Framework to Evaluate the Applicability of Human Reliability Data for HRA Method Development

Yochan Kim^{a*}

^aKorea Atomic Energy Research Institute 111, Daedeok-daero 989, Yuseong-Gu, Daejeon, Korea ^{*}Corresponding author: yochankim@kaeri.re.kr

1. Introduction

Human reliability data empirically collected from various sources provides an important technical basis for the development and improvement of human reliability analysis (HRA) methods. In particular, it is necessary to refer to the analysis results of various recently gathered empirical data in order to improve the understanding of human reliability in the new digital I&C (instrumentation and control)-based main control room, because many human reliability issues in this new environment have been raised but not yet validated sufficiently. However, since each type of human reliability data has limitations and characteristics resulting from different experimental environments and data collection systems, these characteristics should be evaluated and reflected before use of the reliability data.

This study aims to support the selection of meaningful human reliability data in the HRA development process by proposing a framework for evaluating existing human reliability data. While this framework was established for developing an HRA method considering the digital I&C-based main control room, the framework can also be employed for other methods as well. A detailed description of this study is provided in [1].

2. Evaluation Features of Reliability Data

In order to compare and evaluate the suitability of human reliability data for application, evaluation features were surveyed from literature that addresses HRA data requirements, data quality issues, and data research considerations [2-7]. Table I summarizes the evaluation features required for HRA method development. Generally, the features can be classified into the three categories: (1) fidelity of the collection environment, (2) quality of the data collection, and (3) statistical significance of the data analysis. The fidelity of the collection environment indicates whether the environment in which reliability data was collected is sufficient to reflect the operational environment related to the HRA of interest. The quality of data collection deals with how quality control was performed in generating meaningful data without bias. Lastly, the statistical significance of the data analysis means whether the data contains meaningful analysis results that are useful in the HRA application.

Table I: Evaluation features from literature

Category	Feature	Reference
Fidelity of the collection environment	Realism of the plant/simulator functions	[1-3]
	Plant similarity between the HRA application and the data collection	[1–3]
	Realism of the accident situation in the scenario	[1,2,4]
	Realism of operators observed during data collection	[1–3]
Quality of the data collection	Expertise and independence of the data collectors	[1,5]
	Evaluation consistency for human error and situational factors	[1,3,5,6]
	Scope of task and situational information collected	[3]
	Similarity of the unit task / human error definitions between HRA application and data collection	[2,5]
	Qualitative description of human error and context	[1,5]
Statistical significance of the data analysis	Appropriateness of the analysis criteria	[1,2]
	Appropriateness of the analysis techniques	[1,5]
	Amount of data collected	[1,3,6]

3. Importance of Evaluation Features

To determine the importance of the evaluation features presented in Table 1, this study employed an expert elicitation method called AHP (analytic hierarchy process) [8]. AHP is a multi-criteria analysis technique that stratifies evaluation criteria and determines their importance by layer when a decision problem is composed of multiple evaluation criteria. The AHP technique was developed by Saaty in the 1970s; since then, it has been extensively employed to solve a wide range of decision-making problems. There are seven steps to implement the AHP method.

• Define the decision-making problems and research objectives

• Create a hierarchy of decision criteria

• Generate comparison matrices through pairwise comparison

• Calculate relative importance based on the matrices

• Verify consistency (coherency) using consistency indices or consistency ratios

- Combine importance values from multiple experts
- Derive final importance and select an alternative

In this study, a total of 8 experts participated in the importance assessment of the evaluation features. All experts have experience in collecting and analyzing human reliability data with at least 10 years of experience in HRA/PSA analysis. The questionnaire was constructed in such a way that the relative importance of each of the evaluation features is pairwisely assessed by the Likert measure (1 to 9). For measuring the relative importance, the inverse linear scale was used [9]. For example, Fig. 1 implies that 'Quality of the data collection' is judged to be 1.29 times more important than 'Fidelity of the collection environment'.



Fig. 1. Example of pairwise comparison between two features.

The individual importance values determined by each expert were combined into a final importance through taking the geometric average. The average value was then normalized so that the sum of the geometric average values was 1 for interpretation convenience of the results.

The final importance values of the evaluation factors were derived from the AHP analysis as shown in Table 2. To sum up, the experts judged that the fidelity of the collection environment is the most important factor in data applicability. However, the quality of the data collection and the statistical significance of the analysis were also regarded to be important factors. In terms of the evaluation features, it was thought that the realism of operators observed during data collection, the realism of the accident situation in the scenario, and the amount of data collected were particularly influential factors on the data applicability. Because most of the features have importance levels that cannot be ignored, it is expected that all factors should be considered as significant when evaluating applicability.

Table II:	Importance	of the	evaluation	features
1 4010 11.	importance	or the	evaluation	icutures

Catagory	Import-	Feature	Import-
Category	ance	Teature	ance
		Realism of the	
Fidelity of the		plant/simulator	0.099
collection	0.409	functions	
environment		Plant similarity	0.092
		between the HRA	0.082

		application and the	
		data collection	
		Realism of the	
		accident situation in	0.103
		the scenario	
		Realism of operators	
		observed during data	0.126
		collection	
		Expertise and	
		independence of the	0.066
		data collectors	
		Evaluation	
		consistency for	0.074
		human error and	
		situational factors	
		Scope of task and	
Quality of the	0 292	situational	0.056
data collection	0.272	information collected	
		Similarity of unit task	
		/ human error	
		definitions between	0.057
		HRA application and	
		data collection	
		Qualitative	0.000
		description of human	0.039
		error and context	
Statistical significance of the data analysis	0.299	Appropriateness of	0.098
		the analysis criteria	
		Appropriateness of	0.000
		the analysis	0.098
		techniques	
		Amount of data	0.104
1		collected	

4. Evaluation Process of HRA Data Applicability

Based on the AHP analysis results, a procedure to apply human reliability data into HRA method development was established as follows. Fig. 2 schematically illustrates the flow of the procedure.

• Screening analysis: Exclude data under conditions that are inappropriate for use in the environment subject to HRA practice.

• HRA database rating: Evaluate the human reliability data for each evaluation feature as presented in this study to score its HRA applicability (e.g., rate 1 to 10 points for each feature).

• Quantitative priority evaluation: Calculate and rank the applicability of each human reliability data.

• Data conservatism evaluation: Record what kind of conservatism/vulnerability exists in the assumptions and definitions of each human reliability data.

• Data implementation: Develop an HRA method or generate application examples by utilizing high-priority data first.

• Coverage evaluation and alternative search: Evaluate whether the relevant data is not applicable to the HRA method, and supplement any gaps of information not supported with prior data using subsequent-priority data as necessary.

• HRA method conservatism evaluation: Appraise whether the data used has sufficient conservatism compared to the HRA application and provide a reference guideline for the use of the method and estimates. Where necessary, develop strategies to overcome lacking conservatism or uncertainty that may exist in the data.



Fig. 2. Process evaluating data applicability.

5. Conclusions

This study developed a framework to compare and evaluate empirical data for HRA method development and modification. The 12 evaluation features related to the applicability of human reliability data were derived from literature. Expert knowledge was collected from 8 experts with experience in collecting/analyzing human reliability data, and importance level of each evaluation feature was calculated based on the AHP technique. Using these research results, a general evaluation process was established. The evaluation system derived from this study will be used as a procedure for selecting and applying data that will be the basis for the development of HRA methods for digital I&C main control rooms in the future.

Acknowledgement

This work was supported by the Nuclear Safety Research Program through the Korea Foundation Of Nuclear Safety (KoFONS) using the financial resource granted by the Nuclear Safety and Security Commission (NSSC) of the Republic of Korea (No. 2101054).

REFERENCES

[1] Kim, Y., Shin, S., Kim, J. Development of Human Reliability Database Evaluation System for Digitalized MCRs. KAERI/TR-8629/2021. KAERI, Daejeon, 2021.

[2] Collier, S., Ludvigsen, J. T., & Svengren, H. Human reliability data from simulator experiments: principles and context-sensitive analysis. In Probabilistic Safety Assessment and Management (pp. 1480-1485). Springer, London, 2004.

[3] Presley, M., Boring, R., Ulrich, T., Medema, H., Mohon, J., Delvecchio, M., Massaiu, S., Bye, A., Park, J., Kim, Y., Julius, J.A. A Taxonomy and Meta-Analysis Template for Combining Disparate Data to Understand the Effect of Digital

Environments on Human Reliability, PSA 2021, November 7–12, 2021, Columbus, OH, 2021.

[4] Laumann, K., & Skogstad, M. R. Challenge to Collect Empirical Data for Human Reliability Analysis—Illustrated by the Difficulties in Collecting Empirical Data on the Performance-Shaping Factor Complexity. ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg, 6(1), 2020.
[5] Prvakova, S., & Dang, V. N. A review of the current status of HRA data. In Safety, reliability and risk analysis: beyond the horizon: proceedings of the European Safety and Reliability Conference, Esrel 2013, Amsterdam, The Netherlands, 29 September-2 October 2013 (pp. 595-603). CRC Press, 2014.

[6] Kim, Y. Considerations for generating meaningful HRA data: Lessons learned from HuREX data collection. Nuclear Engineering and Technology, 52(8), 1697-1705, 2020.

[7] Basra, G., Dang, V., Fabjan, L., Dereviankine, A. A., Dusić, M., Furuta, T., ... & Zhang, Z. Collection and classification of human reliability data for use in probabilistic safety assessments. IAEA-TECDOC-1048, International Atomic Energy Agency (IAEA), Vienna, Austria, 1998.

[8] Saaty, T. L. How to make a decision: the analytic hierarchy process. European journal of operational research, 48(1), 9-26, 1990.

[9] Ma, D., & Zheng, X. 9/9-9/1 scale method of AHP. In Proceedings of the Second International Symposium on the AHP (Vol. 1, pp. 197-202). University of Pittsburgh, Pittsburgh, PA, 1991.