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Recommending Updates To The EMBRACE HRA Dependency Assessment Method To Account For Multiple HFE Cut Sets

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Abstract

This paper updates aspects of the dependency assessment method developed previously by the Korea Atomic Energy Research Institute (KAERI) and demonstrated for the EMBRACE HRA. This method represents a novel approach to modeling and quantifying dependency between human failure events (HFEs), predicated on shared temporal resources (TRI) and similarities in cue recognition (CRD) and procedure transition (PTS). However, the current version of this method is designed to assess dependency between two HFEs only. The possibility of multiple (i.e., more than two) dependent HFEs in a cut-set requires a corresponding update to the dependency assessment method to ensure that realism and conservatism are properly retained when extending this methodology to multi-HFE cut-sets. Accordingly, this paper proposes an updated methodology to efficiently compute the dependency between three or more HFEs, that is firmly rooted in both theory and empirical data.

Keywords: human reliability analysis, dependency, nuclear

1. Introduction

Dependency assessment in human reliability analysis (HRA) has been the subject of a sizeable body of research in recent years (Kim et al., 2015; Mortenson and Boring, 2021; Paglioni and Groth, 2022). Briefly, dependencies are the causal relationships between the modeling elements in HRA that can alter the human error probabilities (HEPs) used in probabilistic risk assessments (PRAs) (Paglioni and Groth, 2021). Critically, recent work has stressed the importance of moving beyond the dependency framework set up in the Technique for Human Error Rate Prediction (THERP), one of the prototypical HRA methods developed through the 1980s (Swain and Guttmann, 1983). This is an important development because current HRA dependency assessment methods are largely not rooted in empirical data or literature, instead relying upon the rule-based method and equations developed in THERP. Recent work at the Korea Atomic Energy Research Institute (KAERI) has leveraged the availability of HRA data to create an empirically-based dependency assessment methodology, a significant step forward for realism in HRA (Kim et al., 2023). This development coincides with recent work at Idaho National Laboratories (INL) that identified dependency signatures in empirical data (Boring et al., 2023) and at the University of Maryland that developed a causal model structure for HRA dependency informed by data (Paglioni and Groth, 2023a, 2023b).

Focusing on empirical data for developing HRA dependency assessment methods has the distinct advantage of predicating these analyses on observed data, in addition to literature, and improving the realism of HRA dependency assessments. However, the recent method developed at KAERI considers dependency only between two HFEs in a cut-set. This stands in contrast to applications of HRA in the nuclear power industry, where multiple-HFE cut-sets (i.e., those cut-sets with three or more HFEs present) are common. However, the results obtained with the KAERI method are promising, and therefore extending this method to accommodate more HFEs is important to ensuring that such a method is useable in industry. Accordingly, this paper presents recommendations for updating the KAERI dependency assessment method to be applicable to multiple-HFE cut-sets.

The remainder of this paper is structured as follows. Note that there is only limited background information provided on HRA dependency. This has been well-documented in recent research, including in (Boring et al., 2021; Kim et al., 2023). Instead, this paper will focus on the recently-developed KAERI dependency assessment method and the recommendations for extending the method. Section 2 reviews the current state of the dependency assessment method and the different factors used within. Section 3 presents the recommendations for extending the method to multiple-HFE cut-sets. Section 4 discusses the impacts of this method on HRA practice, and Section 5 concludes with a discussion of future research needs to understand dependency in HRA.

2. Background

The HRA dependency assessment method under study was developed by KAERI in 2023, and first implemented within the EMBRACE HRA method, also developed by KAERI (Kim et al., 2019, 2020, 2021). This method incorporates the latest work on HRA dependency and how dependency exists within a system. Critically, this method incorporates four aspects of human performance that are causally important to dependency in HRA, which are briefly explained below (Kim et al., 2023):

- ***Feasibility impact***: an antecedent human action may directly influence the *feasibility* of future human actions, for example by damaging equipment required for successor tasks. This will therefore directly alter the HEP for successor tasks.
- ***PSF impact***: an antecedent human action may cause a change in the performance shaping factors (PSFs) that define the *situation* (e.g., local PSF states) in which successor tasks will take place. This relationship, similar to the situational dependency from (Paglioni and Groth, 2023a), will indirectly affect the HEP for successor tasks by modifying the PSF states surrounding performance.
- ***Resource impact***: two human actions may share temporal or spatial resources, in which case an antecedent HFE could affect the resources available for successor tasks. This relationship, similar to the resource-sharing dependency from (Kichline et al., 2021; Xing et al., 2021), will indirectly affect the HEP for successor tasks by modifying the resources available for performance.
- ***Mental model impact***: two human actions may share aspects of a mental model, the internal model people make of a scenario based on their experience, knowledge, and training. As a result, a mental model shared between two human actions will enforce a dependency similar to the common context dependency described in (Paglioni and Groth, 2023a). Mental models are difficult to represent, and the effects on dependency are still being understood. The authors discuss the incorporation of mental models in dependency in (Kim et al., 2024).

The dependency method incorporates these causal aspects by predicating the computation of conditional human error probabilities (cHEPs) on six factors and using empirical data, expert opinion, and similarity measures to quantify the effects of dependency. Currently, the method is designed for use with positive, HFE-level dependencies, e.g., it does not include interdependencies between PSFs, major crew functions (MCFs), or other lower-level causal modelling elements in HRA. This is in accordance with typical use-cases of HRA, which are focused at the HFE level to facilitate easy incorporation into PRAs. Furthermore, this method assumes (appropriately) that cases in which the antecedent HFE directly affects the feasibility of successor tasks are modelled separately in the fault trees or event trees of the parent PRA. Therefore, the *feasibility impact* above is not included in the dependency assessment discussed herein. Finally, this method is employed when there are two HFEs in the same accident sequence minimal cut-set model.

Equation (1) defines the computation of the conditional probability of a successor HFE, *B*, given the occurrence of an antecedent HFE, *A*, based on six dependency features which are explained in Section 2.1. For a full discussion on this method and the dependency features, see (Kim et al., 2023).

$$HEP(B|A) = [TRI + \{PTS + CRD\} \cdot RF] \cdot CS + HEP_B \cdot ACE_B \tag{1}$$

3. Dependency features

Equation (1) relies on six dependency features that define causal relationships between the antecedent event, *A*, and the successor HFE, *B* (event is used here instead of HFE, because there are cases in which the antecedent event A is technically a success, but still enforces a dependency to the subsequent event/HFE B). Briefly, these six dependency features are:

- ***Temporal resource insufficiency (TRI)***: the probability that the successor event is *temporally* infeasible within the time available following the antecedent event. TRI is computed per Equation (2).

$$TRI = 1 - \Phi\left(\frac{1}{\sigma} \cdot \ln\left\{\frac{\left(T_{a_{B,end}} - T_{r_{A,end}}\right)}{T_{r_{B,end}} - T_{r_{B,start}}}\right\}\right) \quad (2)$$

In Equation (2), $T_{a_{B,end}}$ is the endpoint of the availability window for the successor HFE, *B*, and $T_{r_{A,end}}$ is the endpoint of the required time to perform the antecedent event *A*. The interval $\left(T_{r_{B,end}} - T_{r_{B,start}}\right)$ is the length of time required for performance of successor event *B*. The σ term is the standard deviation of lognormally-distributed performance times.

- Procedure transition similarity (PTS): the similarity between procedural flows in both events A and B. This is computed with the Smith-Waterman algorithm to assess the alignment between procedural sequences.
- Cue recognition dependency (CRD): the HEP for a successor event will increase if performance of that event relies on the same cue (information from procedure or instrument) as a previously-failed event. The reasoning is that, in the absence of new cues, there is no chance for the operators to adjust their mental model or gain new information following a failure, and thus a successor failure is more likely. Two events sharing the same cue have a CRD value of 0.5; the CRD is 0.0 if there are new cues available for the successor event.
- Recovery factor (RF): if the time available for a successor event is sufficiently long, i.e., longer than the sum of the time available for the antecedent event and the 95 percentile of the time required for the successor event, there is a possibility of recovering the failure on the successor event. Empirically, recovery failure probabilities are on the order of 0.5; thus, RF = 0.5 when recovery is possible, and 1.0 otherwise.
- Crew sameness (CS): The sameness of the crew impacts whether the preceding dependency features (TRI, PTS, CRD) are impactful between two HFEs. If the crew is the same between both HFEs, these features are considered in dependency (CS = 1.0). If the crew is different between both HFEs (e.g., due to shift change or performance location change), then these factors are disregarded (CS = 0.0).
- Additional contextual effect (ACE): additional contextual effects are considered when the PSF states for the successor HFE are expected to change from the PSF states assumed in the calculation of the individual HEP (HEP_B). The PSF changes resulting from HFE A occurring are considered, and used to adjust the "baseline" HEP for the successor event to account for these changes.

The dependency assessment method was tested on two case studies in the nuclear power operations context, which revealed that this method is similar in computational intensity to the EPRI dependency assessment method (EPRI, 2016) and arrives at similar or lower HEP values. Therefore, the dependency assessment method addresses the hyper-conservatism present in many HRA dependency assessments (Boring et al., 2021). However, as mentioned previously, the method is designed for use with two HFEs, and is thus not currently applicable to cut-sets featuring more than two HFEs. To rectify this, we provide some recommendations for extending this methodology to three or more HFEs in Section 3.

4. Recommendations

Perhaps the simplest way to extend the current method to three or more HFEs would be to simply perform pair-wise assessments between all the HFEs in a cut-set and use the maximum value to ensure appropriate conservatism. For instance, in a cut-set containing N HFEs, this would involve computing $HEP(j|i)$ for all HFEs $i, j \in \{1, \dots, N\}, j > i$, and then setting $HEP(j|i) = \max\{HEP(j|i) \forall\, j > i\}$. However, doing this neglects scenarios in which a successor event is dependent on ***multiple*** antecedent events, for example an event N that shares a crew with event ***N-1***, temporal resources with event ***N-2***, cues with event ***N-3***, etc. Accordingly, a robust treatment of multi-HFE cut-sets requires assessing the individual dependency features among the HFEs, rather than assessing the total dependency quantification.

Accordingly, this section will review each dependency feature used in the current method, and focus on how that feature could be extended to consider three or more HFEs. These recommendations are meant to promote the incorporation of this dependency assessment method into current HRA assessments. These recommendations have been designed to adjust the validated method with minimal revision to the underlying mathematics in Equation (1). That is, this work does not recommend changes to the theoretical or empirical bases of the method; such recommendations would require significant research into the mechanics of each dependency feature. Research into the theoretical bases of HRA and dependency is ongoing among several research groups.

Sections 4 and 5 will discuss future research areas that should be explored to better understand dependency in HRA and inform the next generation of dependency assessment methods.

5. Temporal resource insufficiency (TRI) extension

The current calculation of the TRI feature is presented in Equation (2), and captures the relationship between the time required for the successor event (i.e., the event for which dependency is being computed) and the antecedent HFE. However, when extending to cut-sets featuring more than two HFEs, it is clear that the temporal resources shared by *all* antecedent events must be considered. For example, if the successor event is the *N*th HFE in a cut-set, there are *N-1* antecedent events that require time for performance, and which thus will impact the time available for performing the *N*th event. As a result, the TRI feature for the *N*th HFE must consider the time intervals used in the preceding events.

Accordingly, it is recommended that the TRI feature for the *N*th HFE in a cut-set be computed according to Equation (3), which considers the time intervals required for performing the preceding events.

$$TRI_N = \left[1 - \Phi\left(\ln\left(\frac{T_{a_{N,end}} - \sum_{i=1}^{N-1}\left(T_{r_{i,end}} - T_{r_{i,start}}\right)}{T_{r_{N,end}} - T_{r_{N,start}}}\right) \cdot \sigma^{-1}\right)\right] \cdot CS_{i,N} \tag{3}$$

In Equation (3), note that the term $T_{r_{A,end}}$, the endpoint of the required time interval for the single antecedent event A, in the numerator of the lognormal function from Equation (2) has been replaced by a sum. Specifically, Equation (3) computes the sum of the time intervals required for all antecedent events. Therefore, Equation (3) considers that the time available for the successor event N may be strained by multiple antecedent events. That is, the time required to perform the antecedent events will reduce the time available to perform the successor event, represented by $T_{a_{N,end}}$.

6. Procedure transition similarity (PTS) extension

The PTS feature quantifies the similarity in procedural sequences between two events using the Smith-Waterman algorithm. This algorithm computes the similarity in the text of procedures, and the PTS metric is based on the assumption that similar procedures will trigger similar mental models and modes of performance. Therefore, if a successor event has a similar procedure flow as a previous failure, it is more likely that the successor event will also be failed. It stands to reason that this effect is not limited to subsequent events, but may exist across multiple events and so it is important to account for PTS across all HFEs in a cut-set.

In order to extend PTS to all HFEs in a cut-set (from the initial consideration of two HFEs), it is recommended that a similar pairwise calculation to the TRI extension be conducted. This will capture the procedure transition similarity between all HFEs in a cut-set. Thus, for a given HFE *N*, the PTS is computed based on the maximum similarity between HFE *N* and all of the antecedent events per Equation (4).

$$PTS_N = \max_i\{PTS(i, N)\} \cdot RF_{i,N} \cdot CS_{i,N} \tag{4}$$

In Equation (4), the PTS computation $PTS(i, N)$ is found using the Smith-Waterman algorithm as before. The maximum value of the PTS metric is taken to identify the antecedent HFE that has the biggest impact on dependency. Then, as in the original calculation (Equation (1)), this value is modified by the recoverability and crew similarity (RF and CS, respectively) between the antecedent HFE and the successor HFE under study.

7. CRD Extension

The CRD feature quantifies the dependency enforced between two events that share the same cue, or “triggering” information. Cues can be generated by procedures (e.g., a step indicating a transition) and/or instruments (e.g., a visual check revealing an anomalous reading). Extending the CRD feature to multi-HFE cut-sets requires similarly discounting the cue similarity based on the time elapsed between the first appearance of the cue (prompting the antecedent event) and the subsequent appearance (or use) of the cue (prompting the successor event). Thus, a similar weighting procedure as in Equation (4) should be applied for the reduction in cue recognition due to intervening events. Note that the memory decay model introduced herein assumes that the mental model associated with a cue decays over time in the same manner that the PSF set decays. This effect has not been fully supported by data, and so should be investigated thoroughly via future research.

The dynamics of memory are still being unravelled, although there is some evidence from psychological studies that points to a passive dissipation of the "task set" during the time intervening a prior response and the appearance of a new cue (Meiran et al., 2000). These experiments indicated a reduction in "switching cost" (i.e., the performance decrease caused by rapidly switching tasks) associated with longer intervals between the previous task and the cue. Further, these experiments found that the "task set" (analogous to internal, cognitive PSFs and biases) employed during Task N-1 dissipates rapidly during the performance of Task N . Therefore, it stands to reason that the cue recognition dependency between two events decreases with the number of events that intervene. Another set of experiments on positional effect in recall for lists of various lengths indicates that cues recall decreases with the time between appearance and retrieval of the cue (Brown et al., 2007).

The evidence from psychological experiments into free recall memory and cue retrieval indicate that the cue retrieval probability declines with time between appearance and retrieval (Brown et al., 2007; Meiran et al., 2000). Further the "task set" imposed by a cue response, that is the set of cognitive PSFs that might be shared between two HFEs prompted by similar cues, is rapidly dissipated after the appearance of a new, dissimilar cue (Meiran et al., 2000). This is to say that the "memory" of a cue, stored in the PSFs, will dissipate between two HFEs and thus decrease the effect of CRD. The decay of higher-level task sets, e.g., the set of PSF states, has been disputed, although the decay theory remains central to current models of cognitive control (Grange and Cross, 2015). Accordingly, it appears appropriate to base the decay of CRD on this decay theory.

Therefore, we propose that CRD be weighted according to the number of intervening events, in accordance with evidence presented in (Brown et al., 2007), which indicates the probability of recall for the first item in a list of varying length is a function of list length, as shown in Table 1. Here, it is assumed that the appearance of a cue, and therefore the presence of the specific PSF set associated with the cue, is analogous to the first item in a list of items to be recalled. For example, if a cue appears in HFE A and then again in HFE F, recalling the cue (and corresponding PSF set) requires recalling the first item in a list of five items.

Table 1. Recall probability as function of list length (Brown et al., 2007)

Intervening Events	Recall probability (1st item)
9	0.7
14	0.6
19*	0.4
29	0.25
39	0.2

*Average of two experiments

Using least squares regression allows the above data to be fit to an exponential decay model for recall probability. The probability of recall for the first item in a list is related to the intervening number of tasks (x) by Equation (5).

$$\Pr(recall) = 1.015 \cdot e^{-0.044x} \tag{5}$$

This may appear to treat the cue itself as an item to be recalled, rather than a prompt to a cognitive process. However, operating under the assumption that a cue prompts the creation (or retrieval) of a specific PSF set, then it is the PSF set that serves as a "recalled object," prompted by the cue. We are therefore assuming that, if recall fails, then the PSF set will be sufficiently different in the second HFE, and thus there will be a lower dependency effect due to CRD. The probability of recall in Equation (5) is therefore analogous to the probability of experiencing the same set of PSFs due to the same cue.

The effect of CRD between two HFEs must therefore be modified by the probability of recalling the PSF set associated with the specific cue, and so the calculation of CRD for the Nth HFE in a cut-set follows Equation (6).

$$CRD_N = \max_i\{CRD(i,N) \cdot 1.015 \cdot e^{-0.044(N-i)}\} \cdot RF_{i,N} \cdot CS_{i,N} \tag{6}$$

In Equation (6), the CRD metric from (Kim et al., 2023) is extended to multi-HFE cut-sets by finding the maximum CRD value between the HFE under consideration (N) and all antecedents. This value is then multiplied by the probability of recalling the PSF set initially formed in the antecedent event (i). Finally, this value is adjusted for recoverability using the RF feature.

8. RF and CS extension

The recovery factor (RF) and crew sameness (CS) metrics from the original method do not require adjustments when extending this method to multi-HFE cut-sets. These metrics modify the other dependency features (TRI, PTS, CRD) in the original method. The extended metrics proposed in Sections 3.1 – 3.3 operate by finding the maximum values between a single successor event (N) and all previous antecedent events. Accordingly, there may be cases in which different preceding events impart the maximum value for different dependency features; for example, HFE N may have a maximum TRI with HFE A, but a maximum PTS with HFE C. As a result, the RF and CS features must be accounted separately in the TRI, PTS, and CRD evaluations, but the calculations of RF and CS themselves do not require change.

Therefore, it is recommended that both RF and CS be computed as described in (Kim et al., 2023) and incorporated into each equation for TRI, PTS, and CRD separately. The RF and CS values should be found using the antecedent event identified as providing the maximum value for that dependency feature. For example, if HFE A is identified as providing the maximum value for TRI, then the CS feature in Equation (3) is computed as $CS_{A,N}$. If HFE B is identified as providing the maximum value for CRD, then the RF and CS features in Equation (6) are computed as $RF_{B,N}$ and $CS_{B,N}$, respectively.

9. ACE extension

The additional contextual effect (ACE) feature describes how local PSF states (around a successor event) are altered by antecedent failures. Antecedent failures can impact the environment around future tasks, for instance by increasing the stress on the operators, and so indirectly affect the human error probability on those successor events. ACE considers the effect of an antecedent HFE on the PSF state, and uses the updated PSF states to modify the HEP of the successor HFE. Understanding and modelling the effects of antecedent HFEs on future PSF states is a complex challenge with multi-HFE cut-sets. Because the mechanics of an HFE's influence on PSF states are often PSF-specific, a robust treatment of extending ACE is beyond the scope of this paper. Such an extension would require robust causal modelling rooted in a firm understanding of PSF mechanics. This is still an area of active research.

10. Final dependency calculation

Taking into account the extensions made to the dependency features in Sections 3.1 – 3.5, the final equation for the conditional HEP of an HFE can be found by combining the new feature equations in the same fashion as Equation (1). Thus, the conditional HEP based on all previous antecedent events in the cut-set can be found through Equation (7):

$$\begin{aligned} HEP(N|i \in \{1,\dots,N-1\}) &= \left[1 - \Phi\left(\ln\left(\frac{T_{a_{N,end}} - \sum_{i=1}^{N-1}\left(T_{r_{i,end}} - T_{r_{i,start}}\right)}{T_{r_{N,end}} - T_{r_{N,start}}}\right) \cdot \sigma^{-1}\right)\right] \cdot CS_{i,N} \\ &+ \max_{j}\{PTS(j,N)\} \cdot RF_{j,N} \cdot CS_{j,N} \\ &+ \max_{k}\left\{CRD(k,N) \cdot 1.015 \cdot e^{-0.044(N-k)}\right\} \cdot RF_{k,N} \cdot CS_{k,N} \\ &+ ACE_{N} \cdot HEP_{N} \end{aligned} \tag{7}$$

11. Impact and discussion

This work aims to provide actionable recommendations for extending a novel dependency assessment method to scenarios with more than two HFEs in a cut-set. This work takes a conservative approach by computing the maximum values of multiple dependency features. However, this approach also provides a holistic view of the dependencies between all antecedent events and the successor event. Investigating the dependencies between the multiple HFEs in a cut-set may also provide important qualitative information that can be used to mitigate the dependency and reduce HEPs.

HRA is both a qualitative and quantitative approach to system safety, and it is important to recognize the values provided to the system by thoroughly performing both pieces. This paper addresses the quantitative assessment of conditional HEPs based on a number of dependency features, updating the equations to account for the presence of multiple antecedent events. However, there is limited extension of the qualitative aspects of this approach. While the conservative method is proposed herein, taking the maximum value of each dependency feature, a more nuanced approach would be appropriate to enforce realism in the assessment. However, in the absence of a nuanced understanding of dependency in HRA, it is appropriate to take a balanced, yet conservative approach such as that proposed herein.

The dependency assessment method developed in (Kim et al., 2023) and extended herein leverages the most current available theoretical and empirical basis for HRA. This is a significant improvement over previous dependency assessment methods based on unvalidated notions of dependency “levels” between HFEs and corresponding equations divorced from both empirical and theoretical foundations. This method therefore represents the state-of-the-art in empirically-based HRA dependency assessment. This dependency assessment method balances a rigorous basis in empirical evidence and cognitive theory with a conservative, piece-wise maximization approach.

Developing such a more nuanced approach to dependency will require additional research into the mechanisms and dynamics that underlie dependency in HRA. Some of this work is already underway around the world, and some of this work needs to begin. Section 5 addresses research that is needed to continue developing our understanding of dependency in HRA.

12. Future research needs

This work has illuminated several interesting areas that will need to be addressed through future research. HRA, and dependency in particular, has been the subject of an increasingly robust research effort across the world in recent years. In the absence of a scientific consensus regarding many aspects of HRA dependency, it is imperative to continue research in this broad field. Within the area of HRA dependency, there are several key aspects that require more research to tackle the remaining uncertainties. Some of these areas were highlighted in this paper, while others, notably related to the foundations of the field, are discussed in (Mortenson et al., 2023; Paglioni and Groth, 2022).

HRA as a field is generally in need of advancement and research on two fronts: 1) foundational technical knowledge and 2) implementation. The remaining uncertainties related to foundational technical knowledge are well enumerated in other works. Here, we will expound on only those related to the work presented in this paper. The remaining uncertainties related to implementation, i.e., of HRA methods and tools, are less studied, but just as important for HRA as critical to ensuring system safety.

The avenues for future research uncovered by this work are mainly focused on understanding the dynamics of human cognition and the connection between human cognition, action, and system responses. For example, the temporal mechanics of “mental models,” the internal representation of the system and its functioning developed over years of experience and training, are poorly understood in regards to their effect on procedural performance and dependency. For example, the assessment of CRD in this work assumes that PSF sets associated with specific cues decay in the absence of the cue, so that cue recognition dependency decreases with the number of events between subsequent appearances of the cue. However, this is based on psychological research on single item recall, not on human reliability. A robust understanding of this effect, if it exists, should incorporate new research that focuses on the idea of a mental model, rather than item recall.

Further research on the foundations of HRA, specifically regarding dependency, should seek data-informed causal models of dependency such as those presented in (Kim et al., 2023; Paglioni and Groth, 2023a). These papers focus on developing data-informed models for assessing and understanding dependency, respectively.

This work also identified potential issues regarding the pragmatic implementation of this method as an end-user tool. Specifically, the complexity of Equation (7) is likely to limit the utility of this method in the field, where the general preference is to lessen the workload on analysts where possible. While this method could be incorporated into a software tool to ease implementation, the complexity of the underlying mathematics would make it difficult to trace and check work. This trade off between realism and ease of use is not unique to HRA, but is especially salient for the field in light of its intrinsic complexity. Thus, future research should investigate how this method could be best translated to a usable software to support implementation.

There are many challenges to HRA that exist contemporaneously with an enormous multidisciplinary effort working to find solutions. To fully realize the power of these different research efforts, there should be renewed interest in sharing not only findings, but the data that was gathered at various experimental facilities. Such data sharing efforts had been discussed in early 2020. The renewed interest in this subject has coincided with the increasing availability of tools to support online meetings and sensitive data sharing. As such, it is important to renew discussions regarding collaboration and data sharing.

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