency, the downstream HFE is not dependent on the upstream HFE merely because both share the same pre-existing factor. Instead, the upstream outcome modifies the future context in which the downstream HFE is performed. The general structure is shown in Figure 4, where Z(t) represents the initial PIF or context state, HFE_A(t) represents the upstream human action, Z(t+1) represents the updated downstream context, and HFE_B(t+1) represents the downstream HFE.

The quantification proceeds in two steps. First, the downstream PIF degradation probability is updated based on the upstream HFE outcome:

$$updated\_P\ (Z_{t+1}) = P(Z_{t+1} \mid HFE_A = F) \quad (6)$$

Second, the updated downstream PIF state is propagated to the downstream HFE:

$$P(HFE_B = F \mid HFE_A = F) = \sum_{Z_{t+1}} (HFE_B = F \mid Z_{t+1} = z) P(Z_{t+1} = z \mid HFE_A = F) \quad (7)$$

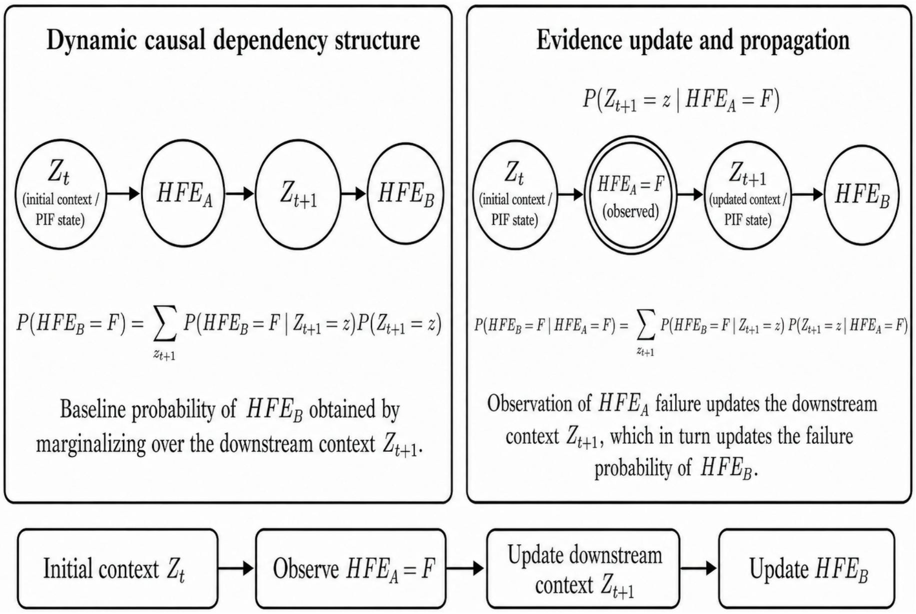

Figure 4 Formalize and quantify dynamic causal dependency through BBN updating algorithm

This structure is appropriate for cases where an upstream failure increases stress, reduces available time, increases workload, changes plant conditions, generates additional alarms, or degrades situation awareness. For example, failure to recover one system may leave the crew with less time and more complex diagnostic demands when attempting a later recovery action. The downstream HEP is then recalculated under the updated context rather than under the original baseline context.

Dynamic causal dependency is particularly important because it captures path-dependent effects. The probability of HFE_B is not fixed for all sequences; it depends on what happened earlier in the scenario. Therefore, the same HFE may have different HEPs in different accident paths, depending on the upstream evidence and the resulting PIF degradation probability updates.

3. Overview of Integrating the proposed method into Phoenix HRA

To demonstrate the compatibility of the proposed dependency analysis method, it is integrated into Phoenix HRA framework, as shown in Figure 2. Phoenix HRA provide qualitative and quantitative analysis consisting of a flowchart for generating Crew Response Trees (CRTs), and a set of Crew Failure Modes (CFMs), Performance Influencing Factors (PIFs), and quantitative scales. The Master Event Sequence Diagram (ESD) models a series of HFEs. The success or failure of each HFE is modeled using a CRT, a forward-branching tree that identifies critical tasks (CTs) by modeling the interaction between the crew and the plant. Next, the crew's failures to perform the CTs are modeled using Fault Trees (FTs), which include the human response model and lead to CFMs. Finally, the influence of the context on the CFMs, represented by the causal model, is modeled using BBNs that consist of CFMs and PIFs. The qualitative analysis consists of 1) identifying and developing the accident scenarios for analysis; 2) developing the CRTs; 3) identifying the CFMs for CRT branches; 4) developing the CRT scenarios for HFEs in terms of CFMs and relevant PIFs; and 5) analyzing the scenario, writing the accident narrative, and tracing dependencies among actions. This results in an integrated model consisting of CRTs, FTs, and BBNs and CFM cut sets. The quantitative analysis is performed through 6) assessing PIFs states; 7) quantifying the integrated model layer by layer from

BBNs, FTs, to CRTs; and 8) calculating the HEPs. The highlighted parts in Figure 4 represents the formalization of dependencies in Phoenix HRA framework.

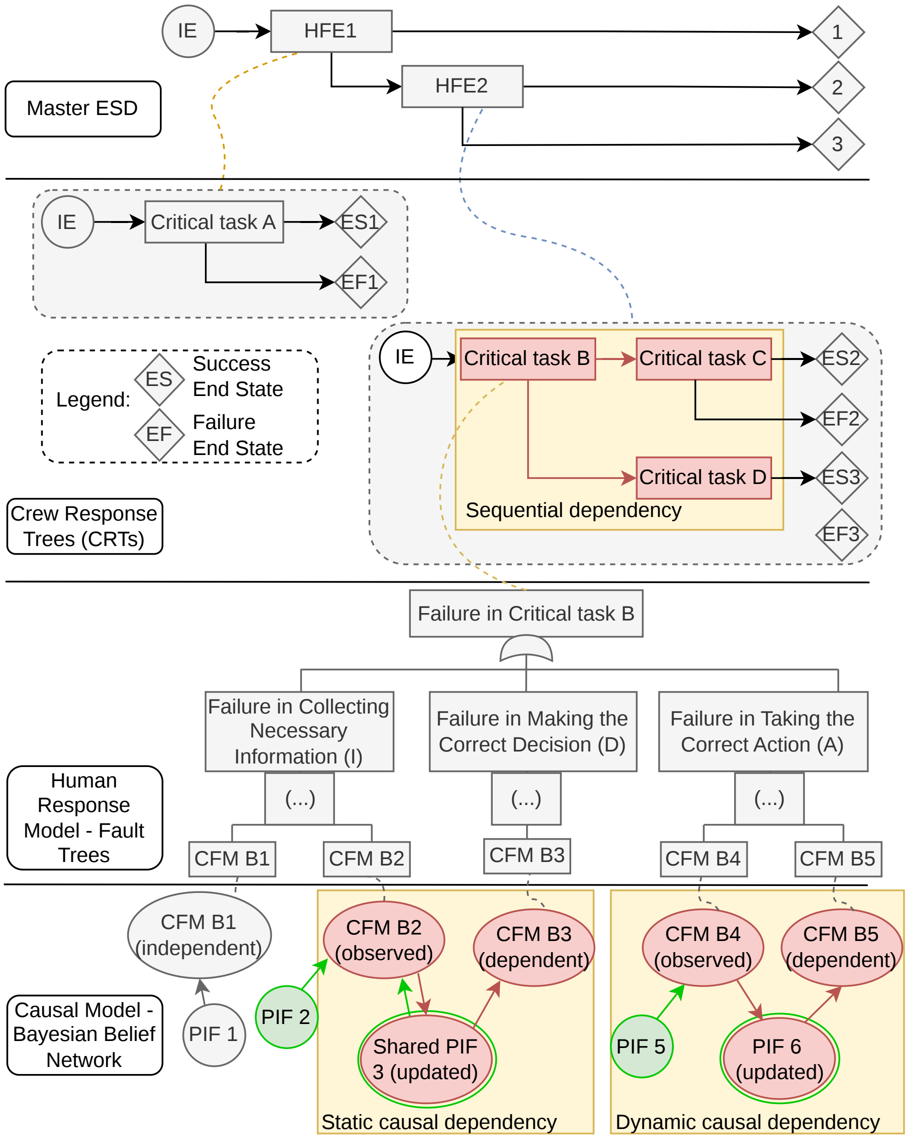

Figure 4 Integrating the proposed methodology into Phoenix HRA as highlighted

4. Case Study

Due to the limited space, this paper presents the analysis of static causal dependency using a scenario as described below. Demonstration for the all dependency types will be presented in a separate paper.

4.1. Scenario description

This demonstration uses the Manual Opening of PORV from the Station Blackout sequence. The action is required after loss of all AC power, when operators D, E, and F move onsite to support cooldown and depressurization by manually opening the main steam relief valves. About 10 minutes after the occurrence of loss of all ac power, operator D, E and F move to onsite for cooldown and depressurization (opening main steam valves). The room temperature is equivalent to the normal operation state and there are no facilities obstructing in the surrounding area. When opening main steam relief valves on site, they use a base fixed with a bolt nut to facilitate valve operation. If the main steam safety valve in the vicinity of the main steam relief valve operates, it may cause noise, so the operators carry the earplug all the time.

The operator action process is below. First, the operators open the main steam relief valves to rapidly decrease the temperature and pressure of the primary cooling system. Second, after cooling is initiated, they adjust the opening degree of the valves to maintain the pressure and temperature of the primary cooling system. Third, after the main steam relief valve adjustment, the turbine-driven auxiliary feedwater control valve is adjusted to maintain the steam generator water level. The AFW adjustment is expected about 1.5 hours after the event and is considered non-urgent; therefore, it is assumed to be handled by one operator, operator E. In total, the operators open three main relief valves. Although this involves manual operation of air-operated valves with approximately 128 valve revolutions, the operators are assumed to be trained and proficient in valve operation.

4.2. HFE and PIF modeling by Phoenix HRA

Manual opening of PORV is considered a critical function (CF) in the Phoenix HRA framework, thus, the critical tasks under this CF are identified and modeled by CRT as shown in Figure 5.

- HFE_1 = Operators D, E, F do not follow the appropriate procedure, representing the procedure-following portion of the task.
- HFE_2 = Operators D, E, F fail to open/operate the valves, which is located on the success path of (HFE_1). Therefore, the HFE_2 is only demanded if the crew successfully completes the HFE_1.

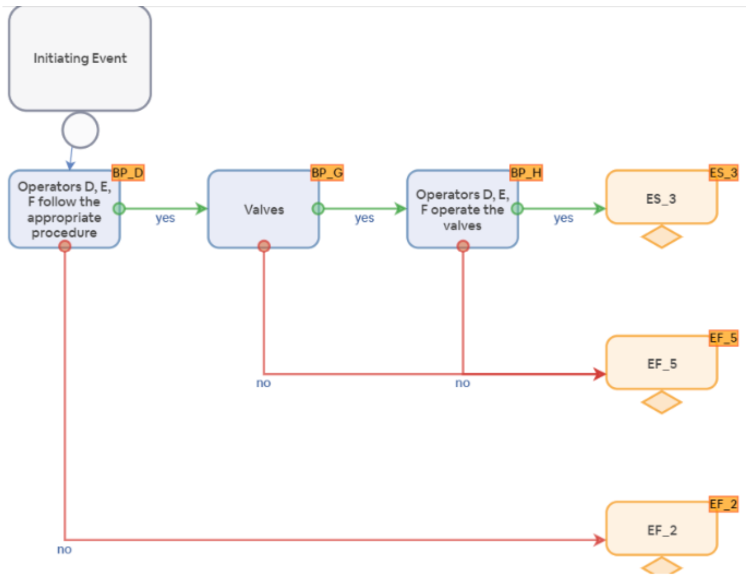

Figure 5 CRT of Manual opening of PORV

CFM in the Phoenix HRA framework describes the specific cognitive or action-based failure mode through which the HFE may occur. For example, the first HFE, “Operators follow procedure,” may fail through reading error, procedure misinterpretation, or information miscommunication; while the second HFE, “Operators operate valve,” may fail through action on the wrong component. Table 1 identifies the CFMs associated with each HFE.

Table 1: CFMs associated with the two HFEs

HFEs	CFMs
1-Operators follow procedure	Reading Error; Procedure Misinterpreted; Information Miscommunicated
2- Operators operate valve	Action on Wrong Component

The relevant PIFs for these CFMs are identified as stress, procedures, and team effectiveness as shown in Table 1. the PIFs marked with “D-” are treated as common PIFs across the HFEs. These shared PIFs provide the basis for dependency modelling. PIF degradation probabilities are evaluated using designed questionnaire, as presented in Table 2.

Table 2: HFEs, CFMs, PIFs and their degradation probabilities

HFE	CFM	PIF	D (degraded) - PIF probability
1-Operators follow procedure	Reading Error	D-Stress	3.33E-01
	Procedure Misinterpreted	Procedures	1.11E-01
		D-Stress	3.33E-01
	Information Miscommunicated	D-Stress	3.33E-01
		D-Team Effectiveness	4.38E-01
2- Operators operate valve	Action on Wrong Component	D-Team Effectiveness	4.38E-01
		D-Stress	3.33E-01

4.3. Dependency modeling and quantification

As shown in Figure 6, the HFE 1 is caused by CFM 1 Procedure misinterpreted, CFM 2 Reading error, and CFM 3 Information miscommunicated, we assume the CFM 3 is observed. Thus, degradation probabilities of PIF Stress and Team effectiveness are updated through BBN updating algorithm. Furthermore, HEP of HFE 2, caused by CFM 4 Action on wrong component, is updated because of the updated PIF Team effectiveness.

Because of the limited space, this paper presents the updating process from CFM3 to CFM4, but excludes CFM1 and CFM2. However, when giving evidences to them, degradation probabilities of the PIFs will be further updated, and HEP of Action on Wrong Component will change accordingly.

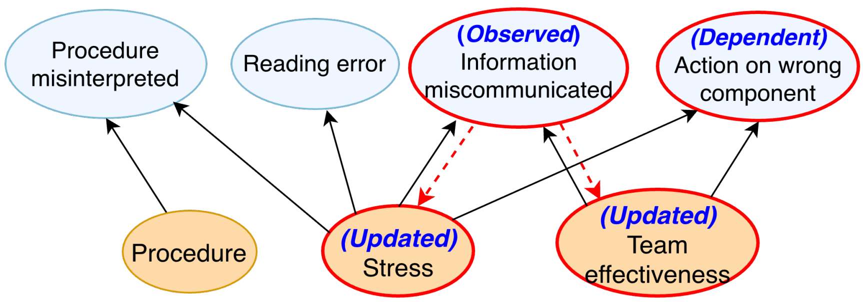

Figure 6 Dependency modeling and quantification through BBN updating

Table 3: Partial conditional probability table (CPT) example of "Information Miscommunicated" with PIF Team effectiveness and Stress

Team Effectiveness	Nominal		Degraded	
Stress	**Nominal**	**Degraded**	**Nominal**	**Degraded**
Information Miscommunicated = Failure	0.000198	0.026893	0.008806	0.035271
Information Miscommunicated = Success	0.999802	0.973107	0.991194	0.964729

The posterior probabilities of the PIFs are generated through BN updating after observed CFM outcomes are entered as evidence. Table 3 presents a partial CPT for Information Miscommunicated, illustrating how this CFM is conditioned on the states of two PIFs: Stress and Team Effectiveness. The complete CPT refers to Guidebook of Phoenix HRA Methodology developed by the GIRS UCLA. Therefore, the following calculation is an example of updating from the observed CFM Information Miscommunicated to the posterior probabilities of Stress and Team Effectiveness. The remaining observed CFMs, such as Procedure Misinterpreted and Reading Error, are incorporated through the same BN updating process. Let T=Team effectiveness, S=Stress:

$$\text{Prior\_P(T=degraded)=0.438, Prior\_P(S=degraded)=0.333}$$
$$\text{Thus, Prior\_P(T=nominal)=0.562, Prior\_P(S=nominal)=0.667}$$

Assuming prior independence:

$$P(T,S)=P(T)P(S)$$

Using the CPT in Table 3, the probability of observing Information Miscommunicated (CFM3) = Success is:

$$\text{P(CFM3 = Success)}=\sum_{t,s}(CFM3 = Success \mid T = t, S = s)\, P(T = t)P(S = s)$$

Given the CFM 3 = Success, meaning P (CFM3 = Success)=1, the posterior probability of degraded Team effectiveness is:

$$P(T = degraded \mid CFM3 = Success)$$
$$= P\,(CFM3 = Success \mid T = degraded)P(T = degraded)/P(CFM3 = Success)$$
$$=(0.991194(0.438)(0.667)+0.964729(0.438)(0.333))/1$$
$$\approx 0.430$$

The posterior probability of degraded Stress is:

$$P(S = degraded \mid CFM3 = Success)$$
$$= P\,(CFM3 = Success \mid S = degraded)P(S = degraded)/P(CFM3 = Success)$$
$$= (0.973107(0.562)(0.333)+0.964729(0.438)(0.333))/1$$
$$\approx 0.323$$

This example shows how the observed outcome of Information Miscommunicated provides evidence about the likely states of its parent PIFs. Since a successful CFM outcome is observed, the posterior probabilities of degraded Stress and degraded Team Effectiveness are updated as shown in Table 4.

Table 4: Updated degraded PIF probability

HFE	CFM	PIF	D (degraded) - PIF probability	Updated D-PIF probability
2- Operators operate valve	Action on Wrong Component	Team Effectiveness	4.38E-01	4.30E-01
		Stress	3.33E-01	3.23E-01

4.4 HEP quantification with and without dependency

HEP without dependency is calculated using the prior PIF degradation probabilities. Let A represent Action on wrong component. In the case of no dependency:

$$\text{HEP(A = true)} = \sum_{t,s} P(A = true) \mid T = t, S = s)\, P_{prior}(T = t)P_{prior}(S = s)$$
$$= 4.566\text{E-}04$$

In the case of considering dependency, the final posterior probabilities in Table 4 are used to propagate HEP of Action on wrong Component through BN updating:

$$\text{HEP(A = true)} = \sum_{t,s} P(A = true) \mid T = t, S = s)\, P_{post}(T = t)P_{post}(S = s)$$
$$= 4.468\text{E-}04$$

5. Discussion

5.1 Dependency modeling and its effect on the downstream HEP in the case study

The Manual Opening of PORV case demonstrates how the proposed method models dependency at the CFM and PIF levels. In this case, HFE_1 represents the failure of Operators D, E, and F to follow the appropriate procedure, while HFE_2 represents the failure to open the valves. HFE_2 is evaluated after HFE_1 succeeds, because the valve-opening action is reached only if the crew has correctly followed the procedure. The dependency is therefore modeled by setting the upstream task outcome as evidence in the BN. Specifically, the success of HFE_1 provides evidence that the shared PIFs affecting the downstream action are less likely to be degraded. The updated PIF probabilities are then used to quantify the downstream CFM, Action on Wrong Component.

The results show that dependency does not always increase the downstream HEP. In this case, upstream success reduces the probability of degraded PIF states. The degraded probability of Team Effectiveness decreases from 4.38E-01 to 4.30E-01, and the degraded probability of Stress decreases from 3.33E-01 to 3.23E-01. After these updated PIF values are propagated to the downstream CFM, the HEP of Action on Wrong Component decreases from 4.566E-04 under the no-dependency case to 4.468E-04 under the dependency case. This reduction occurs because the successful completion of the procedure-following task provides positive evidence about the crew’s performance conditions for the subsequent valve-opening task.

5.2 Traceable and extensible BBN-based dependency analysis

The BBN-based approach makes the dependency treatment more transparent than applying a fixed dependency multiplier. Analyst can identify: 1) which upstream task outcome is used as evidence, 2) which PIFs are updated, and 3) how the updated PIF probabilities change the downstream HEP. For the presented example, the dependency effect is not assigned directly between HFE_1 and HFE_2. Instead, it is quantified through the shared PIFs, especially Team Effectiveness and Stress. This provides a clear explanation for why the downstream HEP changes and avoids treating dependency as an unexplained adjustment factor. Furthermore, another notable merit of BNs is their extensibility, which allows the model to be expanded with richer causal structures and additional influencing factors that may direct to upstream root causes of PIFs, such as organizational factors [8,11].

5.3 PRA implementation: Direct quantification of dependent HEPs

The proposed method has practical value for PRA because it provides a model-based way to quantify dependency-aware HEPs. Although it is demonstrated within Phoenix HRA, it can be also used as a dependency analysis layer on top of other HRA methods, as long as the analyst can identify the relevant HFEs, upstream task outcomes, and PIFs that influence the downstream action.

In many existing HRA/PRA workflows, analysts first quantify individual HEPs and then apply dependency rules or multipliers. This can require repeated calculations and may make the basis for the final dependent HEP difficult to trace. In the proposed method, once the dependency mechanism is identified, BBN directly updates the relevant PIF states and calculates the downstream dependent HEP. The result can be followed from the upstream HFE evidence, to the updated PIF probabilities, and finally to the downstream HEP. Therefore, this method reduces the computational burden by avoiding repeated HEP quantification, and the dependent HEP is not an unexplained adjustment, but a reproducible result based on explicit causal assumptions.

6. Concluding remarks

This study proposes a BBN-based dependency analysis method for HRA, inspired by the Phoenix HRA framework. The method treats dependency as a causal and probabilistic relationship among HFEs, CFMs, and PIFs, rather than as a fixed post-processing multiplier. It first identifies whether HFEs are sequentially related, influenced by shared PIFs, or affected by evolving PIF states. The dependency is then represented in a BBN, where the outcome of an upstream HFE or CFM is used as evidence to update relevant PIF probabilities. These updated PIF states are then propagated to the downstream CFM or HFE to calculate a dependency-aware HEP. Although demonstrated within Phoenix HRA, the method can also serve as a model-based dependency layer for other HRA methods, as long as the relevant HFEs, task outcomes, and influencing PIFs can be identified.

The main merit of the method is causal and probabilistic traceability and . Analysts can identify which upstream outcome is used as evidence, which PIFs are updated, and how the updated PIF states change the downstream HEP. In the Manual Opening of PORV case, upstream success reduces the degraded probabilities of Team Effectiveness and Stress, and the HEP of Action on Wrong Component decreases from 4.566E-04 to 4.468E-04. This shows that dependency does not always increase HEPs. Future work will extend the method to cross-CRT dependency and dynamic PIF evolution over longer accident sequences.

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