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Abstract. This paper introduces the virtual human reliability analyst model (VHRAM). The VHRAM is an approach that automates the HRA process to enable HRA elements to be included in simulations in general and simulation based risk analysis in particular. Inspirations from clinical AI and game development are discussed as well as the possibilities for a VHRAM to be used outside of a simulated virtual twin of a nuclear power plant.

Keywords: Human Reliability Analysis · Computation-Based Human Reliability Analysis · Dynamic Human Reliability Analysis · Virtual Analyst · Virtual Human Reliability Analysis Model

1 Introduction

Through forty years, and at least that many methods, human reliability analysis (HRA) has been used to analyze, explain and predict the human element of complex systems that hold a potential for major accidents. HRA originated in the weapon assembly industry [1], but the nuclear power industry has been the front-runner in both method development [2-4] and application through most of HRA history [1,5,6]. Indeed, other industries have been urged to look towards the nuclear domain for guidance on how they have used HRA to analyze the human aspect of major accident risk (i.e., the petroleum industry after the 2011 Macondo accident, [7]). When other domains have adapted HRA methodology to their needs, the starting point has often been nuclear application intended methods [8-10]. This paper discusses another form of HRA adaptation—not the adaptation from one industry to another, but rather from static paper-based HRA traditionally conducted by an analyst completing worksheets concerning a physical system to computer-based HRA in a virtual simulation of a physical system, i.e., a “virtual twin.” A virtual twin (also known as digital twin, [11]) is a virtual representation created to function similarly as the physical system it is modelled after, and as the name implies it strives to be very similar to the original system. A virtual twin is used for tasks such as design changes, simulation, monitoring or optimization. Depending on what is being evaluated, the virtual twin can include aspects such as the physical measurements and placement of all the components of a system, interactions between the components, process simulation and physics engines. The possibilities of how virtual twins can be used increases as improved computational power is continuously enabling new possibilities to accurately and realistically simulate complex systems (using tools like RAVEN [12] and RELAP-7 [13]). These simulations can among other things be used to increase the understanding of the risks at a nuclear power plant (NPP) through simulating expected plant states over thousands of years or simulating a complex scenario thousands of times. The human element has, however, not been a key element in these simulations despite the fact that control room operators have an important role in both normal operations and particularity in accident scenarios. This paper presents the idea of taking some of the lessons learned from traditional static HRA and using them to capture the human element in computation-based simulations of the same types of complex systems where HRA has been used thus far.

2 Differences Between Traditional HRA and Computer-Based HRA: Opportunities and Challenges

There are many differences between a traditional HRA conducted on a physical installation and the proposed use on a virtual twin of the installation. The main difference is the presence or absence of a human reliability analyst. It is not practical to introduce a person to make manual decisions at each iteration of a simulation. This would be a very resource-demanding task, especially if the simulation is set to analyze the same scenario thousands of times, or simulate a plant state over many years. To avoid this issue, the tasks of the human reliability analyst must be automated, or in other words, the creation of a virtual human reliability analyst model (VHRAM).

While this will enable the coupling with a plant simulation, it will also create some challenges in the use of existing HRA methods, as most of the existing HRA methods have relied heavily on the subjective evaluations of the human reliability analyst [14-16]. However, inter-analyst variability—whether caused by subjective biases or a poor fit of methods to events—serves as a major limitation in conventional HRA. Even if a static HRA method is dynamicized, it is possible to create a VHRAM that uses the method consistently. Subjective assessments can be minimized and replaced by consistent and replicable virtual analyses. For example, an HRA method that models task complexity based on an analyst’s subjective assessment of the level of task complexity can instead be made to autocalculate the level of task complexity based on available parameters of the plant, task, and situation [14-16].

There are several additional advantages of the VHRAM approach. A classic HRA problem has been that the HRA efforts have been performed after most of the risk analysis is already conducted, including how the scenario develops. This leaves less possibility to investigate how human actions would influence the evolution of a scenario rather than following the predefined path outlined during the risk analysis efforts. An automated model on the other hand could feed back into the plant simulation influencing how the scenario develops. Choices made by a human in the NPP can have an extensive effect on how a scenario unfolds, and this should also be the case in a simulation. To support the examination of the human actions, the simulation must be capable of supporting a dynamic scenario in which operator actions can alter the course of the scenario as it develops. An additional advantage of the VHRAM approach is reducing the subjective element from the analyst. The VHRAM approach supports a more standardized method for inputting human error probability (HEP) quantifications for operator actions.

HRA traditionally uses rather simple mathematical formulas to calculate an HEP, often using a version of nominal HEP multiplied with PSFs that degrade or improve performance [3,4,8]. The simple formulas are suitable for the worksheet analysis conducted by hand and provide a high level of traceability, as it is easy to see where and why a human action is predicted to fail. The automation of the human reliability analyst will reduce the need for a simple formula, enabling the possibility to include aspects such as interactions between PSFs, dependencies between tasks, and continuous PSF levels, all of which have been included in few of the traditional HRA methods. This is not to say that the quantification approach used in traditional HRA should or will be discarded, but computerized HRA will have the possibility to refine the quantification approach if it can be shown that it improves the method and reduces epistemic uncertainty in the analysis.

3 Intelligent Agents

The absolute simplest version of automating the HRA process conducted by a human reliability analyst would be to use a nominal HEP or non-informed HEP distribution for all human tasks. This is an approach that has been used in technical quantitative analyses without HRA and in analyses where the goal is to determine if the human has a critical role in the scenario by setting the HEP to 1.0 (or close) to find the likelihood of an accident if human actions fail. However, the introduction of a static HEP for all human tasks, while simple, does not seem to be on par with the high fidelity modeling of the other systems in a plant simulation [17].

On the other extreme, we have a simulated system including a model of human cognition with the ability to perform similarly to a real human operator with all the variability and creativity a human can express. However, artificial intelligence (AI) technology has not yet come to the point where this is entirely feasible.

In the VHRAM we attempt to find a suitable middle ground between these two extremes. Instead of attempting to model the entire cognition of an operator we are instead trying to create a model that evaluates the situation the operator would find himself or herself in by including the most important PSFs. This will create a representation much like the one a human reliability analyst would create using worksheets to evaluate the situation of the operator, instead of attempting to model his or her cognition. To emphasize this focus we have chosen the term VHRAM and not virtual operator model, where it might have seemed that we were attempting to model the full cognition of an operator.

3.1 AI and the concept of the intelligent agent

The idea of an intelligent agent performing human-like actions within a system, for different purposes and with different levels of sophistication is not new and has been explored in several fields. Throughout history many myths and philosophers describe the idea of an inanimate object obtaining a mechanical version of human intelligence. A more direct AI reference is found in the works of Alan Turing including the test of the sophistication of an intelligent agent in the famous Turing Test [18]. AI research generally represents the upper range of this sophistication in the creation of systems that either think rationally and/or emulate human thought [19], but in fact most of computer programming does in some way fit within this sophistication scale through a version of rule based commands executed via provided inputs.

A practical application is seen in several fields where the goal is for the intelligent agent to assist, or even replace, the human performing the task. Several examples of this type of intelligent system are seen in our everyday lives. Google attempts to understand our search phrases and deliver the results we desire, Netflix attempts to anticipate what we want to watch, and online advertisements are personalized in an attempt to increase the chance of user viewing and clicking them. We also find examples of intelligent agents in fields that are traditionally unassociated with academia, such as computer games [20], and the methods used to create these intelligent agents, that aren't in themselves full-blown AI, should not be discounted.

3.1.1 Academic AI

AI is naturally an area of interest for computer science and several engineering disciplines as these are areas where advancements in AI primarily occur. However, it has also created interesting academic discussions in the fields of neurology, psychology and philosophy. Our knowledge of the brain and human cognition expands daily, but we are far away from a complete understanding, of what some, intriguingly and somewhat paradoxically using their human cognition, have described as the most complex system known to the human race. While we have many different models of memory, cognition, intelligence and consciousness, they are all simply models—a simplification of how we understand an abstract and complicated concept. Interestingly, thus far the field of AI—the field that strives to build intelligent entities [19]—are faced with the challenge of creating something which we do not yet fully understand. Some of these questions are outside of the scope of this paper, but it is interesting to note how many different fields are involved in the AI topic and the potential that AI research holds to contribute to all of these topics as the field develops.

3.1.2 Clinical AI

Within medicine, both the desire to increase accuracy of diagnosis and the work towards lowering medical costs has led to many different versions of intelligent agents through wide range of different methods (e.g. [21-23]). A version of a non-disease-specific clinical AI was created using a combination of a Markov decision process and dynamic decision networks [21]. The AI used a combination of existing clinical data and simulation of sequential decisions paths to develop plans that would both reduce patient costs and increase patient outcomes.

While there are naturally many differences between the tasks of a medical doctor and a human reliability analyst, there are similarities in how an intelligent agent could be structured. The way a medical doctor considers symptoms in the diagnosis of a patient is similar to how a human reliability analyst considers PSFs to diagnose how a control room operator is expected to perform.

While there is certainly interest in creating AI that thinks like a doctor, this goal differs from the goals of HRA. The AI mimicking a doctor is designed to function as flawless as possible and no one wishes to make the AI realistically fail like a doctor sometimes does. However, recreating such failures might actually be of particular interest to human reliability researchers, but this is not a mainstream thrust of AI research. Rarely do we design AI to fail intentionally and this goal may be a unique aspect of HRA research.

3.1.3 Interaction and Cooperation With Automation

Another interesting practical use is the partial automation of a role previously performed by a person. This is already a part of most computerized systems. Set criteria, such as the temperature reaching a certain level, are made to trigger certain actions, such as the opening of a valve. These are generally taken for granted as part of a computerized system. However, once the system is intelligent enough to consider a large amount of factors before deciding or suggesting to open a valve, we are approaching the cooperation between the operator and an intelligent agent. In some cases the degree of automation in systems have reached such a high degree that work-roles that previously were manual now mainly consist of monitoring an automated system.

Human-automation interaction or human-automation cooperation has become one of the popular topics in human factors. In a review of all papers published in 2015-2016 in the journal *Human Factors,* [24] found automation, including both human-automation interaction and cooperation, to be the third most popular topic and only beaten by driving and physical workload. Though driving, in at least a few instances, overlaps with human-automation interaction.

3.1.4 Gaming AI

The medical field is known for their meticulous efforts in recording and publishing progress and research. However, game development is on the other side of the scale where knowledge and skills are generally transferred through other more informal channels (or kept as trade secrets within the company) [20].

Introducing simplified AI to games has been an important part of game design ever since Pac-Man implemented intelligent agents (often referred to as non-playable character (NPCs) in games) through non-playable characters that chased and ran away from the player [20]. Earlier games, such as Space Invaders have NPCs in the form of enemy ships, but Pac-Man included decision making where the enemies chose a route at each junction, combining an effort to achieve their goal—which, depending on the situation, meant chasing or escaping—and an element of randomness to keep things interesting [20]. This was done through a simple set of rules and a random number generator. Later games added aspects such as perception to their NPCs, as exemplified in Metal Gear Solid and Goldeneye. This perception provided each NPC with limited knowledge about what was going on in the game and would only react after they "saw" or "heard" something. Another interesting AI element, strategic AI, was introduced at about the same time, where the NPCs would employ a number of different strategies to defeat or cooperate with the player [20]. Since the introduction of these cognition-like elements, new and improved versions have been created to suit the need for each individual game. Today the quality of the AI is often a highlighted aspect in modern day videogame reviews, which can result in the monetary success or failure of a videogame launch.

Although there are naturally many differences between the purpose of AI elements in games and what we are trying to achieve with the VHRAM there are certainly overlaps. The inclusion of a human element in a simulated scenario is in many ways the same as including a game character in a game world. A decision making system is required, the VHRAM should base its decisions on the information it has observed, and it should follow a strategy. Perhaps the largest difference is that we do not intend to introduce a human player to the system, rather let the VHRAM "play" by itself in the virtual world.

4 Implementing the Virtual Analyst

The VHRAM is still in development, and changes can still occur in both the general solution and the details of how we have chosen to include it.The symbolic approach to AI describes it as being made up of two components, knowledge and reasoning [20]. Knowledge is often a database, and reasoning is how this knowledge is used.

In a similar manner, the VHRAM will consist of two main aspects: (1) relevant information prepopulated though task categorization and autopopulated from the simulation—knowledge—and (2) the algorithms—reasoning—that use the inputs to determine the HEP, time spent on the task, and the decisions on which path to take in a dynamic scenario.

4.1.1 Autopopulation

The autopopulated input is automatically gathered from the information already present in the simulation. Examples of the autopopulation are [14-15]:

- Total size of the task or scenario
- Number of tasks per time
- Time in scenario
- Number of procedures used by the operator
- Number of page shifts done by the operator in the procedures

As the VHRAM improves it is likely that more and more aspects are included as autopopulated inputs. However, it is also likely that some information that could be relevant to human reliability will not be available in the simulation, such as the human-machine interface quality or teamwork problems. If specific aspects like these are focus areas of an analysis it should be possible to inform the model through prepopulated factors connected to either the scenario or specific tasks.

4.1.2 GOMS-HRA

In many of the traditional HRA methods it is not specified to which level a task should be decomposed before it is quantified [25]. Depending on the method and situation, quantification could be done anywhere from on a very high level (e.g. Depressurize segment A) to a very low level (Press button A). Methods that do not specify the level at which quantification should occur will have more flexibility, but as the quantification level can influence the results, it is also a source of lower reliability [25].

As the VHRAM is an automated approach it was decided that it would quantify at a low level, a level defined as the subtask level. GOMS-HRA [26-28] is currently in development as a method for standardizing tasks at a subtask level. The subtask level of analysis is suitable more modeling time series activities of operators in dynamic HRA. GOMS-HRA provides task level primitives, which are meant to be universal types of tasks performed by humans. Because activities in NPPs are generally highly proceduralized, it is also possible to map procedure steps to their underlying task GOMS level primitives [29].

4.1.3 HEP equation

The traditional output of an HRA in the evaluation of a task (in addition to any qualitative descriptions and recommendations) is the HEP. The use of the term "human error" is controversial in human factors and safety research [30]. Some argue that the term implies that the human is to blame for the error [31], others that the term is misleading, as the actions made by the operator can be reasonable to the operator at the time only to be considered an error retrospectively [32]. In HRA the term HEP is simply the probability that the operator will not continue on the intended path that avoids an accident from occurring, without blaming the operator for the mistake. In fact, as most of the PSFs included in many HRA methods (e.g. [3,8]) are factors external to the operator HRA is often mainly concerned about which external factors could cause the operator to fail.

Currently the virtual analyst is based on a stochastic multiple regression with each input as a variable. In the future hopefully empirical data, from simulators or actual installations, can be used either to calibrate the coefficients of the stochastic multiple regression equation, or modify the approach if a more suited model is found.

4.1.4 Decision Making

The HEP value can be used as a simple form of decision making, through having human error occur at the probability calculated and have the scenario developed based on this. This would however limit the decision making to a binary success or failure for each junction. A dedicated decision making algorithm will enable more nuanced decisions which can include more than outcomes.

Several different forms of decision making algorithms, like those seen in both clinical AI and game AI, are being considered at the moment to be able to fully integrate the VHRAM into a dynamic scenario where it can contribute to the evolution of the scenario.

4.1.5 Including PSFs

The approach of the VHRAM is to start with a simple version and build upon that to include more aspects. The first PSF that was introduced to the model was complexity [14,15]. Complexity is included in most HRA methods as part of the quantification leading to the HEP [34]. This fits well with our intuitive understanding of complexity and the role it can have in the likelihood of successfully conducting a task. The fact that complexity is a multifaceted concept also means that while it is often modeled as a single PSF it has many differ aspects where the inputs can be collected from several different parts of the simulation.

Currently a second PSF, procedures, is being modeled for autopopulation and inclusion to the VHRAM. Procedures will in the same way as complexity, to inform the model with aspects that are included in HEP calculations and the decision making algorithm. However, procedures also hold another very interesting potential. If the VHRAM includes a text-mining approach that can break down procedures into a standardized unit size (such as GOMS-primitives) they can serve as an input directly to the VHRAM [26-29]. This would be an important step in the direction of a model that can run automatically on any scenario where procedures exist.

5 The way forward

The way forward for the VHRAM is to continue adding new elements and improving its performance as an automatic human reliability analyst. It is a promising path of research, but there are still challenges that need to be solved. The potential value will depend on the quality of the VHRAM, but also the quality of the virtual twin. In an attempt to create a virtual twin, attempts are made to model every aspect of a system virtually. Naturally, in a complex system there will always be discrepancies between the actual system and the “virtual twin.” As this discrepancy increases, the relevance of a VHRAM, and other risk analysis performed using the “virtual twin,” will naturally drop in terms of what you can learn about the real system.

This paper has chosen to describe two examples, clinical AI and game development AI. These were not chosen randomly; rather, they both represent aspects that we want to include in the VHRAM approach. In clinical AI an intelligent agent is created to learn from clinical data and treatment procedures. We want to include this diagnostic element but the clinical data is replaced by empirical or simulated plant and operator performance data and treatment procedures are replaced by operating procedures. We also want to include a decision making algorithm much like the ones developed for the clinical AI applications. The primary difference between the clinical AI and the work here is that the VHRAM model will include the simulation of human error as one of the key aspects. The inspiration for the human error element stems from other fields that developed intelligent agents with inherent limitations as to how well they can perform. For entertainment purposes, an intelligent agent opponent in a game has to provide the player with a challenge, without performing so well that the player is without a chance to win. A chess match between a human and the chess computers of today would not be entertaining, nor would neither a soccer game where every shot made by the opponent is a goal, nor a shooting game where the opponent shoots you repeatedly through the walls. The gaming industry has dealt with these challenges for many years and they provide valuable guidance for how these elements can be included in a simulation of the human component in HRA research. The simulated human has to perform realistically, but that also means it needs to fail realistically, which represents a prominent challenge.

In the future, there could also be other uses for a VHRAM than HRA of a virtual twin. One potential use could be for a combined approach between traditional HRA and VHRAM where the aspects that are autopopulated by the VHRAM could be used as part of the information collected by the analyst conducting the traditional HRA. Another possibility is that a VHRAM is running in real-time at a NPP anticipating when the actual operator will encounter a situation where the PSFs are implying that he or she has an increased chance of making a mistake, as a type of risk monitoring system.

6 Conclusion

This paper presented the ideas around the ongoing development of the VHRAM. We believe it is an approach that will have value through adding a human component to probability risk analysis simulations, and other forms of simulations, where it has been historically under-represented thus far. Furthermore, it is an approach that can have impacts outside of this field by contributing to traditional HRA and risk monitoring systems in physical systems, such as NPPs.

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References

1. Boring, R.L.: Fifty Years of THERP and Human Reliability Analysis. In: Proceedings of the PSAM 11 and ESREL, Helsinki, Finland (2012).
2. Swain, A.D., Guttmann, H.E.: Handbook of human reliability analysis with emphasis on nuclear power plant applications. Final report. U.S. NRC, Washington, DC (1983).
3. Gertman, D.I., Blackman, H.S., Marble, J.L., Byers, J.C., Smith, C.: The SPAR-H human reliability analysis method. U.S. NRC, Washington, DC (2005).
4. Williams, J.C.: A data-based method for assessing and reducing human error to improve operational performance. In: Conference Record for 1988 IEEE Fourth Conference on Human Factors and Power Plants,. pp. 436–450. IEEE (1988).
5. Spurgin, A.J.: Human Reliability Assessment: Theory and Practice. CRC Press, Boca Raton, FL (2010).
6. Rasmussen, M.: The Development of Performance Shaping Factors for the PetroHRA Method: A Human Reliability Method for the Petroleum Industry. Doctoral dissertation, Norwegian University of Science and Technology, Trondheim, Norway (2016).
7. Report to the President National Commission on the BP Deepwater Horizon Spill and Offshore Drilling: Deep Water: The Gulf Oil Disaster and the Future of Offshore Drilling. Washington, DC (2011).
8. Bye, A., Laumann, K., Taylor, C., Rasmussen, M., Øie, S., van de Merwe, K., Øien, K., Boring, R.L., Paltrinieri, N., Wærø, I., Massaiu, S., Gould, K.: The Petro-HRA Guideline (IFE/HR/F-2017/001). Institute for Energy Technology, Halden, Norway.
9. Kim, J.W., Jung, W., Jang, S.C., Wang, J.B.: A Case Study for the Selection of a Railway Human Reliability Analysis Method. In: International Railway Safety Conference, 22-27 October 2006, Belfast. (2006).
10. Kirwan, B., Gibson, H.: CARA: A Human Reliability Assessment Tool for Air Traffic Safety Management — Technical Basis and Preliminary Architecture. In: Proceedings of the 15th Safety-critical Systems Symposium, Bristol, UK, 13-15 Feb 2007. , Bristol, UK (2007).
11. Glaessgen, E.H., Stargel, D.S.: The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. In: 53rd Structures, Structural Dynamics, and Materials Conference: Special Session on the Digital Twin. pp. 1–14. , Honolulu, HI (2012).
12. Rabiti, C., Alfonsi, A., Mandelli, D., Cogliati, J., Martineau, R., Smith, C.L.: Deployment and Overview of RAVEN Capabilities for a Probabilistic Risk Assessment Demo for a PWR Station Blackout Deployment and Overview of RAVEN Capabilities for a Probabilistic Risk Assessment Demo for a PWR Station Blackout (INL/EXT-13-29510). Idaho National Laboratory, Idaho Falls, ID (2013).
13. Anders, D., Berry, R., Gaston, D., Martineau, R., Peterson, J., Zhang, H., Zhao, H., Zou, L.: RELAP-7 Level 2 Milestone Report: Demonstration of a Steady State Single Phase PWR Simulation with RELAP-7 (INL/EXT-12-25924 RELAP-7). Idaho National Laboratory, Idaho Falls, ID (2012).
14. Rasmussen, M., Boring, R.L.: The implementation of complexity in computation-based human reliability analysis. In: Walls, L., Revie, M., and Bedford, T. (eds.) Risk, Reliability and Safety: Innovating Theory and Practice. Proceedings of the 26th European Safety and Reliability Conference, ESREL 2016, Glasgow, Scotland, 25-29 September 2016. CRC Press, Croydon, UK (2017).
15. Rasmussen, M., Boring, R.L.: Auto-Calculation of Complexity in Computation-Based Human Reliability Analysis. In review.
16. Boring, R.L., Mandelli, D., Rasmussen, M., Herberger, S., Ulrich, T., Groth, K., Smith, C.: Light Water Reactor Sustainability Program Integration of Human Reliability Analysis Models into the Simulation- Based Framework for the Risk- Informed Safety Margin Characterization Toolkit (INL/EXT-16-39015). Idaho National Laboratory, Idaho Falls, ID (2016).

17. Boring, R.L., Joe, J.C., Mandelli, D.: Human performance modeling for dynamic human reliability analysis. Lect. Notes Comput. Sci. 9184, 223–234 (2015).
18. Turing, A.M.: Computing Machinery and Intelligence. Mind. 59, 433–460 (1950).
19. Russell, S.J., Norvig, P.: Artificial Intelligence: A Modern Approach. Prentice-Hall International, London, UK (1995).
20. Millington, I., Funge, J.: Artificial Intelligence for Games. CRC Press, Boca Raton, FL (2016).
21. Bennett, C.C., Hauser, K.: Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach. Artif. Intell. Med. (2013).
22. Bennett, C.C., Doub, T.W.: Temporal Modeling in Clinical Artificial Intelligence, Decision-Making , and Cognitive Computing: Empirical Exploration of Practical Challenges. In: Proceedings of the 3rd SIAM workshop of DMMH. , Philadelphia, PA (2014).
23. Bellazzi, R., Zupan, B.: Predictive data mining in clinical medicine: Current issues and guidelines. 77, 81–97 (2006).
24. Laumann, K., Rasmussen, M., Boring, R.L.: A literature study to empirical explore; what is the scientific discipline of human factors and what makes it distinct from other related fields. In: Proceedings of the 1st International Meeting on Human Error, Reliability, Resilience, and Performance. (2017).
25. Rasmussen, M., Laumann, K.: The impact of decomposition level in human reliability analysis quantification. In: Walls, L., Revie, M., and Bedford, T. (eds.) Risk, Reliability and Safety: Innovating Theory and Practice. Proceedings of the 26th ESREL 2016, Glasgow, Scotland, 25-29 September 2016. CRC Press (2017).
26. Boring, R.L., Rasmussen, M.: GOMS-HRA: A method for treating subtasks in dynamic human reliability analysis. In: Walls, L., Revie, M., and Bedford, T. (eds.) Risk, Reliability and Safety: Innovating Theory and Practice. Proceedings of the 26th European Safety and Reliability Conference, ESREL 2016, Glasgow, Scotland, 25-29 September 2016. CRC Press (2016).
27. Boring, R.L., Rasmussen, M., Ulrich, T., Ewing, S., Mandelli, D., Smith, C.: Task and procedure level primitives for modeling human error. In: Proceedings of the 1st International Meeting on Human Error, Reliability, Resilience, and Performance. Los Angeles, CA (2017).
28. Ulrich, T., Boring, R.L.: Operator timing of task level primitives for use in computation-based human reliability analysis. In: Proceedings of the 1st International Meeting on Human Error, Reliability, Resilience, and Performance. Los Angeles, CA (2017).
29. Ewing, S.M., Boring, R.L., Rasmussen, M., Ulrich, T.: Text Mining for Procedure Level Primitives in Human Reliability Analysis. In: Proceedings of the 1st International Meeting on Human Error, Reliability, Resilience, and Performance. (2017).
30. Reason, J.: A life in error: from little slips to big disasters. Ashgate Publishing Limited, Surrey, UK (2013).
31. Whittingham, R.B.: The Blame Machine: Why Human Error Causes Accidents. Elsevier Butterworth-Heinemann, Oxford, UK (2004).
32. French, S., Bedford, T., Pollard, S.J.T., Soane, E.: Human reliability analysis: A critique and review for managers. Saf. Sci. 49, 753–763 (2011).
33. Whittingham, R.B.: The Blame Machine: Why Human Error Causes Accidents. Elsevier Butterworth-Heinemann, Oxford, UK (2004).
34. Rasmussen, M., Standal, M.I., Laumann, K.: Task complexity as a performance shaping factor: A review and recommendations in Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) adaption. Saf. Sci. 76, 228–238 (2015).
35. Boring, R.L., Mandelli, D., Rasmussen, M., Herberger, S., Ulrich, T., Groth, K., Smith, C.: Human unimodel for nuclear technology to enhance reliability (HUNTER): A framework for computational-based human reliability analysis. In: Proceeding of PSAM 13, 2-7 October, 2016, Seoul, Korea. (2016).

36. Boring, R.L., Mandelli, D., Joe, J., Smith, C., Groth, K.: Light Water Reactor Sustainability Program: A Research Roadmap for Computation-Based Human Reliability Analysis (INL/EXT-15-36051). Idaho National Laboratory, Idaho Falls, ID (2015).