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DATA-DRIVEN MODELING OF DEPENDENCIES AMONG INFLUENCING FACTORS IN HUMAN-MACHINE INTERACTIONS

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ABSTRACT

Human performance is currently represented in most Human Reliability Analysis (HRA) models by a set of Performance Shaping Factors (PSFs). The majority of HRA methods have proposed relationships that produce human error probabilities based on the state of these PSFs. What current HRA methods are lacking is a model for human performance that includes dependencies between PSFs based on human performance data.

Using data from the Nuclear Regulatory Commission's Human Events Repository and Analysis (HERA) database and applying iterative principal factor analysis and polychoric correlation, we have developed a methodology to obtain preliminary groupings of PSFs that lead to human errors in specific types of tasks.

The goal is to obtain a greater understanding of how PSFs are interrelated and to determine if certain groups of PSFs can be causally linked to certain types of failures. The final product will be a data-driven methodology to estimate the relationship between PSFs and human error probabilities in nuclear power plants. The methodology will consider systematic dependence between the PSFs and will use Bayesian techniques to integrate different types of data. Application of Bayesian Factor Analysis (BFA) will allow us to fill in gaps in the data and incorporate data types that cannot be used in principal factor analysis. This will enable us to make the best use of the limited amount of data we have available in HRA.

This paper will cover how we have used the data from HERA and will offer preliminary results based on the data currently available. It will also offer a systematic way to define the interrelationships between PSFs in different aspect of human-machine interaction.

Key Words: HRA, human error, performance shaping factors, HERA

1 INTRODUCTION

Human error remains a leading contributor to failure in complex systems like nuclear power plants (NPPs). In the past few decades improved ergonomics and human factors have greatly reduced the occurrence of human action errors, but cognitive errors continue to challenge risk analysts. As the Human Reliability Analysis (HRA) discipline shifts from understanding action errors to understanding cognitive errors, current HRA models are evolving into or being replaced by increasingly complex models.

In most HRA models human performance is represented by Performance Shaping Factors (PSFs), which can be used to estimate human error probabilities (HEPs). The majority of HRA methods have proposed normative relationships that produce HEPs based on the state of the PSFs. Many current HRA methods ignore dependencies among PSFs in estimating HEPs, and often do so without considering their relative importance. These methods may include independent cognitive aspects of behavior, but many neglect to consider how PSFs act both singly and dependently to contribute to human performance.

An operator's state of mind can propagate through different phases of an event and produce a sequence of errors instead of a single error, but these errors are often treated as independent in current HRA models. Likewise current methods ignore how varying amounts of internal and external stimuli throughout an event contribute to an operator's state of mind. As cognitive error producing factors become more salient, it is essential to consider the relationships between the PSFs to better understand how PSFs have varying levels of impact in different cognitive situations.

Two major problems have impeded the development of data-based HRA models: inadequate data collection and inadequate use of data in modeling. However, these issues are not completely independent. Inadequate data collection limits the effectiveness of models, and inadequate modeling impacts how data is collected. Models are only as good as the data that goes into creating them. Without accurate models though, we lack the framework to influence how data is collected.

Through this research we intend to use available data to develop a methodology that can be used to better estimate the relationship between PSFs and errors in human-machine interactions (HMI). To the authors' knowledge, no current HRA method has used data to develop a dependency model. This methodology will be specific to commercial NPPs given the sources of data. The end product will provide a framework for quantitative description of PSF relationships. This will enable the HRA community to refine data collection techniques to support improved modeling. As data collection techniques improve, the methodology will provide a framework to update the relationships based on new information.

The end product will be a set of Bayesian Belief Networks (BBNs) as a model of PSF interdependencies. BBNs will be produced for errors that occur in four phases of human information procession , i.e. *detection*, *interpretation, planning*, and *action* tasks. The BBN structure will allow HEPs to be calculated in cases where partial information is present without requiring analysts to make assumptions about the state of unknown PSFs. BBNs can also be incorporated into current HRA methods and replace the linear structure used to estimate HEPs.

2 MODEL DEVELOPMENT

2.1 Data Sources

The primary data source for the current research is the Human Events Repository and Analysis, HERA, database (Hallbert et al 2006). HERA was developed by the U.S. Nuclear Regulatory Commission and the Idaho National Laboratory to serve as a database for human performance information gathered from NPP events. The events captured in the HERA database are NPP events that met NRC's licensee event reporting requirements specified in Title 10 of the Code of Federal Requirements, Part 50, Sections 50.72 and 50.73 (10 CFR 50.72 and 50.73); in the selected events human error contributed directly to the event sequence. Data used in this paper are the HERA data derived from analyst interpretation of Licensee Event Reports written by power utilities and inspection reports written by NRC inspectors. The HERA database currently contains a detailed evaluation of more than 20 operations events that are broken down into over 1000 sub-events including equipment actions, human actions, and system states.

Among the 1000 sub-events, 337 of them contain detailed human performance analysis and are used in this paper.

The information in HERA is captured using two forms: Worksheet A and Worksheet B (NUREG/CR-6903, Vol. 2). Each HERA event has a single Worksheet A and multiple Worksheet Bs. Worksheet A contains classifying information and a timeline for the entire operating event that is broken down to the greatest level of detail allowed by the source documents. Worksheet A also provides information about the personnel and systems involved in each sub-event and indications of dependency between sub-events. Worksheet B is completed for only human success or failure sub-events. This worksheet contains details about the PSFs that contribute to the human action.

In the initial stage of this research we have limited our use of the database to a subset of information provided in Worksheet B. Section 5 of Worksheet B (**Error! Reference source not found.**) summarizes the positive and negative PSFs that contributed to the human behavior observed in the sub-event. HERA contains 11 PSFs, including *Work Processes*, which is broken down into 4 sub-categories as seen in **Error! Reference source not found.**. The 11 HERA PSFs are tied to the PSFs in the HRA Good Practices (Kolaczkowski et al, 2005).

Table I: PSF summary information from Section 5 of HERA Worksheet B.

PSF	PSF Level / State	Comment
Available Time	☒Insufficient Information	Insufficient information.
Stress & Stressors	☒Insufficient Information	Insufficient information.
Complexity	☒Insufficient Information	Insufficient information.
Experience & Training	☒Insufficient Information	Insufficient information.
Procedures & Reference Documents	☒Insufficient Information	Insufficient information.
Ergonomics & Human Machine Interface	☒Insufficient Information	Insufficient information.
Fitness for Duty / Fatigue	☒Insufficient Information	Insufficient information.
Work Processes	☐Good ☐Nominal ☒Poor	Overall work processes were poor. See below.
Planning / Scheduling	☐Good ☐Nominal ☒Poor	Management policy of allowing a 25% grace period on preventative maintenance contributed to lack of maintenance.
Supervision / Management	☐Good ☐Nominal ☒Poor	Inadequate oversight of maintenance personnel. Poor emphasis on safety.
Conduct of Work	☐Good ☐Nominal ☒Poor	Maintenance personnel did not follow established modification process or consult vendor manual.
Problem Identification & Resolution (PIR) / Corrective Action Plan (CAP)	☐Good ☐Nominal ☒Poor	CTG 11-1 exceeded allowable failures on demand for several years. Management failed to implement preventative measures to ensure that CTG 11-1 would start on demand.
Communication	☒Insufficient Information	Insufficient information.
Environment	☒Insufficient Information	Insufficient information.
Team Dynamics / Characteristics	☒Insufficient Information	Insufficient information.

Each PSF level is determined based on the state of more detailed information in Sections 3 & 4 of the worksheet. For example, the *Procedures and Reference Documents* details include failure to use procedures, unavailability of procedures, and inadequacy of procedures. The PSF details provide expanded information about the state of the PSF. These details provide additional insight into the elements that contribute to human errors, but the small number of events currently in the HERA database precludes the use of the more detailed data at this time.

Section 6 of Worksheet B summarizes the human information processing aspects of each human sub-event. Section 6 identifies the dominant human information phase affecting performance of the sub-event. Four phases are classified: detection, interpretation, planning, and action. Each phase is ranked as either correct, correct based on incorrect information, incorrect, or not applicable (see Table II).

Table II: Task step breakdown from Section 6 of HERA Worksheet B

Task Phase		Comment
Detection: Detection or recognition of a stimulus (e.g., a problem, alarm, etc.)	☐ Correct detection ☐ Correct detection based on incorrect information ☒ Incorrect detection	Personnel did not detect that set point needed to be changed.
Interpretation: Interpretation of the stimulus (e.g., understanding the meaning of the stimulus)	☒ Not Applicable / Insufficient Information	Does not apply
Planning: Planning a response to the stimulus	☐ Correct planning ☒ Correct plan based on incorrect interpretation / detection ☐ Incorrect plan	Personnel did not know they needed to update the set point, so they correctly did not plan to change it.
Action: Executing the planned response	☐ Correct action ☒ Correct action based on incorrect plan / interpretation / detection ☐ Incorrect action	Did not know they needed to update the set point, so they correctly did not change it.

2.1.1 Data coding

Information from the HERA worksheets was recoded into discrete form for analysis. Each PSF in Section 5 is coded for each sub-event. For cases where a PSF state is poor, the PSF is coded as 1. Cases where a PSF state is good are coded as 2. Cases where a PSF is listed as nominal are given a 0. PSFs with insufficient information are also coded 0, because we have interpreted the lack of information to mean that there is no evidence that the case is anything other than nominal. A similar coding scheme is used for the information from Section 6. Each sub-event is coded for each information processing phase, with insufficient information, incorrect, conditionally correct, and correct taking on the values 0-3 respectively.

Since the focus of this analysis is to understand how the PSFs contribute to human errors, our data analysis only involves human error sub-events. Of the thousand sub-events in HERA, 337 are human sub-events coded in Worksheet Bs. Of these events, 213 are coded as human error events (XHE) and the remainder are human success events (HS). We have retained the data for human success events, but for the current analysis we only address XHE events. The XHE events have been separated into groups based on the human information processing phases where the initial error was made. In very few sub-events, errors have been made in multiple phases; these sub-events were placed in both groups.

2.2 Analysis Methods

2.2.1 Polychoric Correlation

Correlation gives a quantitative measure of similarity between two variables – the amount of variance from the common area between them. From this we can garner an initial understanding of the relationship between the variables. There are several different correlation techniques that can be used to develop a matrix of pairwise correlations. For data that are normally distributed, the Pearson product-moment correlation can be obtained using any commercial analysis package. The degree of correlation is indicated by a number between -1 and 1, where a correlation of 0 indicates complete independence between the variables, and a correlation of 1 indicates a perfect increasing linear relationship. A correlation of -1 indicates that the relationship is inverse. However, if data is not normally distributed, regardless of the underlying distribution that produced the data, Pearson correlation values will not represent the reality of the situation.

The distribution of the data depends on the sampling method. Discrete data often model a normally distributed process, but the end product may not be normally distributed. The most prevalent case where this happens is with binary data. Polychoric correlation can be used to determine the correlation of discrete data from processes that follow a normal distribution. Tetrachoric correlation is a form of polychoric correlation that provides results for binary data that is representative of an underlying normally distributed model.

For discrete data, polychoric correlation provides more accurate correlation values than Pearson product-moment correlation. Polychoric correlation assumes that a discrete data set represents a normally distributed process with a threshold value that separates different states. The threshold assumption underlying polychoric correlation is not a valid assumption for some binary data sets. One example is gender; gender is not normally distributed, a person is either male or female, and therefore tetrachoric correlation could not be used on such data. However, most human behavior is not discrete and can be modeled with a normal distribution, so polychoric correlation is particularly useful for human behavior modeling.

2.2.2 Principal Factor Analysis

Factor analysis is a family of multivariate techniques used to identify structure in a set of variables. Different goals can be accomplished depending on what type of factor analysis is used. Principal Factor Analysis (PFA), also called exploratory factor analysis, is a technique well suited for development of hypotheses about data. The basic assumption of factor analysis is that there are underlying influences in the data, and that these underlying influences manifest themselves in patterns of variance that move together. In risk analysis terms, we see many patterns of errors leading to accidents: the difference between these patterns is the variance. The goal of factor analysis is to identify and quantify these patterns of variance. The theory behind PFA is that variance in the observed data is created not only by several measured variables, but also by “invisible” factors that impact the variables. That is, each variable is the product of underlying individual influences [I] and common influences [C], and some amount of random and systematic error.

Factor analysis can be used to help classify variables, but will not provide immediate classification; classification is based on interpretation of factor results. Factor analysis does not define the direction of influence or specify additional elements that indirectly influence the constituents of the factor; factor analysis is used to identify relationships between PSFs and express them mathematically. We can use factor analysis to develop patterns of PSFs that are linked to human errors in specific types of tasks. It provides analysts with an indication of which relationships to explore and justification for exploring specific relationships.

3 RESULTS

Polychoric correlation was run on the entire sample of 213 XHEs and on groups of XHEs sorted by incorrect information processing phase. Correlation values were calculated for nine of the eleven PSFs in HERA. The Work Process PSF was broken down into its four constituent variables: planning, supervision, work conduct and problem identification. The environment PSF was removed from calculation due to inadequate data. The removal of the environment PSF and parsing of the work processes into separate PSFs resulted in 13 PSFs used in the analysis. The correlation table for the entire XHE sample is shown in Table III.

Table III: Table of polychoric correlations for all 213 XHE events

	Available Time	Stress	Complexity	Experience / Training	Procedures	HMI / Ergonomics	Fatigue / Fitness	Planning / Scheduling	Supervision	Conduct	Problem ID	Communi-cation	Team Dynamics
# Observations	26	97	141	103	95	20	13	43	148	198	108	41	63
Available Time	1.000	.	.	.	.	.	.	.	.	.	.	.	.
Stress	0.631	1.000	.	.	.	.	.	.	.	.	.	.	.
Complexity	0.374	0.315	1.000	.	.	.	.	.	.	.	.	.	.
Experience / Training	0.113	0.562	0.551	1.000	.	.	.	.	.	.	.	.	.
Procedures	0.241	0.258	0.421	0.407	1.000	.	.	.	.	.	.	.	.
HMI / Ergonomics	0.015	-.151	0.227	0.305	0.215	1.000	.	.	.	.	.	.	.
Fatigue / Fitness	0.443	0.511	0.286	0.267	0.312	0.309	1.000	.	.	.	.	.	.
Planning/ Scheduling	-.177	0.018	0.421	0.339	0.479	0.333	-.977	1.000	.	.	.	.	.
Supervision	-.245	-.148	0.381	0.443	0.271	0.180	0.409	0.488	1.000	.	.	.	.
Conduct Work	-.285	-.102	0.426	0.200	0.246	0.093	0.917	0.971	0.548	1.000	.	.	.
Problem ID	-.455	-.539	0.240	0.111	0.345	0.131	-.989	0.506	0.455	0.518	1.000	.	.
Communication	0.400	0.672	0.344	0.432	0.244	0.111	0.297	0.573	0.346	0.299	-.163	1.000	.
Team Dynamics	0.144	0.180	0.557	0.086	0.332	0.160	0.017	0.554	0.504	0.155	0.138	0.587	1.000

For the most part, the correlations in Table III appear reasonable. However, the correlation values for *fatigue / fitness for duty* (FFD) with both *planning* and *problem identification* are close to 1, which suggests that the amount of data used to develop these correlations was insufficient to produce accurate results. When polychoric correlation was applied to the four groups of incorrect information processing phases there was an increase in excessively high values. The amount of data that is currently in the HERA database is insufficient to support analysis on the individual phases.

Table IV presents factor analysis results for all of the XHEs currently in HERA. The results were obtained by using the polychoric correlation matrix as the input to an iterative principal factor analysis with orthogonal varimax rotation. Results were corrected for the mean of the observations. Different rotation methods yielded slightly different numerical factor loadings but the pattern of factor loadings was the same. Previous analyses of partial HERA data have also provided the same factor pattern with different factor loadings.

Initial communality estimates for the PSFs were set to the maximum absolute correlation with other PSFs. As communality estimates were updated iteratively we received errors due to Heywood cases, in which the communality exceeded 1. We addressed the Heywood cases by allowing communality estimates to exceed 1 because we are currently more interested in the factor pattern and the relative loadings than in the absolute loadings.

Table IV: Factor analysis results for all 213 XHEs

Rotated Factor Pattern				
	Factor1	Factor2	Factor3	Factor4
Team Dynamics	1.578	0.140	0.176	0.265
Stress	-0.019	1.008	-0.001	0.174
Available Time	0.057	0.658	-0.233	0.129
Communication	0.234	0.639	0.452	0.215
Problem Identification	0.033	-0.626	0.334	0.448
Planning	0.182	-0.020	0.950	0.370
Conduct of Work	-0.024	-0.169	0.906	0.261
Experience / Training	-0.108	0.338	0.133	0.725
Complexity	0.192	0.231	0.191	0.660
Procedures	0.087	0.126	0.176	0.559
Supervision	0.201	-0.177	0.404	0.481
HMI	0.047	-0.067	0.087	0.340

The factor analysis resulted in the creation of four factors from the 13 PSFs used in this analysis. While some of the PSFs load on multiple factors, for this stage in the analysis we are only interested in the highest loading. The four factors interpreted this way are:

1. Team Dynamics;
2. Stress, Available Time, Communication, and Problem Identification;
3. Planning / Scheduling and Conduct of Work;

4. Experience, Complexity, Procedures, Supervision, and HMI / Ergonomics.

PSFs that are highly loaded on the same factor are observed together in the human error data because they either have a direct influence on each other, are mutually influenced by an underlying factor, or have an additive effect. The groups produced by the factors can be supported by intuition and current understanding of human performance. The PSFs within each factor contribute to the presence of the factor, and the presence of any of the factors can be linked to observed errors.

Team Dynamics loads highly on factor 1 (see Table IV), which suggests that poor team dynamics alone may contribute to error. However, this may be due to the overlap between the 13 PSFs, because team dynamics encompasses many aspects of communication and the four subcategories of work practices. It is logical that poor teamwork could produce errors with or without the influence of other PSFs because it is a dominant part of NPP work during abnormal situations.

Factor 2 has high loadings for stress, time, and communication and a high negative loading for problem identification. The association of high stress, insufficient time, and poor communication is intuitive. The inverse relationship between problem identification and the negative states of time, stress and communication may imply a directional relationship wherein limited time induces high stress, which reduces one's ability or desire to communication, but also improves the ability to correctly identify problems. Communication and problem identification may be inversely related because of the way the brain distributes resources in high stress situations. Taken together, the presence of these four PSFs in a single sub-event makes a significant contribution to error, likely because the PSFs directly influence each other.

The elements of factor 3, planning/scheduling and conduct of work, are closely related aspects of work processes. Many of the behaviors associated with poor work conduct can also be associated with poor planning / scheduling and may be rooted in an underlying factor. A negative safety culture or overly relaxed atmosphere could produce relaxed work behaviors that result in inappropriate prioritization of tasks and assignment of personnel which could result in workarounds and reduced adherence to procedures. Organizational factors that contribute to poor scheduling may also contribute to a lack of resources.

Complexity and experience / training can be linked because lack of experience becomes more pronounced as complex situations appear, and inexperienced personnel are more likely to make errors when presented with complex tasks versus simple tasks. Poor procedures and inadequate HMI / ergonomics compound the problem by reducing the resources available to inexperienced personnel. Inadequate supervision and inadequate training could have similar roots in organizational culture.

The factor loadings in Table IV call for cautious interpretation because like correlation values, factor loadings should not exceed 1. However, given that we have limited data it is important to try to draw conclusions from the amount of data we have rather than disregarding the data entirely. While the factor loadings may not be reasonable, the pattern of factors may be. The factors are ordered based on the amount of variance explained by each factor. However, given that the factor loadings exceed 1 and some of the final communality estimates also exceed 1, it is impractical to draw conclusions from the amount of variance explained by each factor.

4 DISCUSSION

The mixed results presented in this paper help expose some of the problems that continue to affect HRA despite the addition of data sources. The sources of data used to populate the HERA database are responsible for many of the data limitations. The nature of retrospective analysis makes it difficult to assess many of the factors captured by the HERA database. Inspection reports are limited in their scope and LERs are not written to capture the conditions affecting human performance unless they directly affect the event. This limits the ability of the HERA analyst to document conditions that are not documented in the original reports.

In these early analyses we have treated each XHE event to be independent of others. This assumption is necessary to ensure that we have enough data to run an analysis. However, the assumption may not be correct given that the small pool of XHEs comes from an even smaller pool of independent events. The HERA database includes sub-events involving a variety of personnel, including operators, maintenance crews, and contractors. While all actors use the same information processing phases to solve problems, the key PSFs that affect performance may be different for different types of personnel. The amount of data currently in HERA is insufficient to allow analysis for different personnel groups.

Of the 213 XHE sub-events currently available in HERA, only 6 sub-events were characterized as non-nominal on the *environment* PSF. Similarly, only 13 of the 213 HERA sub-events were characterized as non-nominal for the FFD PSF. The lack of information on FFD in the LERs is directly related to the rarity of FFD observations in NPPs. Environment is rarely observed to be non-nominal because most of the events in HERA address operational errors or non-emergency maintenance errors that occur in the relatively stable environment of a plant. Both of these PSFs were removed from the final data because they exhibited spuriously high correlations with other variables. For the detection phase, it was not possible to get a correlation between the environment PSF and other PSFs because the environment PSF was nominal in all detection tasks. Analysis results that included FFD and environment produced four factors, with FFD loading on one of the factors alone. Environment loaded on a second factor with ergonomics. Factors three and four included the remaining 12 PSFs.

The low loadings for other PSFs on the FFD-dominated factor are consistent with current understanding of human performance in NPPs. Fatigue / fitness for duty is typically influenced by non-work factors and does not affect environment and HMI / ergonomics. Likewise, the collaborative nature of work in NPPs reduces the impact that a single individual can have on the plant. Most decisions and plans are developed during team meetings, where an underperforming member can be corrected before mistakes happen. The environment / ergonomics factor is consistent with the unchanging conditions of control rooms in all but the most severe incidents.

The results should not be interpreted to say that environment, fatigue and fitness for duty are not elements that contribute to error, but the results do suggest that we need a better way to quantify the relationship between these and other PSFs. It is not possible to manipulate environment and FFD in NPPs, but it is possible to manipulate these elements in simulator exercises. Until these PSFs are manipulated in a simulator, we rely on expert judgment to estimate their impact.

In a similar vein, *Conduct of Work* exhibited spuriously high correlations with other variables because it was characterized as non-nominal so frequently. Of the 213 XHEs in HERA, 198 had a non-nominal state for conduct of work. The over-identification of conduct of work as a factor reduces its usefulness in analysis. The layout of the HERA database is partially responsible for this over-identification. The PSFs used by HERA have different levels of abstraction, and conduct of work is a much broader category than many of the other PSFs. Each of the PSFs has a different number of PSF details contributing to the state of the PSF, and conduct of work has more than triple the amount of details as any other PSF. Some of the PSF details for conduct of work significantly overlap details for other PSFs and results in high correlations with conduct of work only because similar details have been selected.

5 NEXT STEPS

The lack of data on fatigue / fitness for duty and environment calls for a better way to quantify relationships involving these PSFs. The use of Bayesian techniques will allow analysts to use expert information to inform parts of the model that cannot be informed by current data. Bayesian techniques will also enable additional types of data to be incorporated into the framework as they become available. Additional events will be added to the HERA database throughout 2008 and beyond. As more data is added to the HERA system it should increase the statistical power of the database, enabling statistically significant factor results for the individual task steps.

The overrepresentation of conduct of work calls for a more carefully designed framework for capturing this information. The authors are currently mapping the HERA PSF details onto the PSFs defined within the IDAC framework proposed by Chang & Mosleh (2007). The PSFs used in IDAC were developed to be orthogonal, which reduces the overlap between similar PSF details assigned to different PSFs. The set of IDAC PSFs is not fully represented by HERA data, so the use of Bayesian techniques is being explored by the authors to incorporate expert judgment where there is insufficient data.

6 CONCLUSIONS

This research suggests that the HRA community needs to expend further effort in the area of defining PSFs to reduce overlap. The PSF details in HERA go a long way to help clarify the Good Practices PSFs (Kolaczkowski, 2005), but the PSF details in HERA also need to be refined to reduce overlap between PSFs. The details also need to be refined to ensure that each captures a single piece of information. Details such as “necessary tools not provided or used” capture information that can be linked to different actors and organizational levels. The difference between an organization not providing the necessary tools and the personnel not using the necessary tools could provide insight into organizational priorities, personnel training, and safety culture. Lumping provision and use of tools into a single detail limits the ability of the analyst to identify relationships between PSFs on an individual level and an organizational level. Likewise, the “worker distracted / interrupted” PSF limits the ability to differentiate between internal distractions and external interruptions that affect a worker’s state of mind.

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8 REFERENCES

1. Y. Chang and A. Mosleh, "Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents – part 2. IDAC performance influencing factors model," *Reliability Engineering and System Safety*, **92**, pp. 1014-1040 (2007)
2. B. Hallbert, R. Boring, D. Gertman, D. Dudenhoeffer, A. Whaley, J. Marble, & J. Joe, *Human Events Repository and Analysis (HERA) System, Overview,* NUREG/CR-6903, Vol. 1, U.S. Nuclear Regulatory Commission, Washington, D.C., March 2002.
3. A. Kolaczkowski, J. Forester, E. Lois, and S. Cooper, *Good Practices for Implementing Human Reliability Analysis,* NUREG1792, US Nuclear Regulatory Commission, Washington, D.C., 2005
4. I. Männistö. and R. Boring, *Application of HERA in Empirical HRA Study*, HWR-893, OECD Halden Reactor Project, Halden, Norway, April 2008.