Use of a big data analysis technique for extracting HRA data from event investigation reports based on the Safety-II concept

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Abstract

The safe operation of complex socio-technical systems including NPPs (Nuclear Power Plants) is a determinant for ensuring their sustainability. From this concern, it should be emphasized that a large portion of safety significant events were directly and/or indirectly caused by human errors. This means that the role of an HRA (Human Reliability Analysis) is critical because one of its applications is to systematically distinguish error-prone tasks triggering safety significant events. To this end, it is very important for HRA practitioners to access diverse HRA data which are helpful for understanding how and why human errors have occurred. In this study, a novel approach is suggested based on the *Safety-II* concept, which allows us to collect HRA data by considering failure and success cases in parallel. In addition, since huge amount of information can be gathered if the failure and success cases are simultaneously involved, a big data analysis technique called the CART (Classification And Regression Tree) is applied to deal with this problem. As a result, it seems that the novel approach proposed by combining the Safety-II concept with the CART technique is useful because HRA practitioners are able to get HRA data with respect to diverse task contexts.

Keywords

Human reliability analysis, Nuclear power plant, Safety-II, Classification and regression tree, Event investigation report

1. Introduction

The safe operation of complex socio-technical systems (e.g., petro-chemical systems, railway systems, health care systems, and transportation systems) is the most critical precondition for ensuring their sustainability. In this regard, it is very important to point out that a large portion of significant events that can impede the safe operation of the complex socio-technical systems was caused by human errors [Pasquale et al., 2015; Stock et al., 2007; El-Ladan and Turan, 2012, Hughes et al., 2015]. For example, Akyuz (2015) and Evans (2011) stressed that human error is one of the main contributors affecting the risk of gas inerting processes and railway systems, respectively. In addition, accoring to recent statistics obtained from the operating experience of NPPs (Nuclear Power Plants), it is revealed that about 80% of significant events are attributable to human errors, which is almost four times compared to the contribution of equipment failures [IAEA, 2014]. This strongly implies that the management of human errors is key to enhance the safety of the complex socio-technical systems. In this light, the role of an HRA (Human Reliability Analysis) should be emphasized because it allows us to systematically manage the occurrence of human errors by evaluating the likelihood of a huamn error (or HEP, Human Error Probability) under a specific task context [Kirwan, 1994]. In other words, if we are able to properly calculate the HEPs of required tasks to be done by human operators working in the complex socio-technical systems, it is possible to effectively improve their safety by minimizing the occurrence of human errors.

However, conducting an HRA is not a simple work because the spectrum of tasks to be covered by human operators working in complex socio-technical systems has a wide range of variability. This means that HRA practitioners are probably apt to request diverse HRA data that are helpful for understanding the nature of human errors under a given task context. Otherwise, the calculation of HEPs would become inaccurate resulting in the high uncertainty of HRA results (or managing the occurrecne of human errors). From this concern, many HRA practitioners have traditionally pointed out the necessity of typical HRA data (but not limited to) including: (1) the catalog of HEPs with respect to specific task types, (2) the inventory of error forcing factors usually called PSFs (Performance Shaping Factors) or PIFs (Performance Influence Factors), and (3) the effect of PSFs on the HEP of a specific task type (e.g., PSF multipliers) [Gertman et al., 2005; Kolaczkowski et al., 2005; Lois et al., 2009; Park et al., 2017a].

For this reason, many researchers have spent extensive efforts for securing sufficient HRA data from various kinds of available sources, such as operating experiences (e.g., event investigation reports), observations from full-scope simulators, experiment results using partial-scope simulators, expert judgments and interviews with subject matter experts [Park and Jung, 2013]. Of them, both the operating experiences and simulator observations have been regarded as major sources for collecting HRA data for many decades [IAEA, 1998; Kim et al., 2017a; Kim et al., 2017b; Kim et al., 2017c; Labarthe and Garza, 2010; NEA, 2008; Taylor-Adams and Kirwan, 1995]. Table 1 summarizes representative pros and cons pertaining to the collection of HRA data from two representative sources: event investigation reports that reflect operating experiences and observations from full-scope simulators.

< Table 1. Comparing pros and cons pertaining to the collection of HRA data from two representative sources, modified from Park et al. (2016a) >

Source	Pros	Cons
Event investigation reports	• Enable to secure more authentic HRA data that reflect a real task context • Free from a fidelity problem	• Not easy to extract sufficient HRA data for rare events • Difficult to collect HRA data related to dynamic/interactive contexts (e.g., teamwork or team communications) • Need a careful translation due to uneven contents/descriptions
Simulator observations	• Enable to simulate rare (i.e., low frequency) events • Enable to observe the variation of human behaviors with respect to diverse task contexts	• Require a huge amount of resources (e.g., budget, time, and manpower) • Not easy to secure sufficient times for using a full-scope simulator • Need to consider the effect of a fidelity problem

As can be recognizable from Table 1, in terms of gathering sufficient amount of HRA data, the use of a full-scope simulator would be a more practical option because it allows us to observe the performance variation of human operators who are faced with diverse task contexts, of which the frequency is ranging from a *highly unlikely* to a *highly likely*. Unfortunately, although many researchers claimed that the behaviors of human operators observed from simulated task contexts would largely concur with those from a real task context [Gibson et al., 2006; Hirschberg and Dang, 1996; Ohtsuka et al., 1994; Takano and Reason, 1999], it is also true that a fidelity problem would hinder the sole use of HRA data collected from full-scope simulators. In other words, it is still possible that the response of human operators observed from simulated task contexts would not be congruent with those expected from a real situation. Accordingly, in order to properly use HRA data extracted from simulator observations, it is necessary to simultaneously combine HRA data from the two representative sources.

Unfortunately, as summarized in Table 1, there are at least three obstacles impeding the accumulation of HRA data based on the analysis of event investigation reports: (1) it is not easy to extract HRA data from rare events, (2) it is difficult to collect HRA data related to dynamic task contexts such as teamwork or team communications, and (3) it is necessary to extract HRA data from the uneven contents and/or descriptions of event investigation reports. Of them, it is evident that the first and second obstacles cannot be technically resolved. For example, it is unrealistic to expect the existence of detailed investigation reports that explain the chronological sequences with the associated descriptions for rare events. In addition, it is hard to find out investigation reports that contain detailed explanations about the effect of dynamic and/or interactive task contexts (e.g., teamwork or team communications) on the occurrence of human errors resulting in safety significant events. This means that one of the plausible solutions is to develop a framework that allows us to systematically collect HRA data from event investigation reports, which have uneven contents and descriptions.

For this reason, many researchers have tried to collect HRA data from the analysis of event investigation reports for several decades [Basra and Kirwan, 1998; Hallbert et al., 2004, Lucas and Embrey, 1989; Sträter, 2004]. For example, Hallbert et al. (2006) proposed the HERA (Human Event Repository and Analysis) framework that can be used for the analysis of LERs (Licensee Event Reports). Similarly, Kirwan et al. (1997) developed the CORE (Computerized Operator Reliability and Error) database that contains HRA data extracted from not only simulator observations but also the analysis of event investigation reports. However, most of existing HRA data extracted from event investigation reports seem to have a common limitation: focusing on a failure case.

Let us assume that an LER has been issued, which describes the occurrence of a human error during the performance of a required task being described in a test procedure. In this case, the HERA framework can be applied to the analysis of the LER, and it is revealed that there is a critical problem in the design of an HMI (Human-Machine Interface) used for the performance of the required task. Accordingly, from the point of view of determining dominant PSFs, this investigation result would be very critical because it is strong evidence emphasizing the importance of an HMI design. The problem is that this HMI has been already used for many years without any kinds of human errors. This alludes to the fact that the effect of the HMI design on an HEP would be less critical than it seems. If so, it is reasonable to assume that HRA data extracted from the analysis of failure cases could be biased because they are likely to represent the snap-shot of a task context only when a human error has occurred.

Actually, the nature of this problem can be understood on the basis of a difference between the concepts of *Safety-I* and *Safety-II*. That is, from the point of view of the *Safety-I* concept, the safety of complex socio-technical systems can be enhanced by eliminating root causes resulting in failure cases. In contrast, the *Safety-II* concept emphasizes that the safety can be improved by encouraging important factors underlying the occurrence of success cases. Although the ultimate goal of these two concepts is identical, if we remind the fact that the HEP of the complex socio-technical systems is ranging from 1.0E-5 to 1.0E-4, it is likely that the *Safety-I* concept could give a biased insight because the number of failure cases is extremely small than that of success cases (e.g., one failure case vs. 99,999 success cases). In this light, it is possible to expect that most of existing HRA data gathered from event investigation reports could be less informative because they represent failure cases.

For this reason, in this study, a novel approach is suggested based on the *Safety-II* concept, which allows us to collect HRA data from the analysis of event investigation reports including success cases. It should be noted that, from hereafter, HRA data denotes the catalog of dominant PSFs with the associated multipliers. To this end, it is necessary to resolve three kinds of technical challenges: (1) what kinds of information items that could be essential for clarifying dominant PSFs should be collected from event investigation reports? (2) how these essential information items can be collected from success cases? and (3) how we are able to properly analyze a huge amount of information gathered from both failure and success cases? In order to resolve the first and second technical challenges, in this study, the catalog of generic information items suggested by Park et al. (2013) is combined with a framework proposed by Park et al. (2016c). In addition, one of the representative big data analysis techniques called the CART (Classification And Regression Tree) is applied to deal with the third technical challenge.

The structure of this paper is organized as follows. First, the basic concepts of the *Safety-I* and *Safety-II* are briefly explained in Section 2. Then, in Section 3, the three kinds of technical challenges are described in detail with the associated solutions. Based on the descriptions of Section 3, then, Section 4 will explain how to extract HRA data from the analysis of event investigation reports with the results of a case study, which are related to diverse human errors experienced in domestic NPPs. Finally, the limitations of this study will be discussed with a concluding remark in Section 5.

2. Two different approaches to system safety

Recently, a new paradigm of system safety called Safety-II has been introduced [Hollnagel et al. 2013]. The concepts and principles underlying Safety-II allow us to look at the two representative system safety activities, which are retrospective accident investigation and prospective risk assessment including HRA, from a different perspective [Hollnagel, 2002]. Thus they help us to supplement the limitations of traditional approaches to system safety (i.e., Safety-I). In this section, we review the characteristics and limitations of Safety-I and then describe the concepts and principles of Safety-II. In particular, we give a more detailed description about performance variability and the inevitable difference between work-as-imagined (WAI) and work-as-done (WAD), which can be regarded as two fundamental concepts for developing the new system paradigm (Safety-II).

In the traditional paradigm of safety (i.e., Safety-I), safety is defined as the condition where the number of adverse outcomes (accidents and incidents) is as low as possible [Hollnagel, 2014]. When some unwanted things happen in a system, Safety-I attempts to 'find and fix' root causes for the problematic situations (find and fix approach). Thus, it looks for failures and malfunctions, try to find their plausible causes, and then eliminate causes or improve barriers. The philosophy underlying this approach is that success and failure have their different causes (hypothesis of different causes) [Hollnagel et al., 2013]. Thus it has been believed that wrong outcomes, such as accidents or incidents, have their corresponding causes that can be found and treated. This belief called *causality-credo* has been a fundamental principle underlying retrospective accident investigation and prospective risk assessment methods in Safety-I [Hollnagel, 2014]. Additionally, most of the retrospective accident investigation and prospective risk assessment methods in Safety-I paradgm assume an accident model that is based on linear cause-effect relationships. It is also presumed that the influence from contexts or conditions is limited and quantifiable. For all these reaons, the main focus of Safety-I has been on failure cases, rather than whole outcomes including successful outcomes, based on the belief that system safety can be enhanced by finding and fixing the causes of adverse outcomes and by reducing the risks associated with them to acceptable levels [Sujan et al., 2017].

Focusing on accident investigation methods developed under the paradigm of Safety-I, we can summarize the characteristics of Safey-I as follows [Yoon et al., 2017]: (1) they attempt to diagnose an accident with a linear and simple cause-effect relationships, (2) they generally assume a accident causation model and attempt to explain an accident investigation based on the model, (3) they strive to look for a root cause and tend to neglect other possible causes once a root cause is found, (4) they try to understand an accident with a pre-specified set of causal factors linked to a presumed causation model, (5) they have a stance that all adverse outcomes have their unique and respective causes, and (6) they are inclined to seek human errors and regard them as root causes [Hollnagel 2012; 2014; Hollnagel et al. 2013; Shorrock et al. 2014].

The main goal of prospective risk assessment in Safety-I is to identify causes of an accident and contributory factors, based on the assumption that accidents are caused by failures and malfunctions [Hollnagel et al., 2013]. However, prospective risk assessment usually involves the investigation of previous accidents or events to obtain a set of data to be used for assessing human and system reliability. This means that accident investigation is one essential activity of HRA. Thus we can say that traditional HRA in Safety-I also shows the characteristics described above.

However, it has been criticized that the assumptions and theoretical foundations of Safety-I are insufficient as a conceptual basis for effectively enhancing and managing system safety in modern complex socio-technical systems [Hollnagel, 2017]. These systems are increasingly intractable, which means that it is not possible to prescribe tasks and actions in every detail. This negates that the assumptions and foundations of Safety-I can be resonably applied to these systems. A lot of accidents or incidents we have experienced during the last decades also indicate that the failure behaviour of these systems cannot be easily explained in terms of linear cause-effect relationships [Hollnagel, 2012; Leveson, 1995, 2011; Yoon et al., 2016].

Here we need to consider the critical problems of Safety-I in relation to the characterisitcs of modern complex socio-technical systems. As explained above, since the complexity and uncertainty of these systems escalate more and more, they are increasingly intractable [Shorrock et al., 2014]. Therefore, it is actually impossible to predict all task situations and prescribe all the task performance thoroughly. This means that human operators in a system should exhibit some degree of variability or adaptability in order to deal with a range of dynamic situations, including exessive cognitive demands under unexpected situations, thereby making the system work properly [Hollnagel, 2012]. It is necessary to recognize that performance variability is absolutely needed and valuable for the safe operation of a complex socio-technical system. It implies that performance variability or adjustments is the reason for both successful and failed outcomes [Hollnagel, 2014; Sujan et al., 2015]. A same task performance can be variable and thus result in either successful or failed outcomes, depending on a range of factors such as PSFs [Hollnagel, 2009]. This is the view contrasted with the hypothesis of different causes in Safety-I. The concept of performance variability implies that it is necessary to understand the characteristics of everyday performance variability to enhance system safety, rather than looking for ways in which something can fail or malfunction [Patterson et al., 2015].

Another important issue can also be identified from the fact that modern systems are increasingly intractable. If we assume that task situations can be completely analyzed and prescribed, work-as-imagined (WAI) will properly correspond to work-as-done (WAD). However, it is highly likely that WAD is significantly different from WAI under an intractable system. This is highly related to the concept of performance variability. We admit that when a system work reliably, it is because human operatorss exhibit performance adjustment or performance variability, rather than the system is perfectly designed or all the task situations are completely prescribed. This implies that system safety efforts should focus on understanding WAD rather than WAI and considering how to support WAD in order to enhance the ability of performance adjustment [Hollnagel, 2016; Lundberg et al., 2010; Sujan et al., 2017].

It should be noted that Safety-I approach does not well consider those two important things: performance variability and inevitable difference between WAD and WAI [Hollnagel, 2014, 2016]. Considering the importance of them, we can say that an approach to enhancing system safety should understand everyday performance varibility and correspond to WAD rather than WAI [Woljter et al., 2015]. However, Safety-I begins by asking why things go wrong and then attempts to find the assumed causes for the purpose of ensuring that it does not happen again. This means that it tries to reestablish WAI. Then, what is a resonable alternative approach to system safety? It is to ask why things go right in most of task situations and then attempts to ensure that this happens again. This is the motivation of developing Safety-II approach for the purpose of supplementing the drawbacks of Safety-I. In terms of efficiency of using the information we can obtain, it can be said that Safety-I focuses only on failure cases, which are very small sample in comparison to success cases. Thus we can say that it is more desirable to make use of various successful stories to derive insights useful for improving system safety, as well as limited unsuccessful cases.

It should be again emphasized that we need to examine what things go right to understand how unacceptable outcomes happen, instead of only looking at what goes wrong. We need to admit that systems work right because human operators are able to adjust their performance rather than they are perfectly designed and work-as-imagined. The reason why human operators able to work effectively and successfully is that they continuously adjust their activities to the current dynamic situations. Thus understanding how successful outcomes happen is the necessary basis for understanding how wrong outcomes happen [Hollnagel, 2016]. For this reason, when some bad things happen, we should begin by investigating how they usually work successfully, instead of searching for a set of plausible causes for explaining only the failures. Based on these theoretical bases, Safety-II defines safety as a condition where the number of successful outcomes is as high as possible and regards it as the ability to succeed under varying conditions. Safety-II is achieved by trying to make sure that things go right, instead of preventing them from going wrong. Accordingly, the basis for system safety activities in Safety-II must be understanding of why systems work successfully in many situations, which means an understanding of everyday performance variability.

Previously, we summarized the six characteristics of Safety-I, focusing on accident investigation methods. Here, based on the concepts and principles of Safety-II, we can also summarize the following six characteristics of Safety-II, which correspond, in order, to those of Safety-I [Yoon et al., 2017]: (1) an accident analysis method should admit that an accident cannot be sufficiently explained by linear, simple cause-effect relationships, (2) an accident needs to be investigated without too much relying on an accident causation model, (3) an accident is not so simple that it can be sufficiently explained only with a root-cause, (4) it should be acknowledged that the currently assumed set of causal factors may not be actual causes of the accident and that other contextual factors assumed not to be problematic may be actual causes, (5) the causes of successful outcomes and adverse outcomes are not different but the same, and (6) an accident analysis method should focus on the performance variability in terms of resource demands and resources available in the situation of an accident, instead of human errors [Hollnagel 2012; 2014; Hollnagel et al. 2013; Leonhardt et al. 2009; Shorrock et al. 2014]. Considering the characteristics above, we can say that the purpose of prospective risk assessment in Safety-II is to understand the conditions where performance variability can become difficult or impossible to monitor and control [Hollnagel et al., 2013].

However, one should not think that traditional approaches are useless due to their drawbacks. In spite of those shortcomings, they are still useful in retrospective accident investigation and prospective risk assessment [Salmon et al., 2012; Shorrock, 2014; Yoon et al., 2017]. Nonetheless, it should also be noted that there is a growing number of accidents in modern complex socio-technical systems where Safety-I approach cannot be effectively used [Hollnagel 2014]. For this reason, system safety engineer should always keep in mind the limitations of Safety-I paradigm and attempt to overcome them. It is important to acknowledge that Safety-I and Safety-II represent two complementary views of safety; they are never two incompatible or conflicting approaches. Thus, we can say that it is desirable to develop a method that can support the use of traditional approaches to system safety as well as help analysts avoid their drawbacks.

Lastly, there is one point that we should not misunderstand in regard to the focus areas of the two safety paradigms. One misunderstanding we should avoid is that Safety-II is only concerned with successful outcomes, excluding unsuccessful outcomes. It should be emphasized that Safety-I is only concerned with a set of limited unsuccessful outcomes such as human errors, whereas Safety-II focuses on a lot of diverse successful outcomes as well as a set of limited unsuccessful outcomes [Hollnagel, 2014; Hollnagel et al., 2013]. However, their critical difference should be found in their viewpoint on system safety and several principles for ensuring system safety, though they are different in terms of focus areas as well. As explained above, because each of the two paradigms has its own advantages, it is desirable to integrate them, not replacing Safety-I with Safety-II. Resilience engineering is a new academic discipline addressing this issue [Hollnagel et al., 2010]. It does not claim the wholesale replacement of Safety-I by Safety-II, but rather proposes a systematic combination of the two ways of thinking on safety [Hollnagel, 2016]. In order to enhance system resilience, it emphasizes that a system should exhibit four abilities: learning (knowing what has happened), responding (knowing what to do), monitoring (knowing what to look for), and anticipating (knowing what to expect) [Hollnagel et al., 2010]. However, as resilience engineering is beyond the scope of this paper, we do not delve into it further.

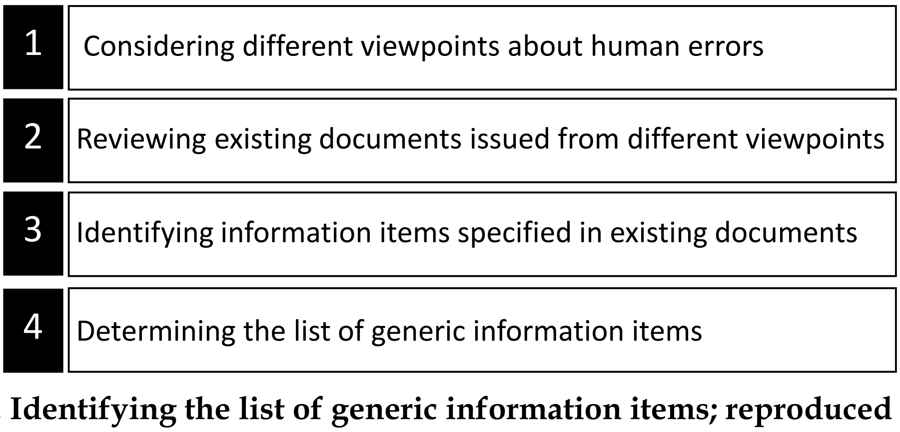
3. Resolving technical challenges

As briefly mentioned at the end of Section 1, from the point of view of the Safety-II concept, at least three kinds of technical challenges should be addressed for the collection of HRA data from the analysis of event investigation reports. In this regard, this section will explain how to actually resolve these technical challenges.

3.1 Essential information to be collected from event investigation reports

The first technical issue to be resolved is to determine the contents of information to be collected from the analysis of event investigation reports. Basically, it is evident that the contents of information extractable from a given event investigation report are largely dependent on its description level (i.e., the more the event investigation report tells detailed task contexts, the more the amount of extracted information increases). In addition, since the purpose of this study is to accumulate HRA data (i.e., the catalog of dominant PSFs with their multipliers) for supporting HRA practitioners, the following fundamental rule should be emphasized for analyzing event investigation reports: *All kinds of information should be supportive of an HRA*.

Accordingly, it is natural to expect that that the contents of information can be determined by the following two phases: (1) selecting the catalog of PSF-related information items from generic information items that are needed for supporting the conduction of an HRA, and (2) narrowing down the catalog of PSF-related information items that are actually collectable from the description of an event investigation report. For this reason, the list of generic information items proposed by Park and Jung (2013) is regarded as a starting point to resolve the first technical issue. Figure 1 succinctly depicts how the list of generic information items was decided.



<Figure 1. Identifying the list of generic information items; reproduced from Park and Jung (2013) >

As can be seen from Fig. 1, the first step is to distinguish diverse viewpoints about the definition of human errors. Then, as the second step, various kinds of existing documents (such as requirements, standards, guidelines, and good practices), which have published based on the reflection of each distinctive viewpoint are reviewed in detail. Consequently, it was possible to figure out several groups of information items that are necessary for supporting HRA practitioners who will probably use different HRA methods and/or techniques. The last step is to integrate these groups into the list of genetic information items.

As a result, Park and Jung (2013) identified a total of 89 generic information items belonging to the following 7 categories: (1) Environment, (2) HMI, (3) Organization, (4) Procedure, (5) Task, (6) Success criteria, and (7) Actual condition. At the same time, they also proposed detailed instances that can be regarded as specific indicators for each generic information item. From these generic information items, the catalog of PSF-related information items is selected with and the associated instances. For example, Table 2 shows a part of PSF-related information items, which belong to the categories of *Task* and *Actual condition*.

< Table 2. A part of PSF-related information items and the associated instances >

<table>
<tr><th>Category</th><th>Information item</th><th>Suggested instances</th></tr>
<tr><td rowspan="5">Task</td><td>Expected cues for task initiation</td><td rowspan="2">Alarm(s), Indication alerts, Parameters, Symptoms, Person (supervisor request), Procedure step, and Self-initiation</td></tr>
<tr><td>Expected feedback information</td></tr>
<tr><td>Expected cue observer</td><td rowspan="2">Operator working in an MCR (Main Control Room), Local (or auxiliary) operator, Maintenance personal, Engineer, and Subcontractor</td></tr>
<tr><td>Expected task performer</td></tr>
<tr><td>Expected task demand</td><td>High-precision reading, Status check readings, Rapidly comparing separate readings, Monitoring data over time, Monitoring rapidly changing data, Performance of repetitive computations, Execution of rapid, fixed sequences, and Any task for satisfying real-time constraints (e.g., pressurizer pressure control)</td></tr>
<tr><td rowspan="3">Actual condition</td><td>Task load</td><td>Task situation requiring: (1) short-term memory, (2) long-term memory, and (3) decision-making</td></tr>
<tr><td>Workload</td><td>Cognitive, Physical, and Serial/parallel overlap of task elements</td></tr>
<tr><td>Nature of decision making</td><td>Relative decision making, Absolute decision making, and Probabilistic decision making</td></tr>
</table>

For example, for the PSF-related information item of *Expected cues for task initiation* belonging to the category of *Task*, existing documents suggested several instances (i.e., practical and/or tangible entities) such as *Alarm, Indication alerts, Parameters, Symptoms, Person, Procedure step,* and *Self-initiation*. This means that, in terms of *Expected cues for task initiation*, most of existing HRA methods provides detailed methods and/or techniques for estimating HEPs based on the values of diverse cue types suggested as instances. Accordingly, if we consider these instances (for the sake of convenience, the term of *PSF-related instances* will be used hereafter) from the beginning of the analysis of event investigation reports, it is possible to provide HRA data that can support HRA practitioners in more effective manner (i.e., direct use of collected HRA data without further modifications or translations).

3.2 Collecting information from success cases

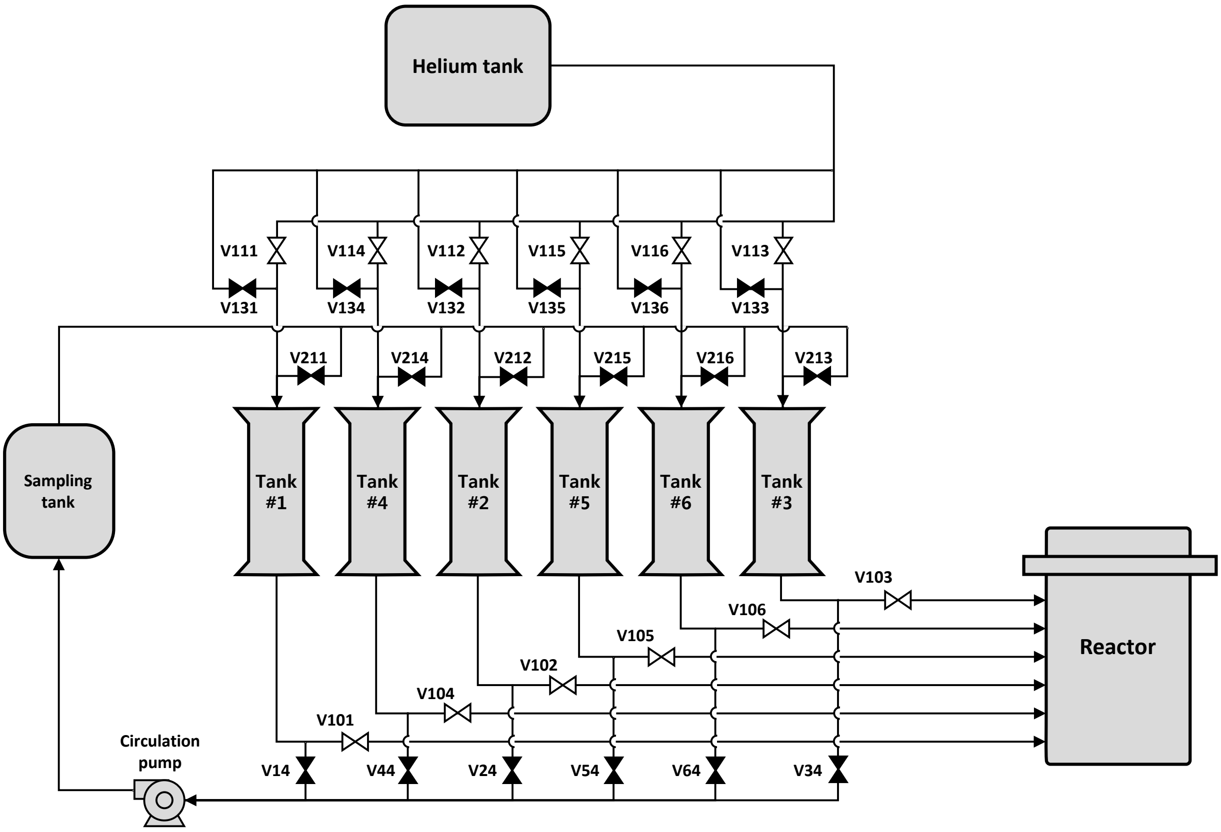
The second technical issue is to collect the values of PSF-related instances with respect to success cases. In order to clarify this issue, let us consider an unanticipated reactor trip event that has occurred in one of the commercial NPPs in the Republic of Korea on December 4, 2008 [Park et al., 2016c]. Brief explanations about this event are given as below, and more detailed information can be found from NEED (2017).

On December 4, 2008, while the unit was operating at 100% power, a local operator was performing a surveillance test procedure entitled 'Gadolinium Sampling of Poison Tank for the Reactor Shutdown System No. 2(SDS-2).' Since one of the main purposes in conducting this surveillance test procedure is to check the concentration of a Poison Tank, it is necessary to sample a small amount of Gadolinium liquid from it. During the surveillance test, however, the local operator opened the recirculation valve of the Poison Tank #2 by mistake when he should have opened the corresponding valve of the Poison Tank #4. As a result, due to the injection of Gadolinium into the moderator system, an unexpected reactor trip has occurred.

From a detailed investigation, it was found that one of the root causes for a wrong valve manipulation was an inherent problem in the surveillance test procedure. That is, since the surveillance test procedure was developed so that the surveillance test of six Poison Tanks can be implemented by using a single procedure, it is expected that a human error was triggered by an unclear component specification.

From the above explanations, it is evident that one of the root causes triggering a wrong valve operation is the inappropriate description of a task included in the surveillance test procedure (for convenience, the term of *test procedure* is used hereafter). Fig. 2 shows a part of the test procedure with the associated component configuration, which will be helpful for understanding why the wrong valve operation has occurred.

Required tasks described in the test procedure	[…] • Verify the valve of 13@ is CLOSED. • Verify the valve of V10@ is CLOSED. • Open the valve of V21@. […]



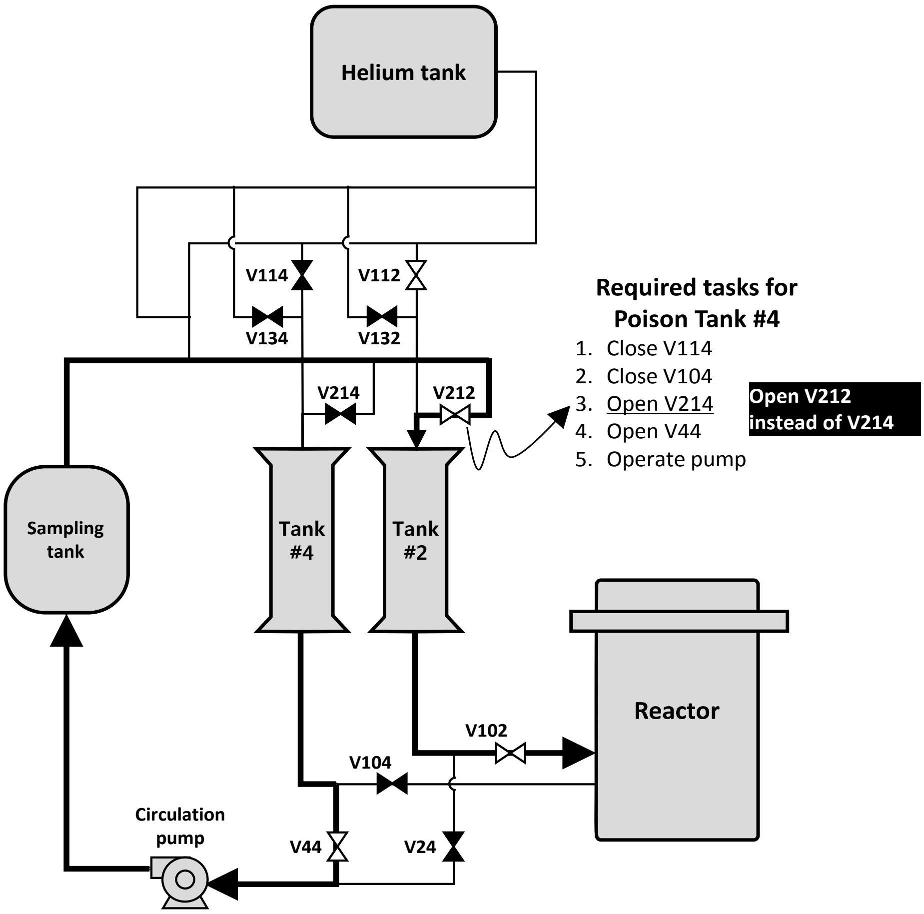
< Figure 2. A part of the test procedure with the associated component configuration, adopted from Park et al. (2017b) >

As can be seen from Fig. 2, a local operator has to carry out the surveillance test of six equivalent Poison Tanks. To this end, the local operator needs to conduct a series of required tasks being described in the test procedure once in every seven days. For example, when the local operator finished the surveillance test of the Poison Tank #1 this week, he or she has to accomplish the surveillance test of the Poison Tank #4 in the next week. An interesting point is that, instead of using a dedicated test procedure for each Poison Tank, a single test procedure has been used for many years for their surveillance test. Subsequently, the description of the test procedure should be prepared based on a kind of generalized notation, such as the mark of '@' underscored in Fig. 2. For example, when a local operator wants to sample a small amount of liquid from Poison Tank #4, he or she needs to switch the mark of '@' to the number of '4.' This means that, in order to clarify the contents of required tasks, the description of the test procedure exemplified in Fig. 2 should be read as follows:

- Verify the valve of V13**4** is CLOSED.
- Verify the valve of 10**4** is CLOSED.
- Open the valve of V21**4**.

Unfortunately, even though the local operator tried to sample Poison Tank #4 on December 8, 2008, he accidently opened the valve of V212 instead of V214. As a result, an injection path was activated from Poison Tank #4 to a reactor, which caused an unexpected reactor trip (refer to an injection path highlighted by a thick line in Fig. 3). Based on this finding, one of the countermeasures to prevent from the recurrence of similar events was decided as the provision of dedicated test procedures for six Poison Tanks.

If we extract HRA data from this event, it is natural that the quality of a procedure (i.e., an inappropriate task description) would be regarded as one of the dominant PSFs. However, this decision seems to be impetuous because it was drawn based on the sole consideration of a failure case. In other words, if the quality of the test procedure is critical for triggering a wrong valve operation, it is not possible to properly explain the reason why the identical test procedure has been carried out for many years without any kinds of human errors. This alludes to the fact that the selection of dominant PSFs may need to simultaneously consider the values of PSF-related instances (refer to Table 2) from two different cases: failure and success cases. Here, it is relatively easy to determine the values of PSF-related instances from failure cases because event investigation reports are available. Unfortunately, determining the values of PSF-related instances from success cases is not easy because of a lack of available documents clarifying success cases, which correspond to event investigation reports. For this reason, a framework proposed by Park et al. (2016) is partially adopted to systematically gather information from success cases in this study. More detailed explanations about how to determine the values of suggested instances will be given in Section 4.



< Figure 3. An injection path activated by a wrong valve operation, adopted from Park et al. (2017b) >

3.3 Introduction to the CART technique

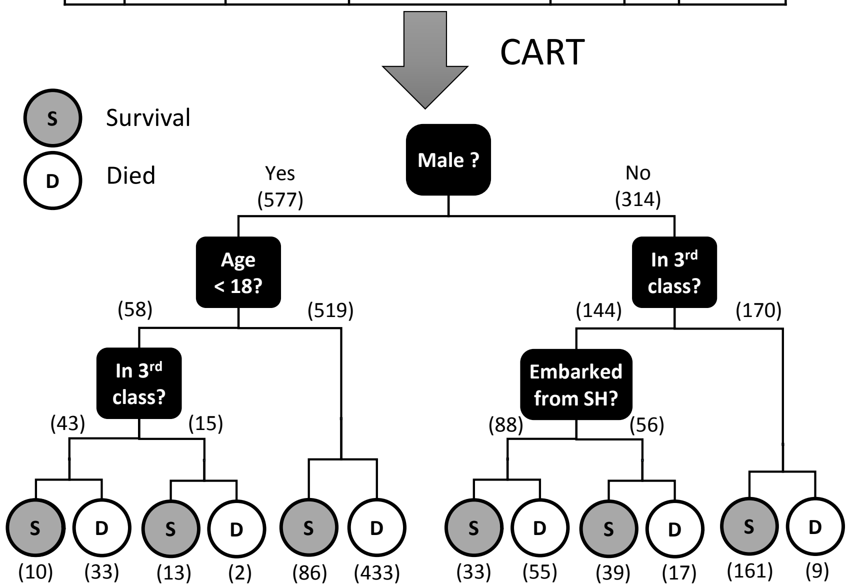
The last technical issue is originated from a practical problem: *how we are able to deal with a huge amount of information gathered from both failure cases and success cases*? For example, let us recall a wrong valve operation explained in Section 3.2. In this case, although we have only one failure case, the number of success cases would be significant because the test procedure should be repeatedly performed once in every seven days. In other words, if the test procedure has been performed for seven years, the number of success cases would be over 300. This means that the amount of information to be processed (i.e., the values of PSF-related instances) would drastically increase along with the increase of the number of success cases. For this reason, the CART which is one of the well-known techniques for analyzing big data is introduced in this study.

Although there are many definitions that emphasize slightly different aspects of big data analytics, without loss of generality, it is possible to say that the big data analytics is "the process of examining large and varied data sets (i.e., big data) to uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful information that can help organizations make more-informed business decisions [SBA, 2017]." To this end, many kinds of techniques have been developed, and seven widely used big data mining techniques are grouped into: (1) associated rule learning, (2) CART analysis, (3) genetic algorithms, (4) machine learning, (5) regression analysis, (6) sentiment analysis, and (7) social network analysis [Firmex, 2017].

Of them, the CART technique is very useful because it allows us to identify unique and/or hidden categories from big data. The more interesting point is that its confidence level drastically increases along with the increase of data size. In order to clarify these benefits of the CART analysis, let us consider Fig. 4a that shows the result of the CART analysis based on available data from the Internet [Kaggle, 2018], which contain the information of 891 passengers embarked on the Titanic sank in the North Atlantic Ocean on April 15, 1912.

Passenger's information in the Titanic

No	Gender	Age	Embarked	Class	...	Survival
1	Male	22	Southampton (SH)	3		No
2	Female	38	Cherbourg (C)	1		Yes
3	Female	26	Southampton (SH)	3		Yes
4	Female	35	Southampton (SH)	1		Yes
5	Male	35	Southampton (SH)	3		No
6	Male	Unknown	Queenstown (Q)	3		No
...						
891	Male	32	Queenstown (Q)			No



< Figure 4a. Explanatory result of the CART analysis, modified from Bigwhalelearning (2014) >

As can be seen from Fig. 4a, the result of the CART analysis allows us to estimate the chances of survival based on the values of several instances (such as *Gender*, *Age*, and *Class*). For example, from this available information, it is possible to say that the chance of survival for female passengers in Titanic is about four times higher than that of male passengers based on the following formulas:

$$\text{p(survival}|Male\ in\ Titinic) = \frac{Total\ number\ of\ survived\ male\ passengers\ in\ Titanic}{Total\ number\ of\ male\ passengers\ in\ Titanic}$$

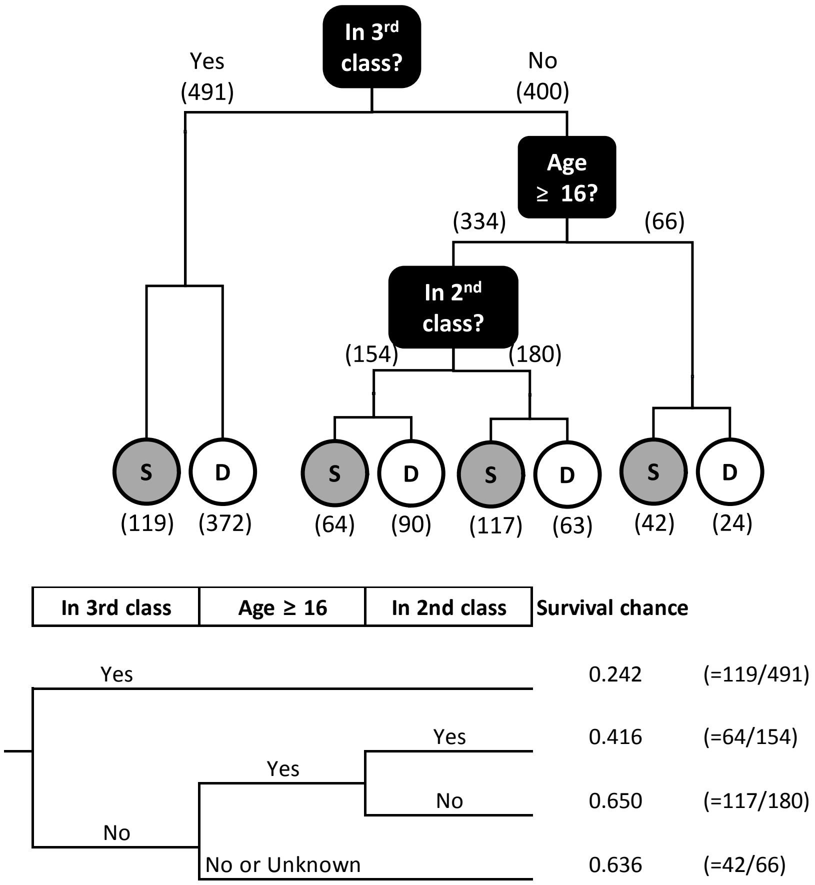
$$= \frac{10 + 13 + 86}{577} = 0.189$$

$$\text{p(survival}|Feale\ in\ Titinic) = \frac{Total\ number\ of\ survived\ female\ passengers}{Total\ number\ of\ female\ passengers}$$

$$= \frac{33 + 39 + 161}{314} = 0.742$$

More interesting point is that the CART analysis can be conducted with respect to the catalog of specific factors. For example, Fig. 4b hypothetically depicts the result of the CART analysis, which is classified from the information of all passengers based on two kinds of dedicated factors, *Class* and *Age*. With this result, the chances of survival can be visualized in the form of a decision tree which is given at the bottom of Fig. 4b. Although this decision tree is hypothetical, it demonstrated that the chance of survival for passengers who brought the 3rd class ticket is about one third compared to those of the first class passengers whose age were greater than 16 (i.e., 0.242 vs. 0.650). Or it is possible to say that the first class ticket increased the survival chance of passengers those whose age is greater than 16 about 56% compared to that of the second class ticket (i.e., 0.650 vs. 0.416).

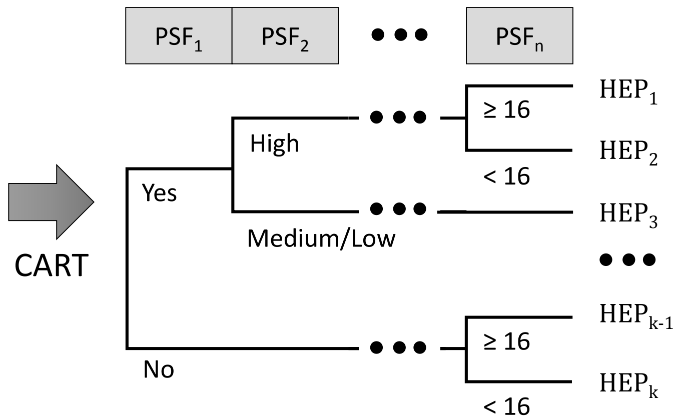
Here, if we focus on the applicability of the CART technique to the extraction of HRA data, it is evident that both HEPs and the catalog of dominant PSFs can be systematically selected with the associated relative weights (i.e., PSF multipliers). Figure 5 will be helpful for elucidating this idea. Let us assume that there is a big data containing the values of diverse instances (i.e., PSF-related instances for describing the context of each task). At the same time, the result of each task performance is also known as either *success* (i.e., a required task is completed without any kinds of human errors) or *failure* (i.e., the occurrence of a human error). If we apply the CART technique to this big data, a kind of decision tree can be created as exemplified in Fig. 5. Once this decision tree is developed, it is possible to distinguish the catalog of dominant PSFs which largely affect the occurrence of human errors (i.e., HEPs). In addition, if we compare HEPs with respect to diverse PSF-related instances, it is possible to estimate relative weights among them (i.e., PSF multipliers).



< Figure 4b. Hypothetical decision tree with respect to Class and Age, modified from Frendly (2015) >

PSF-related instances for each task

Task No.	PSF_1	PSF_2	...	PSF_n	Error
1	Yes	High	...	15	No
2	No	High	...	8	No
3	No	Medium	...	23	Yes
4	No	Low	...	4	No
...					



< Figure 5. Extracting HRA data using the CART technique: Underlying idea >

4. Case study

4.1 Framework to determine the values of PSF-related instances

As explained at the end of Section 3, it is expected that the CART analysis allows us to extract HRA data in a systematic manner. To this end, however, it is indispensable to determine the values of PSF-related instances representing various kinds of contexts, in which human operators have to accomplish required tasks. This means that the catalog of required tasks should be specified prior to determining the values of the PSF-related instances. In addition, in order to determine the values of the PSF-related instances for success cases, it is necessary to set up dedicated rules for calculating the number of success cases from the contents of event investigation reports. For these reasons, two kinds of cornerstones are established as follows.

First of all, in terms of preparing the catalog of required tasks, a total of 21 task types which were proposed by Park et al. (2016b) are borrowed in this study. Table 3 epitomizes the inventory of task types with the associated abbreviations. From Table 3, these 21 task types are self-explainable because they were distinguished based on four kinds of representative cognitive activities: (1) information gathering and reporting (IG), (2) situation interpretation (SI), (3) response planning and instruction (RP), and (4) execution (EX).

For example, the second task type of Table 3 is *Verifying state of indicator*, which denotes a task type demanding the status check reading of a specific indicator, while the fifth task type (i.e., *Comparing parameter*) corresponds to the rapid comparison of two or more process parameters from separated readings, such as pressurizer pressure and main steam pressure. Moreover, the features of three kinds of task types pertaining to the cognitive activity of *Execution* can be summarized as follows.

- *Manipulating simple (discrete) control*: a task type to be accomplished by the performance of a binary control (e.g., On-Off, Start-Stop, and Open-Close);
- *Manipulating simple (continuous) control*: a task type to be completed by either selecting a target (or necessary) state from two or more discrete states or selecting a specific value within a given continuous range (e.g., setting *Manual* mode from five selectable operation modes such as *Manual*, *Auto*, *Modulate*, *Slow close,* and *Fast close*);
- *Manipulating dynamically*: a task type requiring the real-time control of a target component and/or parameter through integrating diverse information (e.g., controlling a feedwater flow rate in accordance with the water level of a steam generator).

< Table 3. Inventory of task types, modified from Park et al. (2016b) >

ID	Cognitive activity	Task type	Abbreviation
1	Information gathering and reporting (IG)	Verifying alarm occurrence	IG-alarm
2		Verifying state of indicator	IG-indicator
3		Synthetically verifying information	IG-synthesis
4		Reading simple value	IG-value
5		Comparing parameter	IG-comparison
6		Comparing in graph constraint	IG-graph
7		Comparing for abnormality	IG-abnormality
8		Evaluating trend	IG-trend
9	Situation interpretation (SI)	Diagnosing	SI-diagnosis
10		Identifying overall status	SI-identification
11		Predicting	SI-prediction
12	Response planning and instruction (RP)	Entering step in procedure	RP-entry
13		Transferring procedure	RP-procedure
14		Transferring step in procedure	RP-step
15		Directing information gathering	RP-information
16		Directing manipulation	RP-manipulation
17		Directing notification/request	RP-notification
18	Execution (EX)	Manipulating simple (discrete) control	EX-discrete
19		Manipulating simple (continuous) control	EX-continuous
20		Manipulating dynamically	EX-dynamic
21		Notifying/requesting to the outside of a control room	EX-notification

It should be noted that the task types of Table 3 properly cover the instances of *Expected task demand* (refer to Table 2). For example, *Status check reading* and *Rapidly comparing separate readings* are directly comparable to the task types of *Verifying state of indicator* and *Comparing parameter*, respectively. In addition, it is evident that *Any task for satisfying real-time constraints* corresponds to the task type of *Manipulating dynamically*.

Second, in order to calculate the number of success cases, three kinds of practical rules are considered. Actually, the underlying idea for calculating the number of success cases is very straightforward. For example, let us assume that a local operator who is working in an NPP has to carry out a specific test procedure once in every seven days (T_{Period}) during a power operation, which consists of many tasks. In addition, it is already known that this test procedure has been conducted for seven years without any kinds of human errors. In this case, if we know how many days the NPP has been continuously operated with a full power (T_{FP}), the number of successful performance of the test procedure ($N_{s,p}$) can be estimated by Eq(1).

$$\text{Number of successful performance for a procedure } (N_{s,p}) = \frac{T_{FP}}{T_{Period}} \cdots\cdots\cdots \text{ Eq. (1)}$$

If so, the key problem is to reckon T_{FP}. To this end, Park et al. (2016c) proposed three principal rules for calculating T_{FP}. Unfortunately, these three rules are not directly applicable to calculating the number of success cases when an off-normal event has occurred. For example, let us assume that an event report indicated that there was a human error during the performance of an abnormal operating procedure (AOP) which can deal with the trip of a main feedwater pump. The question is that, when a human error was observed during the performance of the corresponding AOP, how many times this AOP has been successfully conducted in the past.

In this light, Park et al. (2016c) proposed a practical method based on the representative frequencies of 101 abnormal events, which are determined by scrutinizing various kinds of component failure data collected from of domestic NPPs [KHNP, 2011]. According to the catalog of the representative frequencies, for example, it is anticipated that the trip of a main feedwater pump is supposed to occur about twice a year. This means that the number of a successful performance with respect to the AOP of a main feedwater pump trip can be calculated by using Eq. (1), if we divide T_{FP} by its representative frequency. That is, the number of a successful performance for the AOP of a main feedwater pump trip can be obtained by quantifying $T_{FP}/2.0$. More detailed explanations can be found from Park et al., (2016c).

4.2 Analyzing event investigation reports

In order to make sure the applicability of the framework described in Section 4.1, event investigation reports stored in a database called NEED (Nuclear Event Evaluation Database) are revisited in this study. The NEED is operated by the regulator body of the Republic of Korea (i.e., KINS, Korea Institute of Nuclear Safety), which contains various kinds of investigation reports issued for safety significant events including: (1) an unexpected automatic and/or manual reactor trip, (2) the initiation of ESFs (Engineered Safety Features), and (3) the violation of LCOs (Limiting Conditions for Operations) [NEED, 2017]. That is, when one of the safety significant events has occurred in a domestic NPP, a special inspection team is temporally established by the KINS, which consists of several specialists for investigating what went wrong. Once the investigation is finished, all kinds of information (e.g., the cause and progression of an event, investigation results, and countermeasures to prevent the reoccurrence of same or similar events) should be released to the public via the Internet.

From the NEED, a total of 193 investigation reports that have issued from January 2002 to December 2013 were reviewed in detail. As a result, 16 event investigation reports were selected, of which the root causes include a wrong device operation, the omission of a procedural step, and providing a wrong control input. Here, during the period of January 2002 to December 2013, the statistics of the NEED revealed that the total number of significant events caused by human errors is 41 [NEED, 2017]. This means that about 40% of significant events which were related to human errors are analyzed in this study. It should be noted that the 60% of significant events were not considered if the associated procedures were either not available or uncertain. For example, several significant events have occurred during the initial start-up operation of newly constructed NPPs (i.e., a test period before starting the first fuel cycle). This means that most of set-points and/or task descriptions included in procedures are apt to be vastly changed as time goes by. In addition, since a large portion of the corresponding procedures which are directly related to the occurrence of significant events was abandoned when revised procedures came in, it is not possible to identify the contents of tasks resulting in the associated human errors.

After the selection of 16 event investigation reports, their contents were prudently checked in order to clarify the inventory of PSF-related instances, of which the values can be actually identifiable. Table 4 summarizes a part of this PSF inventory with the associated values collectable from the contents of event investigation reports. For example, the third instance of Table 4 (i.e., *Procedure conformity*) implies whether or not the description of a required task in a procedure is congruent with the situation at hand. This is because the drastic change of one or more process parameters could bring about the distortion of an original intention being described in a task. In addition, *Clarity of decision-making criteria* denotes whether or not criteria for judgment or decision-making included in the task description of a procedure are clear and evident. The meaning of this instance becomes more evident if we compare the following two tasks: (1) *verify whether or not SG level is <u>rapidly lowering</u> and (2) verify that SG level is greater than <u>70%</u>*. Comparing to the decisive criterion of the latter task, that of the former task is somewhat subjective due to the term of '*rapidly*.' In this way, a total of 27 PSF-related instances are used in this study. It is to be noted that more detailed explanations about each PSF-related instance can be found from Park et al. (2013).

< Table 4. A part of PSF-related instances, of which the values can be extractable from the contents of event investigation reports >

ID	Suggested instance	Meaning/Example
1	HMI (human machine interface) type	HMI used in the performance of a required task (*Analog* or *Digital*)
2	Operator	Operator who conducted an error (*MCR** or *Local staff*)
3	Component manipulation mode	Type of control to accomplish a required task (*On/Off* or *Adjusting control*)
4	Procedure conformity	The conformity of task contents described in a procedure with an on-going status
5	Clarity of decision-making criteria	Judgment (or decision-making) criteria included in the task description of a procedure
6	Clear description of an object	Whether or not a specific component designator (identifier) is described in a task description (e.g., Open *flow control valve* vs. Open *valve #123*)
7	Clear description of means	Whether or not a specific method for a component manipulation is manifested in a task description (e.g., Maintain SG pressure vs. Maintain SG pressure using *atmospheric dump valve*)
8	Information clarity	Whether or not an HMI provides necessary information for conducting a required task
9	Feedback information	Whether or not an HMI provide feedback information followed by the manipulation of a certain component
10	Conformity of standards	Whether or not an HMI is designed along with standards, conventions and nomenclature (e.g., abbreviations and acronyms)

*Main Control Room

Based on the PSF inventory, the context of a task included in a specific procedure is characterized. For example, let us assume a hypothetical test procedure containing many tasks. Here, if there is an event investigation report that describes the occurrence of a human error during the performance of this test procedure, the number of successful performance for the test procedure (i.e., $N_{s,p}$) can be calculated along with concepts explained at the end of Section 4.1 (e.g., three practical rules for routine test and maintenance procedures, and representative frequencies for event response procedures). After that, in terms of success cases, the context of task types included in the test procedure can be characterized by the values of PSF-related instances which are distinguishable from diverse efforts, such as talk-through with experienced human operators and walk-through in a working place.

It should be noted that since there was no human error in success cases, the values of PSF-related instances for each task type are duplicated by $N_{s,p}$ times. In other words, it is assumed that all the values of PSF-related instances are identical for success cases. In contrast, in the case of a failure case, the values of PSF-related instances for each task type can be determined based on the description of the corresponding event investigation report.

For example, an event investigation report revealed that a wrong valve operation has occurred because a local operator who carried out the test procedure did not have any feedback information at that time due to the failure of indicator. In this case, the value of *Feedback information* that is one of the PSF-related instances epitomized in Table 4 should be marked as *No*. In this way, a total of 47,219 records representing the contexts of all tasks included in diverse procedures were secured, which are related to the occurrence of human errors described in 16 event investigation reports (refer to Fig. 6).

1	EventID	Error	HMIType	Operator	TimePressure	ProcConformity	CompManipMode
47201	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47202	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47203	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Simple manipulation
47204	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47205	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47206	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47207	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Simple manipulation
47208	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47209	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47210	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Simple manipulation
47211	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47212	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47213	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47214	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Simple manipulation
47215	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47216	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47217	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47218	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Not applicable
47219	Event16UA	No	Analog	MCR crew	Before diagnosis	Yes	Adjusting control
47220	Event16UA	Yes	Analog	MCR crew	Before diagnosis	Yes	Adjusting control

< Figure 6. A part of records for the values of the suggested instances summarized in Table 4 >

4.3 Applying the CART analysis

Based on the values of the suggested instances shown in Fig. 8, the CART analysis was carried out by using R package [R Project, 2013]. Table 5 highlights a part of important results obtained from the CART analysis. As can be seen from Table 5, of 27 PSF-related instances summarized in Table 4, significant results are obtained with respect to 14 PSF-related instances. For example, the PSF-related instance of *Procedure conformity* denotes whether or not the description of a given procedure is well congruent with a real situation. In other words, there was no difficulty in conducting required tasks as written because hypothetical conditions assumed for the development of a procedure are properly matched with those of a real situation (e.g., WAD and WAI are similar). In this case, *Procedure conformity* is marked as *Yes*. In contrast, if there is any mismatch between these two conditions (i.e., *Procedure conformity* corresponds to *No*), it is not easy for human operators to carry out the procedure as written.

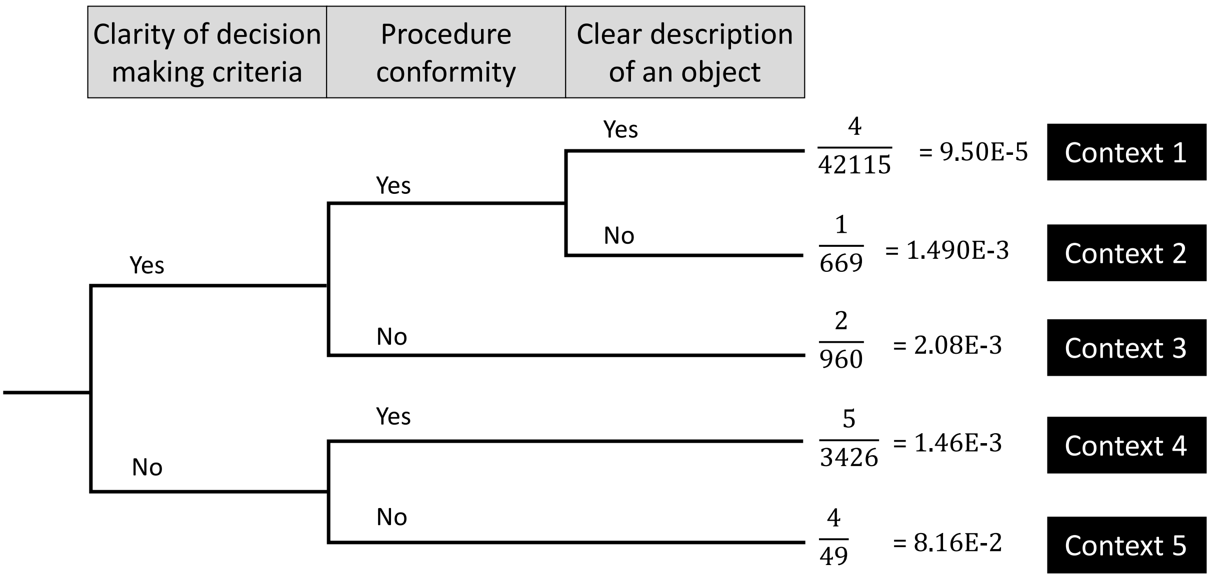
< Table 5. Selected significant results obtained from the CART analysis >

PSF-related instance	Value	HEP	HEP ratio
HMI type	Analog	3.01E-4	1.0 (base)
	Digital	3.08E-3	10.2
Operator	MCR staff	1.27E-3	8.4
	Local staff	1.52E-4	1.0 (base)
Component manipulation mode	Simple control	4.78E-4	1.0 (base)
	Adjusting control	2.52E-3	5.27
Procedure conformity	Yes	2.16E-4	1.0 (base)
	No	5.95E-3	27.5
Clarity of decision-making criteria	Yes	1.60E-4	1.0 (base)
	No	2.59E-3	16.2
Clear description of an object	Yes	1.84E-4	1.0 (base)
	No	2.20E-3	12.0
Clear description of means	Yes	1.81E-4	1.0 (base)
	No	2.74E-3	15.1
Information clarity	Yes	2.75E-4	1.0 (base)
	No	1.03E-1	374.5
Feedback information	Yes	2.54E-4	1.0 (base)
	No	8.89E-2	350.0
Conformity of standards	Yes	1.03E-4	1.0 (base)
	No	5.03E-4	4.9

In this regard, it is estimated that the HEP of human operators who had performed required tasks when *Procedure conformity* was *Yes* is 2.16E-4. Meanwhile, the HEP becomes 5.95E-3 when human operators are exposed to the context when *Procedure conformity* was *No*. This alludes to the fact that, the effect of *Procedure conformity* on the HEP of human operators (or the PSF multiplier of *Procedure conformity*) would be 27.5 that can be calculated by dividing the HEP of the latter by that of the former (i.e., 5.95E-3/2.16E-4).

Similarly, in the case of *Clarity of decision making criteria*, it is observed that the ratio of HEPs is 16.2. Here, the description of required tasks can be subdivided into twofold, such as clear decision making criteria marked as *Yes* (e.g., *Verify the pressure of Tank #5 is greater than 12kg$_f$/cm^2*), and unclear decision making criteria denoted by *No* (e.g., *Verify the pressure of Tank #5 is stable*). In other words, the decision criterion of the former is obvious (i.e., *12kg$_f$/cm^2*), while that of the latter (i.e., *stable*) is so clumsy that it can be differently understood by human operators.

The more interesting point is that the CART technique allows us to identify the combined effect of two or more PSF-related instances. That is, as explained at the end of Section 3.3 and Fig. 4b, it is possible to selectively apply the CART technique for specific PSFs. In this regard, for example, Fig. 7 shows the result of the CART analysis pertaining to three kinds of PSF multipliers.



< Figure 7. Decision tree with respect to three kinds of PSF-related instances >

As depicted in Fig. 7, this decision tree is created by considering three kinds of PSF-related instances, such as *Clarity of decision making criteria, Procedure conformity,* and *Clear description of an object*. Here, it is to be noted that the meaning of the last PSF-related instance is the specification of a target object to be manipulated by human operators. That is, it is evident that human operators easily identify what should be manipulated if they have to conduct a task with the description of *Open Valve #123*. In contrast, some human operators are apt to feel a frustration because of the absence of a specific component to be manipulated, if they are forced to carry out a task institutionalized as *Open Valve #12@*, which is one of the root causes resulting in an unexpected reactor trip on December 4, 2008 (refer to Section 3.2).

With these PSF-related instances, Fig. 7 shows that the value of an HEP would be drastically decreased if the values of all the PSF-related instances are positive (i.e., *Context 1* in Fig.7). In addition, it is possible to distinguish the relative importance of each PSF-related instance based on the HEP of other *Contexts* with that of *Context 1*. That is, the relative importance of Contexts 2, 3, 4, and 5 are 15.7 (1.49E-3/9.50E-5), 21.9 (2.08E-3/9.50E-5), 15.4 (1.46E-3/9.50E-5), and 85.9 (8.16E-2/9.50E-5) respectively. Moreover, if the context of tasks being considered is explained by the PSF-related instances of Fig. 7, HRA practitioners can directly use this decision tree for determining HEPs that are necessary for conducting their HRA.

5. Discussions and conclusion

It is evident that managing human errors in complex socio-technical systems is critical for enhancing their operational safety. In this regard, the role of an HRA is worth emphasizing because one of its applications is to systematically distinguish the inventory of error-prone tasks that could trigger safety significant events. However, in order to enjoy the full advantage of an HRA, it is prerequisite to secure sufficient data that are helpful for understanding how and why human error has occurred (i.e., HRA data).

For this reason, many researchers have tried to extract HRA data for several decades through revisiting the contents of event investigation reports which include detailed descriptions about what went wrong (i.e., failure cases). At glance, this approach seems to be reasoble for extracting HRA data. Nevertheless, it is suspected that HRA data identified from the analysis of failure cases could be biased because they just delineate a small piece of information representing the time point when a human error has occurred. In this light, a promising solution is to collect HRA data from the analysis of both failure cases and success cases.

To this end, in this study, the catalog of PSF-related instances which are actually identifiable from the contents of event investigation reports was proposed. In addition, three kinds of practical rules were applied to calculate the number of success cases with respect to detailed task types. As a result, a total of 47,219 records containing the values of 27 PSF-related instances were acquired from the analysis of 16 event investigation reports which have experienced from domestic NPPs for 12 years (i.e., January 2002 to December 2013). Then these records were scrutinized by using the CART technique which is a very useful for distinguishing unique and/or hidden categories from big data. Consequently, it is expected that the CART analysis allows us to calculate HEPs based on the combination of two or more PSF-related instances.

Basically, a spread sheet software (e.g., MS Excel) can be used to distinguish (or create) a decision tree based on big data as shown in Fig. 8. The problem is that the spread sheet software is not helpful in terms of identifying the most representative value of each instance. For example, let us assume that accident investigators want to the effect of *Class* and *Age* on the chances of survival. In this case, if accident investigators use MS Excel, they have to sort all kinds of information for passengers along with the diverse criteria of *Age* (e.g., less than 10, less than 15, and less than 20). The problem is that the number of required assortments (or the amount of effort for sorting) would exponentially increase if either the number of factors or the amount of data to be scrutinized increases. Accordingly, it is reasonable to say that the use of big data mining tools (e.g., CART) is indispensable.

It should be noted that there are at least two technical limitations for the approach of this study. First limitation is that the catalog of PSF-related instances only includes those which are actually collectable from the contents of event investigation reports. This means that the coverage of PSF-related instances is apt to be confined to *static* information. For example, it is not possible to collect the values of PSF-related instances belonging to the category of *Actual condition* (e.g., *Task load*, *Workload*, and *Nature of decision making*) because it is very seldom to find out an event investigation report which includes necessary contents for clarifying *dynamic* information. Accordingly, it is indispensable to collect the dynamic information from other sources in parallel, such as observations from a full-scope simulator.

The second limitation is the assumption of a homogeneous context for success cases. As explained in Section 4.2, it is surmised that the context of each task being experienced in all success cases is identical. In addition, if it is not possible to clarify the exact values of PSF-related instances by reviewing the contents of a test procedure, walk-through and talk-through, it is expected that all the values of PSF-related instances for each task type are positive (e.g., *Allowable time* is *No*, *Time pressure* is *Low*, and *Multiple initiating events* is *No*), and they are duplicated by $N_{s,p}$ times (refer to Fig. 7). This means that HEPs estimated by using the CART analysis become optimistic if there are times when several failure cases were not properly documented due to a less significance (e.g., they did not cause an unexpected automatic reactor trip or the initiation of ESFs). In order to overcome this limitation, it is necessary to incorporate the contents of other available reports including CAP (Corrective Action Program) reports.

For example, when an event of which the significance level corresponds to the *Critical* or *Important* has occurred, it is recommended to identify its cause in detail, which is helpful for preventing the recurrence of similar events. In contrast, instead of a detailed investigation, an event belongs to the *Minor* level is usually stored in a specific database that will be used as a source for further responses, such as a trend analysis. Although there are some differences in identifying the significance level of an event, EPRI (2008) suggested that events to be included in *Critical* level are: (1) Unit trip or major loss of electric production, (2) Safety incident (fatality or lost time injury), and (3) Significant reportable environment incident. In addition, the following events belong to *Important* level: (1) Startup failures, (2) Safety incidents resulting in recordable injury, and (3) Reportable environmental incidents. Here, it seems that the coverage of Critical level being considered in the CAP is comparable to that of safety significant events for issuing event investigation reports of the NEED. This alludes to the fact that, if CAP reports pertaining to the *Important* level are available, it is promising to gather additional information about human errors with respect to the performance of a test procedure in the past, which are counted as success cases in this study.

In spite of the technical limitations above, the implication of this study is quite positive because it can be regarded as a starting point to enhance the quality of HRA results by providing a novel aspect for collecting HRA data from the analysis of event investigation reports. That is, the contribution of this study can be considered from the viewpoint of the two different approaches to system safety. As stated in Section 2, although Safety-I suffers from several critical drawbacks pointed out by Safety-II approach, it is still valuable in a range of retrospective accident investigation and prospective risk assessment situations [Shorrock, 2014]. It should be again noted that Safety-II does not claim the uselessness of Safety-I; Safety-II should be regarded as a new system safety paradigm for supplementing the drawbacks of Safety-I, which have been observed in several accident situations during the last decades [Hollnagel, 2014]. Therefore, a desirable way for enhancing system safety is to integrate the two alternative approaches in a meaningful way [Sujan et al., 2017]. Then an arising question is how to integrate them. With regard to this issue, unfortunately, there is no widely accepted solution at this time. However, there are two approaches we can follow in relation to this issue [Yoon et al., 2017]. Firstly, when we use system safety methods developed under Safety-I paradigm, we need to acknowledge their limitations and attempt to overcome them with the concepts and foundations of Safety-II. Secondly, it is necessary to develop a new system safety method that well reflects the concepts and foundations of Safety-II which is good at investigating how things go right and understanding how humans manage performance variability.

In this light, this study can be regarded as an attempt for realizing the first approach described above. Acknowledging the shortcomings of traditional methods for obtaining HRA data including PSF-related information and HEPs, this study proposed a new way of complementing them based on the concepts of Safety-II, without losing the benefits of using traditional methods. There is a practical reason why this study adopted the first approach for integrating Safety-I and Safety-II. Practically, it is difficult to obtain materials that describe a great deal of everyday diverse successful activities, whereas it is much easier to obtain materials that reports a set of accident or event situations (e.g., event investigation reports). Thus this study aims to infer the number of successful cases from the information reporting unsuccessful cases in event investigation reports and to use the inferred number for extracting HRA data (i.e., PSF multipliers). And we need to remind that prospective HRA usually begins with a retrospective event analysis that investigates a set or previous human error-related unsuccessful cases. For this reason, we can say that although the method proposed in this study begins with the examination of human error-related unsuccessful cases, the method considered successful cases to reflect the concepts of Safety-II. The core concepts or principles underlying Safety-II include: (1) the same origin of successful and failed outcomes, (2) performance adjustment or performance variability, (3) the inevitable difference between WAI and WAD. We can discuss how the proposed method attempted to embed Safety-II paradigm into traditional HRA methods in terms of the three aspects.

The approach implemented in this study rejects the view that the plausible causes of failure cases are different from those of success cases; it has a stance that they come from the same origin, as assumed in Safety-II. Accordingly, it negates the simple viewpoint that human errors or human error-related events can be significantly reduced by manipulating PSFs which are identified to increase HEP by analyzing only a small sample of failure cases. The proposed method assumes that PSFs influencing human performance negatively at one time in the execution of a task can be positive factors enhancing human performance at other times in the execution of the same task. Thus it claims that the meaning of a specific PSF needs to be examined from both success and failure cases of a same task. Additionally, it asserts that there could be other more meaningful PSFs related to human errors and other hidden relationships between PSFs in the execution of a task, which would not be easily identified by analyzing only failure cases. Although there could be various approaches to resolving these issues, this study suggested the extensive use of success cases of a same task, not only failure cases.

As stated in Section 2, performance adjustment or performance variability is absolutely needed for the safe operation of modern complex socio-technical systems. It is highly related to the viewpoint that successful and failed outcomes have the same origin. Performance variability is believed to be the actual reason for both successful and failed outcomes. It is true that performance variability is particularly important in task situations that could not be expected and thus useful task procedures could not be provided for. However, the approach proposed in this study is mainly concerned with the task situations where a set of task procedures are effectively used. For this reason, one may argue that the concept of performance variability is not well reflected in the proposed approach. We also admit that it is likely that human task performance could not be significantly variable in the procedure-based task situations. However, the concept of performance variability in Safety-II paradigm should be considered in relation to the situation where performance adjustment is needed to address dynamic task demands, without regard to the size of performance variability. Rather, what is important is the amount of performance variability aggregated as humans conduct a series of tasks [Hollnagel, 2012]. Then we need to consider various situations where performance adjustment is absolutely needed. One of the situations is when humans need to interpret and apply task procedures to match the current task conditions when they must be applied [Grosdeva and Montmollin, 1994; Hale, 1990; Hollnagel, 2014; Park, 2009; Kim et al., 2012; Kim et al., 2013]. In this situation, the variability of human performance can be influenced by a range of factors (i.e. PSFs). In this regards, it cannot be said that the proposed method does not reflect the concept of performance variability.

A design philosophy underlying the procedures of complex socio-technical systems is that human operators should strictly follow them when they need to be applied. However, it has been reported that humans sometimes do not follow task procedures completely with several reasons [Grosdeva and Montmollin, 1994; Hale, 1990; HSE, 2004; Norros et al., 2015; Reason et al., 1998]. Those reasons include: the preference to use another short-cut for finishing a task based on experience, unexpected cognitive demands making it difficult to follow prescribed procedures, and unavailability of resources to be used to follow prescribed procedures. This situation represents the inevitable difference between WAI and WAD. Performance variability is needed in these situations as well. When human operators work differently from the way prescribed in a procedure, their performance can be influenced by diverse PSFs and their dynamic relationships. In this case, it is necessary to understand why and how humans do not follow the procedure, and to examine an effective method of utilizing PSF-related information for the understanding of WAD. In this regard, it can be said that the proposed method is one attempt to address this issue.

As we described in Section 2, the four abilities of resilient systems are beyond the scope of this paper. However, it would be meaningful to consider the contribution of the proposed method in relation to the four abilities. In this study, we inferred a reasonable number of successful task cases, based on the information of human error-related events that can be obtained from event investigation reports. This means that we did not observe everyday successful task situations, and neither did we examine documents reporting a range of various successful tasks. For this reason, it is very cautious to associate the proposed method with the four abilities that are necessary to succeed under varying conditions. However, the HRA data extracted by using the proposed method can give more realistic information for assessing human reliability and understanding how and how significantly a particular PSF influence the likelihood of human error. Then it is likely that the resulting outputs of HRA can give more practical insights on the following issues: (1) learning-how can we understand a previously experienced human error-related event more systematically, particularly focusing on what kinds of PSFs are more highly related to the event?, (2) monitoring-what kinds of PSFs are more significant to induce human errors under current task situations?, and (3) anticipating-how can we know the influence of changing the state of a PSF on the likelihood of human errors? As such, we can cautiously find the meanings of this study in association with the three abilities of resilient systems, although it would be not easy to justify them objectively.

In terms of securing realistic HRA data, therefore, it would be necessary to think about further research directions for enjoying the fruit of Safety-II concept and big data mining techniques. Firstly, as already mentioned, it is important to continuously operate a specific database or program such as CAPS, which includes not only failure cases but also success cases. To this end, it is indispensable to set up firm criteria which define (or distinguish) what are success and/or failure cases. Unfortunately, since the distinction of success (or failure) would be varied with respect to industries, organizations, workplaces, and even individuals, the second research direction would be the provision of a common definition about the success/failure cases. The last research direction would be the development of a standardized guideline that allows us to actually collect HRA data from diverse industries, organizations and workplaces, which belong to different countries. Although there would be more critical research directions, it is highly expected that the collection of realistic HRA data can be started from the abovementioned three research directions. In this regard, the meaning of this paper is to mark the starting point of the associated researches, which demonstrates the benefit of Safety-II concept for securing realistic HRA data.

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