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Original Article

Inter-relationships between performance shaping factors for human reliability analysis of nuclear power plants

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ABSTRACT

Performance shaping factors (PSFs) in a human reliability analysis (HRA) are one that may influence human performance in a task. Most currently applicable HRA methods for nuclear power plants (NPPs) use PSFs to highlight human error contributors and to adjust basic human error probabilities (HEPs) that assume nominal conditions of NPPs. Thus far, the effects of PSFs have been treated independently. However, many studies in the fields of psychology and human factors revealed that there may be relationships between PSFs. Therefore, the inter-relationships between PSFs need to be studied to better reflect their effects on operator errors. This study investigates these inter-relationships using two data sources and also suggests a context-based approach to treat the inter-relationships between PSFs. Correlation and factor analyses are performed to investigate the relationship between PSFs. The data sources are event reports of unexpected reactor trips in Korea and an experiment conducted in a simulator featuring a digital control room. Thereafter, context-based approaches based on the result of factor analysis are suggested and the feasibility of the grouped PSFs being treated as a new factor to estimate HEPs is examined using the experimental data.

1. Introduction

A performance shaping factor (PSF) is defined as a variable that may affect human performance in a human reliability analysis (HRA) [1,2]. Most currently applicable HRA methods for nuclear power plants (NPPs) use PSFs to highlight human error contributors and adjust basic human error probabilities (HEPs) that assume nominal conditions in NPPs [3,4]. PSFs that are generally adopted in HRA methods include experience, complexity, stress, adequacy of procedure, human–system interface, and workload. They are also called by different terminologies depending on the HRA methods, such as performance influencing factors (PIFs) in Holistic Decision Tree (HDT) [5], performance affecting factors (PAFs) in Cognitive Reliability Assessment Technique (CREATE) [6], error producing conditions (EPCs) in Human Error Assessment and Reduction Method (HEART) [7], or common performance conditions (CPCs) in Cognitive Reliability and Error Analysis Method (CREAM) [8].

There is sufficient evidence in the fields of psychology and human factors to indicate that there exists inter-relationship between PSFs. The term of *inter-relationship* comprehensively includes all the possible interactions between the states of the PSFs and between the influences of the PSFs on human performances, such as correlation, dependency, overlapping, or combinational effects with the causal relations, i.e., the direction of influence. First, Park and Jung showed that the task complexity of emergency operating procedures has a relationship with the operator's workload in NPPs [9]. Second, the relationship between experience and workload has been reported in various areas: for example, in driving [10], aviation [11], and NPPs [12]. However, most HRA methods treat PSFs independently, although they already recognized that the PSFs undoubtedly contain some overlap and are thus non-orthogonal [13]. If a HRA ignores the inter-relationships of PSFs, it is possible that HEPs may be over- or under-estimated. For example, when a complex task imposes a high workload on operators, separate consideration of the task complexity and workload may double-count the effect of complexity and lead to the over-estimation of HEPs or vice versa. However, most HRA methods treat PSFs independently and generally do not consider this combined effect of PSFs on human performance in the estimation of HEPs.

Recent interest in the inter-relationships of PSFs has been

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increasing in the HRA field. A few approaches deal with the mutual dependency between PSFs in a systematic way, such as CREAM [8], Standardized Plant Analysis Risk-HRA (SPAR-H) [13], and Information, Decision, and Action in Crew context (IDAC) [14]. CREAM describes how PSFs affect each other in a qualitative way [8], whereas IDAC tries to analytically describe the mutual relationships among the states of PSFs and is a very complex application that requires a great deal of effort by the analyst [14]. Boring [15] introduced a statistical correlation between PSFs and discussed the proper number of PSFs that should be considered by HRAs. Groth [16] performed correlation and factor analyses on PSF data and found four groupings to be the best fit for the data. De Ambroggi and Trucco [17] suggested a systematic approach for modeling and assessing dependent PSFs using the analytic network process, based on expert judgments. Although a few studies suggested a quantitative relationship between PSFs, they did not provide procedural guidance on using it to estimate HEP. In addition, a more objective guide needs to be developed so that analysts can handle inter-relationship between PSFs.

This study aims to investigate the inter-relationship between PSFs using two data sources and suggest context-based approaches based on the result of a factor analysis. First, this study analyzes the correlation between PSFs in NPPs. The data sources used are event reports for unexpected reactor trips in Korea from the Operational Information System (OPIS) database and an experiment conducted in a simulator featuring a digital control room. Correlation and factor analyses were performed to investigate the relationship between PSFs and thus, perform PSF grouping. A few groups of PSFs were identified from the factor analysis. Thereafter, context-based approaches based on the result of a factor analysis are suggested and the feasibility of the grouped PSFs being treated as a new factor to estimate HEPs is examined using the experimental data.

2. Review of current techniques: modelling inter-relationships among PSFs

2.1. Application of PSFs in HRA methods

Most HRA methods select PSFs that are the most relevant to and influential in the task analyzed, and then calculate HEPs by consolidating the respective effects of PSFs through simple multiplication or addition. Table 1 shows how HEPs are calculated in popular HRA methods. In the Technique for Human Error Rate Prediction (THERP) [1] and Korea standard HRA [18], HEPs of diagnosis and execution are calculated using the product of basic HEPs and PSF multipliers, and then these are summed for the final HEPs, as shown in Eqs. (1) and (2), respectively. In the Success Likelihood Index Method using the Multi-Attribute Utility Decomposition [19] method, the values of Success Likelihood Indexes (SLIs) are calculated by multiplying the normalized weight and state of PSFs, and then the final HEP is computed with a logarithmic equation using the values of SLIs, as in Eq. (3). SPAR-H [13] considers two equations: Eq. (4) is used to calculate the HEP when negative PSFs are fewer than three, and Eq. (5) is applied to situations with more than three negative PSFs. Lastly, HEART [7] estimates final HEPs by multiplying nominal human unreliability with assessed effects which are calibrated from the multiplier of each EPC as shown in Eq. (6). Though these methods use different equations for calculating HEPs, they fundamentally handle PSFs independently in the formulas.

2.2. Approaches to modeling inter-relationships among PSFs

Some HRA methods and studies have tried to consider and model inter-relationships between PSFs. CREAM [8], SPAR-H [13], and IDAC [14] try to provide guidance on how to consider mutual relationships between PSFs at the level of factor assessment. In addition, some researchers, such as Boring [15], Groth [16], De Ambroggi and Trucco [17], and Groth and Swiler [20], have raised an issue about the inter-relationship between PSFs. The following sections provide a brief description of the HRA methods and studies.

2.2.1. Cognitive Reliability Error Analysis Method (CREAM) [8].

The CREAM method briefly discussed how each CPCs may influence the others among nine CPCs in Chapter 6.5 of [8]. For example, *the adequacy of organization* has an effect on the general *working condition*. On the other hand, the *working conditions* have a direct impact on *the number of simultaneous goals* that the user must attend to in the sense that improved working conditions may lead to a reduction in the number of goals. It also discusses the qualitative relationship between CPCs, e.g., if the working conditions improve, the number of simultaneous goals is reduced. However, quantitative relations are not provided in the method.

2.2.2. Standardized Plant Analysis Risk-human reliability analysis (SPAR-H) [13].

SPAR-H provides guidance for HRA practitioners regarding the issue of mutual relationships between PSFs, though it does not attempt to quantify every aspect of the mutual influences and relationships between PSFs [13]. SPAR-H provides information for preventing analysts from double-counting PSF influences. Table 2 can be used as a guide to assigning a qualitative rank (low, medium, or high) to the degree of correlation between the eight PSFs that are used in this method. Below are the strongest correlations in the relationship:

- Available time on stress—insufficient available time increases the stress on each operator.
- Stress on complexity—stress can make the situation appear more complex because it prevents the operator from perceiving information.

From Table 2, SPAR-H can be used to draw two preliminary conclusions. First, the influence between PSFs may be one way. In other words, PSF 1 may have a strong effect on PSF 2, while PSF 2 may have little or no influence on PSF 1. For example, the available time has a strong correlation with stress, but stress has a low influence on available time because available time is sensitive to the product of system conditions and equipment unavailability. Second, some PSFs have an inverse relationship. That is, when the effect of PSF 1 increases, that of PSF 2 decreases. For example, if an operator's experience is higher, they may have a higher tolerance for stressful situations through their ability to deal with the conditions effectively.

2.2.3. Information, decision, and Action in Crew context (IDAC) model [14].

The IDAC model was developed for use in a computer simulation platform to probabilistically predict the responses of NPP control room crews in dealing with system anomalies, and considers inter-relationships between PSFs [14]. IDAC considers 50 PSFs, which are entirely composed of 11 hierarchically structured groups. Each group consists of several PSFs; for example, the physical factor group includes fatigue and physical limitations. The PSFs within each group are independent, while PSFs in different groups may have mutual influences on each other.

2.2.4. Some recent studies on inter-relationships between PSFs

Some researchers have raised an issue about the inter-

Table 1
Equations for human error probabilities (HEPs) in several human reliability analysis (HRA) methods.

HRA methods	Equations for HEPs	
A technique for human error rate prediction (THERP) [1]	$HEP_{Final} = BHEP_{Diagnosis} \cdot \prod_1^n PSF_{Diagnosis,i} + BHEP_{Execution} \cdot \prod_1^n PSF_{Execution,i}$	(1)
Korean standard-HRA (K-HRA) [18]	$HEP_{Final} = BHEP_{Diagnosis} \cdot \prod_1^n PSF_{Diagnosis,i} + BHEP_{Execution} \cdot \prod_1^n PSF_{Execution,i}$	(2)
Success Likelihood Index Method using Multi-Attribute Utility Decomposition (SLIM-MAUD) [19]	$SLI = \sum (Normalized\ Weight(PSF_i) \cdot State(PSF_i))$ $Log(1 - HEP) = a \cdot SLI + b$ ("a" and "b" are constants that can be obtained by two sets of known HEPs at least.)	(3)
Standardized plant analysis risk HRA(SPAR-H) [13]	$HEP = NHEP \cdot \prod_1^8 S_i$	(4)
	$HEP = \frac{NHEP \cdot \Pi_1^8 S_i}{NHEP \cdot (\Pi_1^8 S_i - 1) + 1}$ (S_i is the multiplier associated with the values of corresponding PSF levels. Nominal HEP (NHEP) for diagnosis tasks is 0.01, and NHEP for action task is 0.001)	(5)
Human Error Assessment & Reduction Technique (HEART) [7]	$Assessed\ effect = ((Multiplier\ of\ EPC - 1) \times Assessed\ proportion\ \ of\ effect) + 1$ $HEP = Nominal\ human\ unreliability \cdot \prod Assessed\ effect_i$	(6)

Table 2
The relative relationships among SPAR-H PSFs [13].

Influence of X upon Y	Available Time (X1)	Stress/Stressors (X2)	Complexity (X3)	Experience /Training (X4)	Procedures (X5)	Ergonomics /HSI (X6)	Fitness for duty (X7)	Work Processes (X8)
Available Time (Y1)	1.0	Medium to high	Medium to high	Medium	Medium to high	Medium	Low to medium	Low to moderate
Stress/Stressors (Y2)	High	1.0	Medium to high	Medium	Low to medium	Low to medium	Low	Low
Complexity (Y3)	Medium to high	High	1.0	Medium to high	Medium	Medium	Medium	Medium
Experience /Training (Y4)	Low	Medium	Low	1.0	Low	Low	Low	Low
Procedures (Y5)	Low	Low	Medium	Low	1.0	Low	Low	Medium
Ergonomics /Human-System Interface (HSI) (Y6)	Low	Low	Low to medium	Low	Low	1.0	Low	Low
Fitness for duty (Y7)	Low	Medium to high	Medium	Low	Low	Low	1.0	Low to medium
Work Processes (Y8)	Medium	Medium	Medium	Medium	Medium	Low	Low to medium	1.0

relationship between PSFs in HRA. First, Boring [15] analyzed the correlation of PSFs based on 82 incident reports from the U.S. In his research, which PSFs should be used in HRA and how many PSFs should be included in an analysis are the main contents, based on Galyean's suggestion, which is to account for the entirety of human performance using only three PSFs—the individual, the organization, and the environment [21]. Correlation analyses for the 8 SPAR-H PSFs across 651 subtasks were performed, and significant correlations that had mutual relations above ±0.20 and a significance level at a p-value of <0.05 were collected to show heavily related PSFs. As a result, the significant correlations, particularly for the action PSFs, suggested two groupings of PSFs:

- *Grouping 1*: Available time, stress/stressors, complexity, experience/training, fitness for duty
- *Grouping 2*: Procedures, ergonomics/human-system interface (HSI), work processes

In the case of Galyean's suggestion, the first group contains factors related to the individual (experience/training and fitness for duty), the environment or situation (available time and complexity), and a combination of the two. The second group consists of factors related to the organization and environment (procedures, ergonomics/HSI, and work processes). While the grouping does not exactly match Galyean's proposed PSFs, it does lend credence to Galyean's concerns about the possibility of double-counting performance effects.

Groth [16] also developed a "9-Bubble" model that provides a quantitative model of the inter-relationships between PSFs and links PSFs to error contexts. First, in order to reduce sets of PSFs to error contexts, a correlation analysis was performed to determine which PSFs could be combined. Then, a factor analysis was carried out to link the PSFs to error contexts. Below are the results of the factor analysis for the 9 PSFs; 4 error contexts were created:

- Error Context 1: Training, team, loads/perceptions, complexity
- Error Context 2: Organizational culture, attitude, knowledge
- Error Context 3: Organizational culture, attitude, loads/perceptions, complexity
- Error Context 4: Resources, complexity

De Ambroggi and Trucco [17] modeled and assessed dependent PSFs through the Analytic Network Process (ANP). This study dealt with the development of a framework for modelling the mutual influences existing among PSFs and a related method for assessing the importance of each PSF in influencing the performance of an operator, in a specific context, considering these interactions. ANP is a method for deciding comparative importance in multi-criteria decision making, and it is very useful for structuring problems that are judged on the basis of the knowledge or experience of the subjects [22]. The core of the method lies in the modeling process, which is divided into two steps: first, a qualitative network of inter-relationships between PSFs is identified, and then the importance of each PSF is quantitatively assessed using the ANP.

Groth and Swiler [20] suggested a Bayesian network model to represent PSFs' interactions. Bayesian networks offer a framework for integrating different sources of information into one model, and they can be easily updated or expanded with new information. For HRA purposes, a Bayesian network provides the opportunity to explicitly contain multiple types of information and data (e.g., cognitive literature, insights from operational events, statistical data, and expert judgments) in the HRA process. In their work, a Bayesian network was developed for inter-relationships among the PSFs with SPAR-H guidance.

2.3. The treatment of inter-relationships between PSFs in HRA

There is a consensus that HRA methods need to consider the inter-relationships between PSFs in estimating HEPs. However, it is known that one of the main weaknesses of current HRA methods is their limited ability to model the mutual influences among PSFs and PSFs' influences on human performance [23]. Traditional methods including THERP, the Accident Sequence Evaluation Program (ASEP) [24], and the Cause-Based Decision Tree (CBDT) [25] method developed by the Electric Power Research Institute (EPRI) do not directly address the inter-relationships between PSFs.

SPAR-H and CREAM try to provide guidance on how to adjust the levels of PSFs based on dependencies but do not consider the categorization of PSFs or the quantitative impact of one PSF on another when estimating HEPs. However, some recent studies, such as those by Boring [15] and Groth and Swiler [20], analyzed the inter-relationships between PSFs based on the SPAR-H method and suggested a few groups in which some PSFs show similar patterns through factor analysis. However, these studies do not provide guidance on how to use the PSF groups to estimate HEPs. Therefore, the characteristics of PSF inter-relationships, as well as how to treat the inter-relationships in the HRA, have to be further studied.

This study attempts to answer three questions regarding the treatment of inter-relationships between PSFs. The first question is, which PSFs have inter-relationships and how strong are the relationships between them? For identifying the relationships between PSFs and estimating their correlation coefficients, this study carried out a correlation analysis using two data sources: 1) the event history of unplanned trips and unplanned actuation of safety systems in Korean NPPs, and 2) an experiment conducted in an NPP simulator with high fidelity and licensed operators. The two data sources considered in this study may report different types of information on PSF inter-relationships. Analyzing the PSF inter-relationships from event reports where the events already occurred by mechanical or human failures may find those correlations among PSFs that is likely to lead to human error. On the other hand, the PSFs collected from the simulation experiments may include all the joint occurrences, even those that may not be related to the human error. In this study, it is assumed that the PSFs have correlation to each other regardless of whether human errors occur or not, but it affects only the strength of the correlations.

The second question is, are the PSFs correlated each other and can PSFs that influence others or each other be categorized into groups? To answer this question, we reviewed several statistical approaches such as structural equation modeling [26], Bayesian modeling [16], exploratory factor analysis [27], and confirmatory factor analysis [27]. First, the structural equation and Bayesian modeling are more specialized to identify potential cause and effect relations between variables. Second, the exploratory factor analysis is a method to combine multiple variables that are highly correlated, then uncover their relationships, i.e., factor groups, where the researcher does not have a priori hypothesis about factor groups or patterns of variables. Lastly, the confirmatory factor analysis is used to verify and test the hypothesis that a relationship between the variables and their underlying latent factors or constructs is adequate and needs to have an authoritative theory underlying their model before analyzing data. In this study, the exploratory factor analysis was selected as the most adequate method to identify a PSF group in which PSFs showed similar patterns, because there is no fixed group of PSF. It may be also effective to reduce the number of PSFs considered in an HRA, because the excess of PSFs is a problem with existing HRA methods [15].

The third question is, how can a group of PSFs be applied to the quantification of HEPs? This study suggests context-based approaches based on the results of the factor analysis and investigates the feasibility of the grouped PSFs being treated as a new factor to estimate HEPs using the experimental data. The reason why we only considered the PSF groups from the experiment is that it is favorable to verify the effect of PSF groups on HEPs with error rates which are estimated by experiment data. Meanwhile, the PSF groups identified from the event reports do not include the information for the error rates. For the PSFs identified from the event reports, it is compared with other studies related to the inter-relationship of PSFs.

It is also possible to model some sorts of inter-relationships of PSFs for estimating a HEP using some existing HRA quantification techniques such as Bayesian network [16] or decision trees [28]. Many researchers, such as Groth and Swiler [20], and De Ambroggi and Trucco [17], have modeled the relations between PSFs with considering casual relationships. However, in order to model these relations, it is important to generate statistical evidences for supporting the relationships between PSFs. In this study, we tried to suggest the way to transparently estimate the inter-relationships from the empirical data and to model the mathematical equation of HEP as a case study.

3. Inter-relationships of PSFs based on event reports

This study analyzed the inter-relationships of PSFs based on event reports for Korean NPPs. First, eight PSFs were selected using the SPAR-H method. Then, event reports on unexpected reactor trips and initiations of safety systems from the OPIS database were reviewed and analyzed with respect to the selected PSFs. A correlation analysis was performed to quantify the inter-relationships between PSFs. Finally, an exploratory factor analysis was performed to generate a couple of PSF groups in which some PSFs were closely related to each other.

3.1. PSF selection

Eight PSFs from SPAR-H were considered for the analysis: 1) experience/training, 2) stress/stressors, 3) complexity, 4) procedures, 5) ergonomics/HSI, 6) available time, 7) work processes, and 8) fitness for duty. Brief descriptions of those PSFs are given below [13]:

3.1.1. Experience/training

This PSF refers to the experience and training of the operator involved in the task. This includes years of experience of the individual or crew, whether or not the operator/crew has been trained in the relevant type of accident, and whether or not the operator/crew has been involved in a similar scenario.

3.1.2. Stress/stressors

Stress refers to the level of undesirable conditions and circumstances that impede the operator from easily completing a task. Stress can include mental stress, excessive workload, or physical stress.

3.1.3. Complexity

Complexity refers to how difficult the task is to perform in the given context. Complexity considers both the task and the environment in which it is to be performed.

3.1.4. Procedures

Procedures refer to the existence and use of formal operating procedures for the tasks under consideration. This includes situations where procedures give wrong or inadequate information regarding a particular control sequence.

3.1.5. Ergonomics/HSI

Ergonomics/HSI refers to the equipment, displays, controls, layout, and quality and quantity of information available from instrumentation, and the interaction of the operator/crew with the equipment while carrying out tasks.

3.1.6. Available time

Available time refers to the amount of time that an operator or crew has to diagnose and act upon an abnormal event. A shortage of time can affect the operator's ability to think clearly and consider alternatives.

3.1.7. Work processes

Work processes represent factors that can affect operators while performing tasks: for example, inter-organizational factors, safety culture, work planning, communication, coordination, management support, and policies. How work is planned, communicated, and executed can affect individual and crew performance.

3.1.8. Fitness for duty

Fitness for duty refers to whether or not the individual performing the task is physically and mentally fit to perform the task at the time. Things that may affect fitness include fatigue, sickness, drug use, overconfidence, personal problems, and distractions.

3.2. Analysis of PSF contributions to human errors

Event reports from the OPIS database [29] were reviewed to investigate the correlations between PSFs in NPPs. In Korea, when an NPP experiences an unplanned reactor trip, actuation of engineered safety systems, or actuation of an emergency diesel generator, the regulatory body carries out an in-depth investigation through various approaches, such as a review of the plant's operational log and parameter history, interviews with operators, and a work-down of the plant. Then, a detailed event report, including the cause, progress, consequence, and corrective actions of the event, is added to the OPIS database. The report contains the following information:

- Event sequence with timestamps
- Cause of event
- The trend of main plant parameters
- Adequacy of plant operation status at the time of event initiation
- Adequacy of the response operation
- Evaluation of safety
- Lessons learned and corrective actions

A review of the causes, errors, and failures of 222 events from 2002 to 2017 was conducted. Among them, 64 events contained operator errors in the cause and/or mitigation. PSFs that contributed to human errors in 64 events were analyzed with respect to the 8 PSFs mentioned above. Fig. 1 shows an example of the analysis of PSF contributions to human errors. If the event report mentioned that a PSF contributed to human errors, the PSF was coded as "1" on the spreadsheet; if not, it was coded as "0."

Table 3 shows the percentage of events in which a PSF influenced human errors. Two or more PSFs can influence a human error in a single event. The procedure was the influential factor in the largest percentage of events (73%), followed by experience and training (63%). Fitness for duty was identified as the lowest influencing factor in only 6%.

3.3. Inter-relationships of PSFs: correlation and factor analyses

3.3.1. Correlation analysis from event reports

A correlation analysis was carried out on the results for the PSFs' contribution to human errors in the event reports. For the correlation analysis between the PSFs which are composed of binary data, *Phi correlation coefficient* that represents a measure of the degree of correlation between two binary variables is applied [30], while the correlation analysis is generally carried out between two continuous variables and its result is indicated as *Pearson correlation coefficient*. Table 4 shows the results of correlation analysis from event reports. The results indicated that noticeable correlations existed between the PSFs with p-values, which mean the probabilities that we would have found the current result if the correlation coefficient were in fact zero (null hypothesis). If the p-values are lower than the conventional 5% (P-value < 0.05), the correlation coefficient is called statistically significant with 95% confidence level. As a result, a statistically significant and very strong correlation was found between stress/stressor and available time ($R = 0.651$). Relatively strong relations ($R > 0.5$) were also found between procedures–experience/training ($R = 0.646$), fitness for duty–stress/stressors ($R = 0.593$), complexity–stress/stressors ($R = 0.588$), work processes–complexity ($R = 0.526$), and available time–complexity ($R = 0.524$). Fig. 2 illustrates the relationships between the PSFs, along with the range of correlation factors.

3.3.2. Exploratory factor analysis and PSF grouping

As introduced in Section 2.3, the exploratory factor analysis is a method to combine multiple variables that are highly correlated, then uncover their relationships, i.e., factor groups, where the researcher does not have a priori hypothesis about factor groups or patterns of variables [27]. In this study, an exploratory factor analysis was performed to investigate PSFs' relationships and then to identify groups in which some PSFs had similar patterns. Table 5 shows the results of factor analysis based on event reports. The

No.	Plant	Unit	Date	Initiating event	Performance Shaping Factors							
					Ergonomics /HSI	Available time	Procedures	Work processes	Complexity	Experience / training	Stress/ Stressors	Fitness for duty
1	Hanul	5	2016-12-20	Hardware Failure	0	0	0	0	0	0	0	0
2	Shin-gori	3	2016-10-31	Hardware Failure	0	0	1	1	0	0	0	0
3	Wolsong	4	2016-09-12	External Event	0	0	0	0	0	0	0	0
4	Wolsong	3	2016-09-12	External Event	0	0	0	0	0	0	0	0
5	Wolsong	2	2016-09-12	External Event	0	0	0	0	0	0	0	0
6	Wolsong	1	2016-09-12	External Event	0	0	0	0	0	0	0	0
7	Shin-wolsong	1,2	2016-09-12	External Event	0	0	0	0	0	0	0	0
8	Gori	1,2,3,4	2016-09-12	External Event	0	0	0	0	0	0	0	0
9	Shin-gori	3	2016-08-20	Hardware Failure	0	0	0	0	0	0	0	0
10	Hanul	5	2016-07-25	-	0	0	0	0	0	0	0	0
11	Wolsong	1	2016-07-22	Hardware Failure	0	0	0	0	0	0	0	0
12	Wolsong	2,3,4	2016-07-05	External Event	1	0	0	0	0	0	0	0
13	Shin-gori	3	2016-07-04	Hardware Failure	0	0	0	0	0	0	0	0
14	Shin-gori	3	2016-06-13	Hardware Failure	0	0	0	0	0	0	0	0
15	Hanul	2	2016-05-12	Hardware Failure	1	0	0	0	0	0	0	0
16	Wolsong	1	2016-05-11	Hardware Failure	0	0	1	0	0	0	0	0
17	Hanul	4	2016-05-09	Hardware Failure	0	0	1	0	0	0	0	0
18	Shin-gori	3	2016-03-29	Hardware Failure	0	0	0	0	0	0	0	0
19	Hanul	3	2016-03-04	-	0	0	0	0	0	0	0	0
20	Hanbit	1	2016-02-27	Hardware Failure	0	0	1	1	0	1	0	0
21	Shin-wolsong	2	2016-01-28	Hardware Failure	0	0	0	0	0	0	0	0
22	Shin-gori	3	2016-01-24	Hardware Failure	0	0	0	0	0	0	0	0
23	Hanul	1	2016-01-19	Hardware Failure	0	0	0	0	0	0	0	0
24	Wolsong	2	2015-10-30	External Event	0	0	0	0	0	0	0	0
25	Gori	4	2015-09-03	Hardware Failure	0	0	0	0	0	0	0	0
26	Hanbit	2	2015-08-08	Hardware Failure	0	0	0	0	0	0	0	0
27	Hanbit	2	2015-06-03	External Event	0	0	0	0	0	0	0	0
28	Wolsong	4	2015-05-14	Human Error	1	0	1	1	1	1	0	0
29	Hanbit	3	2015-04-16	Hardware Failure	0	0	0	0	0	0	0	0
30	Hanbit	3	2014-10-17	Hardware Failure	1	0	1	0	0	0	0	0
31	Shin-gori	1	2014-10-10	Hardware Failure	0	0	0	0	0	0	0	0
32	Hanbit	2	2014-10-01	Human Error	1	0	1	1	1	1	0	0

Fig. 1. An example of the analysis of PSFs' contributions.

Table 3
The percentage of contributions to events by PSFs.

PSF	Percentage of events to which the PSF contributed
Ergonomics/HSI	36% (23 out of 64)
Available Time	16% (10 out of 64)
Procedures	73% (47 out of 64)
Work Processes	50% (32 out of 64)
Complexity	19% (12 out of 64)
Experience/Training	63% (40 out of 64)
Stress/Stressors	17% (11 out of 64)
Fitness for Duty	6% (4 out of 64)

factors, i.e., Factor Group 1 and 2, are defined as a construct operationally defined by its factor loadings, which mean the correlations between a variable and a factor. The numbers in Table 5 represent the factor loadings that are the correlations between each PSF and Factor Group 1 or 2. Only PSFs that the factor loadings over 0.5 are generally included in the factor groups, while the others are removed. The eigenvalue indicates the total amount of variance for the factor. Only factor groups that have eigenvalues greater than 1 are recognized as the result of factor analysis. Lastly, % of variance indicates how much each factor group accounts for the total variance.

The factor analysis identified two factor groups on the basis of eigenvalues that were over 1.0, as shown in Table 5. Factor Group 1 included five PSFs: ergonomics/HSI, procedures, work processes, complexity, and experience/training. Those factors were related to the design elements of human factors engineering (HFE) in NPPs. HFE aims at designing staffing, procedures, training programs, and HSI to improve human performance [31]. The work process and complexity were largely affected by staffing and procedures, respectively. Therefore, it could be said that Factor Group 1 represents design factors in the HFE.

Factor Group 2 included available time, complexity, stress/stressors, and fitness for duty. These factors were those that influenced the workload perceived by operators in the task. Available time, complexity, and fitness for duty were factors that typically affected an operator's mental workload. Stress/stressors directly indicated the operator's workload. Therefore, it could be concluded that Factor Group 2 represents the PSFs that are related to the operator's mental workload.

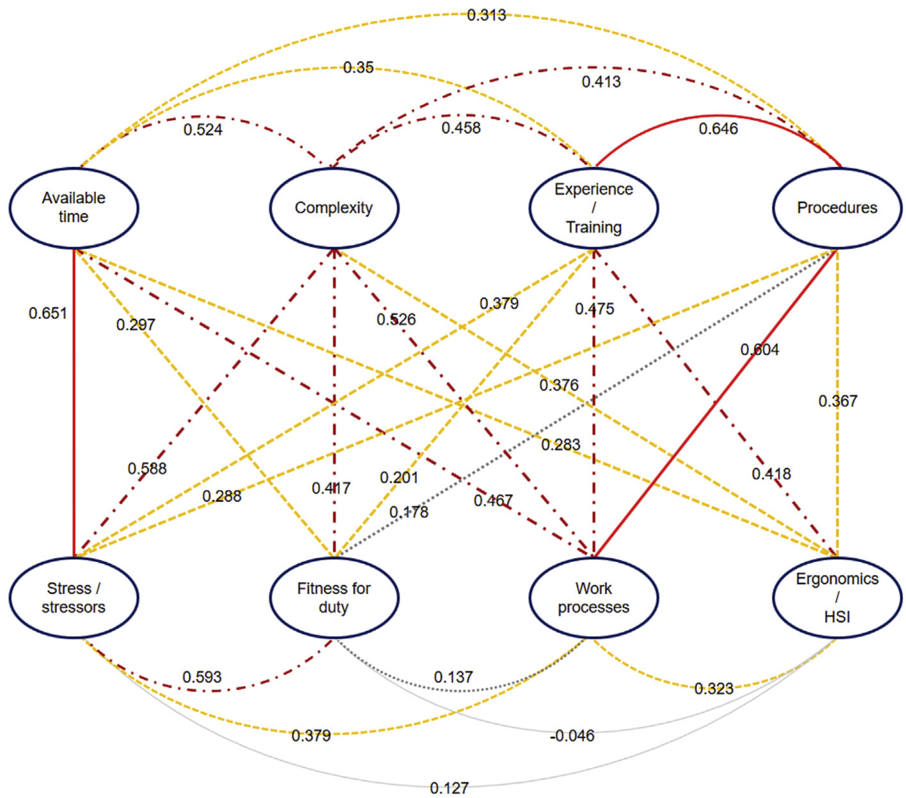
4. Correlations between PSFs based on an experiment in a simulator with a digital control room

This study investigated the relationships between PSFs in the

Table 4
Results of correlation analysis from event reports.

	Ergonomics/HSI	Available Time	Procedures	Work Processes	Complexity	Experience/Training	Stress/Stressors	Fitness for Duty
Ergonomics/HSI	1							
Available Time	0.283^{**}	1						
Procedures	0.367^{**}	0.313^{**}	1					
Work Processes	0.323^{**}	0.467^{**}	0.604^{**}	1				
Complexity	0.376^{**}	0.524^{**}	0.413^{**}	0.526^{**}	1			
Experience/Training	0.418^{**}	0.350^{**}	0.646^{**}	0.475^{**}	0.458^{**}	1		
Stress/Stressors	0.127	0.651^{**}	0.288^{**}	0.379^{**}	0.588^{**}	0.379^{**}	1	
Fitness for Duty	−0.046	0.297^{**}	0.178^{**}	0.137^{*}	0.417^{**}	0.201^{**}	0.593^{**}	1

Note: $^{**}p < 0.01$, $^{*}\ 0.01 \le p < 0.05$.



Value of Correlation Coefficient	Line Shape & Color	P-value
± 0.8 – ± 1.0	· ·	≤0.05
± 0.6 – ± 0.8	Red	≤0.05
± 0.4 – ± 0.6	Red Brown	≤0.05
± 0.2 – ± 0.4	Orange	≤0.05
± 0.0 – ± 0.2	Gray	≤0.05
·	Light Gray	>0.05

Fig. 2. An illustration of relations between PSFs with the range of correlation coefficients.

Table 5
Results of factor analysis based on event reports.

PSFs	Factor Group 1	Factor Group 2
Ergonomics/HSI	0.726	
Available time		0.654
Procedures	0.795	
Work processes	0.721	
Complexity	0.509	0.631
Experience/training	0.759	
Stress/stressors		0.883
Fitness for duty		0.825
Eigenvalue	2.714	2.471
% of variance	33.923	30.882

digital control room of an NPP, based on the authors' previous experiment [12]. One of the benefits of this experiment was that it was possible to control and measure the PSFs directly, which is almost impossible when analyzing event reports. Therefore, more flexibility was possible in the experiment for the study of inter-relationships between PSFs. This study selected six PSFs that were controllable and measurable. Then, correlation and factor analyses for those PSFs were performed using the experiment's results.

4.1. PSF selection

Six PSFs were selected for the analysis: operator experience, available time, task complexity, workload, situation awareness, and secondary task. Among them, two PSFs— operator experience and task complexity—were controlled in the experiment, while three PSFs, —workload, situation awareness, and the secondary task—were measured. Available time was a combination of controlled and measured variables.

4.1.1. Operator experience

Operator experience is equivalent to experience/training in Section 3.1. The experiment saw subjects divided into two groups: an experienced group and a less-experienced group. All crew members in the experienced group had operating licenses for a reactor of the same type as the simulator. The less-experienced crew group was composed of operators possessing operating licenses for reactors that were different from the simulator.

4.1.2. Available time

Available time was defined by comparing the time available and the time required. Time available (i.e., defined differently from the available time) was the period within which the operators should perform the task. Time available was identified from the assumption of a deterministic safety analysis as well as from operator time windows from a probabilistic safety assessment. The time required was the duration of time the operators take to complete the task. It was obtained by averaging task completion times in the experiment. The available time is determined as a ratio of time required to time available. This study used three levels of available time—sufficient, nominal, and insufficient—as follows:

$$\textit{Sufficient}: \text{time required} \le 0.2 \times \text{time available} \\ (\text{equivalent to time available} \ge 5 \times \text{time required} \\ \text{in the SPAR} - \text{H})$$

$$\textit{Nominal}: \ 0.2 \times \text{time available} < \text{time required} \\ \le 0.8 \times \text{time available}$$

$$\textit{Insufficient}: \text{time required} > 0.8 \times \text{time available}$$

4.1.3. Task complexity

To control task complexity, which is equivalent to complexity in Section 3.1, the scenarios were divided into three groups: (1) nominal, (2) moderate, and (3) complex. The nominal group of scenarios included design-based accidents. The moderate group included a scenario where there existed a masking of information or a minor discrepancy from procedures (or operator's expectancy). The complex group contained scenarios of beyond-design-based accidents. Additionally, this classification was also evaluated by the factors contributing to task complexity suggested in the SPAR-H method. The large number of actions required, misleading or absent indicators, or a large amount of communication required are the examples of the contributing factors.

4.1.4. Workload

Workload corresponds to stress/stressors in the SPAR-H method. A modified Cooper-Harper rating scale [32] was used for measuring the workload in the experiment.

4.1.5. Situation awareness

Situation awareness refers to the perception of elements in the environment within an extent of time and space and the comprehension of the meaning and projection of the status of the elements in the near future [32]. Situation awareness is not a general PSF considered in HRAs, although it is a popular human performance measure in the fields of human factors engineering and psychology. However, situation awareness is considered a cognitive factor affecting operator performances in HRA methods: for example, THERP. In particular, situation awareness is more emphasized in a digital control room, where operators' cognitive behavior plays a more important role in the operation than in analog control rooms [33]. A situation awareness rating technique (SART) was used to measure the subjects' situation awareness in the scenario.

4.1.6. Number of secondary tasks per instruction

Secondary tasks are also called interface management tasks. They refer to the tasks required to access information in a digital control room, such as configuring, navigating, arranging, interrogating, and automating the interface. They are considered as a potential PSF in a digital control room [31,34,35]. The number of secondary tasks per procedural instruction was also counted in the experiment.

4.2. Experimental design

4.2.1. Scenarios

Six scenarios were developed to reflect the different conditions of two PSFs (available time and task complexity). They are summarized in Table 6. Scenarios 1, 2, and 3 included actions that needed to be performed within 30 min after the initiation of a failure or reactor trip. The PSF of available time was calculated by using the completion time of subjects: that is, the time required. In Scenario 2, the failure of N16 indicators—that is, the radiation indicator on the steam line—was expected to make the diagnosis of a steam generator tube rupture (SGTR) difficult since the detection of radiation in the steam line is a critical cue in determining such an accident. The SGTR with the failure of N16 indicators was also used as a difficult scenario in the human factors engineering validation for NPPs [32]. An interface loss of coolant accident (LOCA) was evaluated as being moderately complex because the plant behavior was different from typical LOCAs.

4.2.2. Subjects

Six crews (18 operators) participated in the experiment. Each crew included three operators: a shift supervisor, a reactor operator, and a turbine operator. All of the operators in the experienced group had operating licenses for the reference plant, which was a pressurized water reactor with a digital control room. The other nine operators in the less-experienced group did not have operating licenses for the reference plant, but had licenses for other

Table 6
Summary of the scenarios.

No.	Scenario	Time available	Task complexity
1	Loss of offsite power + spurious opening of an atmospheric dumping valve	30 min	Nominal
2	Steam generator tube rupture + failure of N16 indicators (masking of information)	30 min	Moderate
3	Loss of coolant accident + failure of safety injection system	30 min	Complex
4	Interface system loss of coolant	None	Moderate
5	Excessive stem demand event + failure of N16 indicators	None	Nominal
6	Loss of all feedwater	60 min	Complex

Table 7
Comparison of the two groups with respect to operator experience.

Groups	Number of operators	Average age	Average work experience	License
Experienced	9 (3 crews)	42	13 years	Reference plant and other types of plant
Less Experienced	9 (3 crews)	44	12 years	No reference plant, but other types of plant

Fig. 3. APR1400 simulator.

types of plant. The average age of the participants was approximately 43 years, and the average experience in plant operation was approximately 12.5 years, as shown in Table 7.

4.2.3. Experimental facility

An NPP simulator with high fidelity was used as the experimental facility (see Fig. 3). It contained digital instrumentation and control and a digital main control room. The advanced control room design incorporated extensive computerization and automation of facilities to enhance operator decision-making and reduce operator workload. The simulator consisted of a large display panel and an operator console that could accommodate three operators. Each operator had three computer screens. Operator performance data, such as time, error rate, and secondary tasks, were collected through observation, audio/video recording, and simulator log data. Three or four HRA experts observed the operators' task performance to collect operator error data in the scenario. Audio/video recordings were also used to analyze time performances and errors. Operator log data in the simulator were stored to analyze the time and secondary tasks.

4.2.4. Experimental procedure

Each crew dealt with six scenarios; performance data for a total of 36 scenarios were collected. Each crew took approximately 6 h to address the six scenarios. Prior to conducting the scenarios, an introductory session was held to provide an overview of the experiment and convey information on the tasks that needed to be performed within 30 min. An additional day of training was conducted for the less-experienced group, to allow them to familiarize themselves with the digital MCR. A test scenario confirmed that the groups showed a consistent level of performance prior to entering the scenarios.

4.3. Inter-relationship of PSFs: correlation and factor analyses

In the experiment, a total of 36 scenarios were conducted. Two PSFs were controlled by the experimental conditions: experience and task complexity. Three were measured in the experiment:

Table 8
Experimental conditions of PSFs.

Crew	Scenario	Experience		Task Complexity		Available Time	
		Level	Quantity	Level	Quantity	Level	Quantity
1	1	High	0.5	Nominal	1	Sufficient	0.1
	2	High	0.5	Moderate	2	Nominal	1
	3	High	0.5	Complex	5	Nominal	1
	4	High	0.5	Moderate	2	Sufficient	0.1
	5	High	0.5	Nominal	1	Sufficient	0.1
	6	High	0.5	Complex	5	Nominal	1
2	1	High	0.5	Nominal	1	Sufficient	0.1
	2	High	0.5	Moderate	2	Nominal	1
	3	High	0.5	Complex	5	Nominal	1
	4	High	0.5	Moderate	2	Sufficient	0.1
	5	High	0.5	Nominal	1	Sufficient	0.1
	6	High	0.5	Complex	5	Sufficient	0.1
3	1	High	0.5	Nominal	1	Nominal	1
	2	High	0.5	Moderate	2	Nominal	1
	3	High	0.5	Complex	5	Nominal	1
	4	High	0.5	Moderate	2	Sufficient	0.1
	5	High	0.5	Nominal	1	Sufficient	0.1
	6	High	0.5	Complex	5	Nominal	1
4	1	Low	3	Nominal	1	Sufficient	0.1
	2	Low	3	Moderate	2	Nominal	1
	3	Low	3	Complex	5	Insufficient	10
	4	Low	3	Moderate	2	Sufficient	0.1
	5	Low	3	Nominal	1	Sufficient	0.1
	6	Low	3	Complex	5	Nominal	1
5	1	Low	3	Nominal	1	Sufficient	0.1
	2	Low	3	Moderate	2	Nominal	1
	3	Low	3	Complex	5	Nominal	1
	4	Low	3	Moderate	2	Sufficient	0.1
	5	Low	3	Nominal	1	Sufficient	0.1
	6	Low	3	Complex	5	Nominal	1
6	1	Low	3	Nominal	1	Sufficient	0.1
	2	Low	3	Moderate	2	Nominal	1
	3	Low	3	Complex	5	Nominal	1
	4	Low	3	Moderate	2	Sufficient	0.1
	5	Low	3	Nominal	1	Sufficient	0.1
	6	Low	3	Complex	5	Nominal	1

Table 9
Results of the correlation analysis for six PSFs from the experiment.

	Experience	Available Time	Task Complexity	Number of Secondary Tasks	Workload	Situation Awareness
Experience	1					
Available Time	0.155	1				
Task Complexity	–	0.394*	1			
Number of Secondary Tasks	0.08	−0.076	−0.159	1		
Workload	0.399*	0.053	0.131	0.507**	1	
Situation Awareness	−0.223	−0.114	−0.429**	−0.434**	−0.551**	1

Note: ** = $p < 0.01$, * = $0.01 \le p < 0.05$.

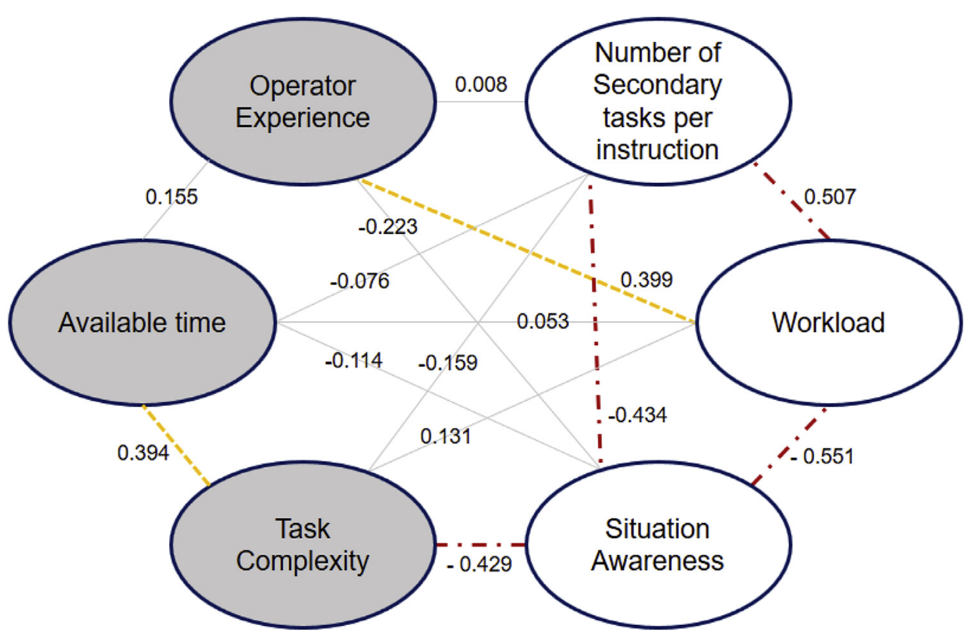
workload, situation awareness, and the number of secondary tasks. Available time was estimated by using a combination of controlled and measured variables. Table 8 shows the experimental conditions of the PSFs for the 36 scenarios and the quantitative values of the conditions used for the correlation analysis. The quantitative value is based on the multiplier of PSFs in the SPAR-H method.

Table 9 presents the results of a correlation analysis between PSFs. The correlation between experience and task complexity was not analyzed because both were controlled variables. The results indicate that the relationships of six pairs of PSFs were statistically significant. Fig. 4 shows the relationships between the PSFs with correlation coefficients and statistical significances. A strong correlation was found between workload and the number of secondary tasks ($R = 0.507$). Workload and situation awareness showed a strong negative correlation ($R = -0.551$).

Two factor groups were identified through the exploratory factor analysis, on the basis of their eigenvalues being over 1.0, as shown in Table 10. In Factor Group 1, three PSFs—workload, situation awareness, and the number of secondary tasks—showed a similar pattern, while the Factor Group 2 included experience and available time PSFs. For the workload and number of secondary tasks in Factor Group 1, these contributed positively to this group, while situation awareness contributed negatively.

5. Context-based approaches to treating the interrelationship of PSFs

This section suggests a context-based approach based on the PSF



Value of Correlation Coefficient	Line Shape & Color		P-value
± 0.8 – ± 1.0	·	·	≤0.05
± 0.6 – ± 0.8		Red	≤0.05
± 0.4 – ± 0.6		Red Brown	≤0.05
± 0.2 – ± 0.4		Orange	≤0.05
± 0.0 – ± 0.2		Gray	≤0.05
·		Light Gray	>0.05

Fig. 4. An illustration of the correlations between six PSFs from the experiment.

Table 10
The results of the exploratory factor analysis from the experiment.

PSFs	Factor Group 1	Factor Group 2
Operator experience		0.709
Available time		0.760
Task complexity		
Number of secondary tasks	0.808	
Workload	0.837	
Situation awareness	−0.774	
Eigenvalue	2.044	1.253
% of variance	40.876	25.068

groups identified from experimental data. Then, the feasibility of the grouped PSFs being treated as a new factor to estimate HEPs is examined using experimental data.

This study identified two PSF groups from the experiment. Fig. 5 shows the two factor groups and the factor scores of PSFs, which indicate the weightings between a PSF and the factor. Using the definitions of the factor analysis, Factor Group 1 from the experiment consists of three variables: the number of secondary tasks, workload, and situation awareness, while Factor Group 2 includes two PSFs, i.e., operator experience and available time. The contribution of PSFs to the factor group can be represented by their factor scores, as shown in Fig. 5.

This section shows a case study for the feasibility of applying PSF groups to the estimation of HEPs. The experiment in Section 4 also measured operators' errors while following the instructions for the procedures used in each scenario. This section investigates how the results of the factor analysis could be used to estimate the HEP in the experiment. First, we defined a PSF group score to evaluate the effect of a PSF group that contained PSFs. A PSF group score can be calculated by the sum of multiplications with a factor score of PSF (See Fig. 5) and a normalized score of an individual PSF. This also corresponds with the method to estimate a factor group score in the theory of exploratory factor analysis [27]. The normalized score of an individual PSF represented the result of a PSF evaluation in the HRA. For instance, if the scenario was evaluated as "extremely complex," we assigned "1 (highest score)" to the normalized score of complexity. Thus, the PSF group value was calculated as follows:

$$\text{PSF group score} = \sum_{i}^{n} \textit{factor score of PSF i} \times \textit{normalized score of individual PSF i} \tag{7}$$

(n = the number of PSFs in the group).

Table 11 shows an example of the normalized scores of individual PSFs for Scenario 2 in the experiment. Workload, situation awareness, and number of secondary tasks in the scenario were evaluated as 0.30, 0.53, and 0.49, respectively. Then, the PSF group score for Group 1 for the scenario could be calculated using the factor scores in Fig. 5, as shown below:

$$\text{PSF group score for Group 1} = 0.394 \times 0.30 - 0.368 \times 0.53 + 0.438 \times 0.49 = 0.14$$

Next, the process to calculate the total PSF score was outlined. As mentioned in Section 3.3.2, a factor is defined as a construct operationally defined by its factor loadings in the exploratory factor analysis. The factor is a condensed statement describing the relationship between a set of variables, while the factor loadings are the correlations of a variable with a factor. The sum of squares of the factor loadings for each factor reflects the proportion of variance explained by each factor. An eigenvalue is the total amount of variance for the factor. The average of the squared loadings of a factor (i.e., eigenvalue/the number of variables in the factor) shows the percentage of variance explained by that factor. For instance, if a factor has an eigenvalue of 1.74 and four variables, then, 1.74/4 = 0.43; thus, the factor can explain 43% of the variance in the correlation matrix.

The total PSF score is the weighted sum of the PSF group scores. This score evaluates the effect of total PSFs that were influential in a scenario. As a weighting factor, the score used the "eigenvalue of a factor/the number of variables in the factor," which means the extent to which the factor could explain the variance in the correlation matrix, as mentioned above. The total PSF score could be calculated by using the following formula:

$$\text{Total PSF Score} = \sum_{j}^{m} \frac{\textit{Eigenvalue of Group j}}{\textit{The number of PSFs in Group j}} \times \textit{PSF group score for Group j} \tag{8}$$

(m = the number of PSF groups).

The total PSF score for the scenario was calculated as follows:

$$\text{Total PSF Score for Scenario 2} = \frac{2.044}{3} \times 0.14 + \frac{1.253}{2} \times 0.063 = 0.13$$

In addition, we performed multivariable linear regression analysis for both factor groups, PSF Group 1 and 2 with error rate. equation (9) below indicates the relationship between the error rate and PSF group scores. It is also satisfied with a statistically significant level (p-value < 0.05) and indicates an R-square value of 0.281, which means a goodness-of-fit measure for the regression model. In the equation, the coefficients for PSF group score of group 1 and 2, i.e., 0.026 and 0.008, are statistically significant (p-value < 0.05), while the constant, i.e., 0.0013, is not satisfied with statistical confidence level.

$$\textit{Error rate} = 0.0013 + 0.026 \times \textit{PSF group score of group } 1 + 0.008 \times \textit{PSF group score of group } 2 \tag{9}$$

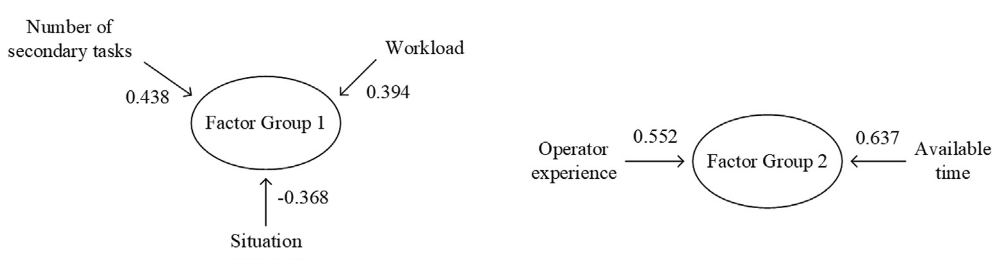


Fig. 5. Identified PSF groups from the experiment.

Table 11
An example of calculating PSF group scores.

Scenario	Normalized Score of Individual PSFs for Group 1			Group Score of Group 1	Normalized Score of Individual PSFs for Group 2		Group Score of PSF Group 2
	Workload	Situation Awareness	Number of Secondary Tasks		Available Time	Operator Experience	
2	0.30	0.53	0.49	0.14	0.10	0	0.063

Lastly, we performed the correlation analysis on 1) PSF group score of group 1, 2) PSF group score of group 2, 3) total PSF score, 4) error rate predicted by equation (9), and 5) SPAR-H PSF score with error rate estimated by the experiment. For the SPAR-H PSF scores, the experimental conditions of PSFs in Table 8 were used. For instance, the multiplication of PSF quantities for Scenario 1 of Crew 1 could be calculated as follows:

$$\begin{aligned} SPAR-H\ score &= \prod_{1}^{3} PSF\ Quantity_i \\ &= 0.5\ (\text{experience}) \times 1(\text{Task Complexity}) \\ &\quad \times 0.1\ (\text{Available Time}) \\ &= 0.05 \end{aligned}$$

Table 12 presents the results of the correlation analysis. The results show that the correlations on PSF group score of group 1, PSF group score of group 2, total PSF score and error rate predicted by equation (9) with error rate estimated by the experiment are statistically significant, respectively. Especially, the error rate predicted by equation (9) showed a stronger correlation with the error rate estimated by the experiment. However, the SPAR-H PSF score did not show any statistical correlation with the error rates.

6. Discussion

6.1. Comparison of the results with those of other studies

The PSFs collected from event reports in this study are found in the SPAR-H method which has been broadly used by both industry and regulators in its intended area of use (i.e., NPPs in the U.S.), as well as in other industries [36,37]. Moreover, these are also relatively common when comparing with the other studies.

This section compares the results of this study from the event report analysis with those of others related to the inter-relationship of PSFs—that is, Groth's [16], Boring's [15], and Gaylean's [21] works. Table 13 summarizes the comparison of PSF grouping from those studies.

Some similar patterns can be observed in the groupings of PSFs. First of all, the results of this study showed a similar pattern to Boring's study. Three PSFs—ergonomics/HSI, procedure, and work processes—are common between Group 1 (i.e., HFE design factor) resulting from the event report analysis of Section 3 and Grouping 2 of Boring's study. The HFE design factor also shares three PSFs (ergonomics/HSI, procedure, and experience/training) with the organization environment in Gaylean's study.

Group 2 (i.e., workload factor) from Section 3 of this study also includes common PSFs with Error Context 1 of Groth's study and Grouping 1 of Boring's study. Three PSFs (available time, complexity, and stress/stressor) are shared by all three. Additionally, fitness for duty is found in the groups of this study and in that of Boring. Even though the data were obtained from different countries (i.e., Korea and the U.S.), these studies showed similar patterns in the grouping of PSFs.

In summary, these comparison results may indicate that the PSFs which have been considered individually in the existing HRAs could be combined into a lower number of PSF groups. As a next step, an approach to treat these PSF groups needs to be further suggested for estimating HEPs while reflecting the effect of inter-relationships between the PSFs.

6.2. Feasibility of context-based approaches to treating the inter-relationship of PSFs

This study suggests two different context-based approaches to treat inter-relationship of PSFs based on the PSF groups. One is to calculate the total PSF score, while the other one is to use multi-variable linear regression analysis for factor groups. In Table 12, it is identified that the both approaches are statistically significant, but the latter one shows the higher correlation coefficient.

For the total PSF score, it is useful to combine all the effects of PSF into a value. The method for calculating the total PSF score basically depends on weighting values, i.e., factor scores or eigenvalues, which are based on the results of the factor analysis having statistical backgrounds [38]. However, it may be difficult to generalize that the total PSF score could be accountable for error rates, even if we identified a statistically significant relation between the total PSF score and error rates. It's because this study does not include how much the total PSF score indicates the error rates. Therefore, this study may conclude that the latter approach is more feasible to treat the inter-relationship of PSFs. The approach showed the higher correlation coefficient as well as the direct relation between the PSF group score and error rates.

The SPAR-H PSF score did not show any statistical correlation with the error rates. In fact, the multiplier values for the eight SPAR-H PSFs are mapped from the data suggested by THERP [39]. However, most of the available data for estimating HEPs in THERP are basically relying on expert judgment, and sparse empirical and experience-based data mostly from non-nuclear experience [40]. Therefore, this result may highlight a fundamental issue of current HRA which is still a lack of data in terms of addressing the effects of the PSFs on a HEP and estimating the HEP with determination of

Table 12
Correlation analysis for the PSF group values and error rates in the experiment.

Relationship	Correlation Coefficient (p-value)
PSF group score of group 1 vs. error rate	0.444 ($p < 0.05$)
PSF group score of group 2 vs. error rate	0.376 ($p < 0.05$)
Total PSF score vs. error rate	0.487 ($p < 0.05$)
Error rate predicted by equation (9) vs. error rate	0.530 ($p < 0.05$)
SPAR-H PSF score vs. error rate	0.085 ($p > 0.05$)

Table 13
Comparison of PSF groupings from four studies.

This study (from the event report analysis	Groth [16]	Boring [15]	Gaylean [21]
• Group 1 (HFE design factor): ergonomics/HSI, procedures, work processes, complexity, and experience/training • Group 2 (workload factor): available time, complexity, stress/stressors, and fitness for duty	• Error Context 1: Training, team, loads/perceptions, complexity • Error Context 2: Organizational culture, attitude, knowledge • Error Context 3: Organizational culture, attitude, loads/ perceptions, complexity • Error Context 4: Resources, complexity	• Grouping 1: Available time, stress/ stressors, complexity, experience/ training, fitness for duty • Grouping 2: Procedures, ergonomics/ HSI, work processes	• Population Capability: intelligence, experience, and general education • Organizational Environment: work-related training, procedure, instrument, and safety culture • Event Specifics: time constraints, uniqueness of situation

PSF quantification values [41,42].

This study tried to treat PSF inter-relationships by involving all the possible interactions between the states of the PSFs and between the influences of the PSFs on human performances, such as correlation, dependency, overlapping, or combinational effects with the causal relations. Then, as a relatively simple approach, we suggested how to estimate HEPs based on the result of factor analysis, i.e., PSF groups combining all the possible interactions between PSFs. However, identifying and understanding these interactions are still remaining issues in this research. In fact, the factor analysis only shows that there are relations between the variables, but cannot explain the reasons why there are the relations or how they are related each other. In HRA, it is important to account for whether there are relationships with casual effects, whether some of PSFs always affect each other, whether the PSFs have different phenomena affected by the same cause, or whether the experimental design is misconstrued. Representatively, the grouped PSFs in this study might be influenced by the experimental design, because how a PSF related to other PSFs was controlled by experimental design. For example, for Factor Group 2 (See Table 10), the available time and operator experience PSFs are grouped into a factor, although these do not have any correlation. In fact, the available time is independent with experience because it is determined by scenario or accident severity. Nevertheless, they might be grouped into a factor because the relation between available time and experience simultaneously shapes a temporal pressure to operators. If this is true, these two PSFs have a relation supporting a combinational effect. This effect has been observed in the other study. Kim et al. [43] identified that some sort of HEP can dramatically increase when quality of procedure and experience are evaluated as low, although these PSFs may not have any correlation. Therefore, these issues need to be further studied in the future.

7. Conclusion

This study investigated the inter-relationships between PSFs for HRAs of NPPs. Although it is obvious that PSFs have relationships with each other, current HRA methods do not treat the combined effect of PSFs on human errors sufficiently. Based on the two data sources of event reports from Korean NPPs and an experiment with a simulator, this study performed correlation and factor analyses. As a result, several PSF groups in which PSFs showed a similar pattern were identified. Finally, this study discussed the feasibility of using the identified PSF groups to estimate HEPs in the results of the experiment.

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