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Research article

Quantification of human behavior levels by extending Rasmussen's SRK model and the effects of time pressure and training on the levels switching

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A R T I C L E I N F O

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A B S T R A C T

Human factor-related accidents account for an increasing portion of the total accidents through the advancing level of system automation. Human reliability becomes the key issue in human-machine systems especially for safety-relevant tasks and operations. Rasmussen's SRK (skill-rule-knowledge) model is well known in the field of human factors. Likewise, it is well known that skill-based behaviors have the highest human reliability, while knowledge-based behaviors are associated with the lowest reliability scores. Although numerous studies exist on human error probability (HEP), correspondingly typically attributed directly or indirectly to these three levels of behavior, a coherent, consistent representation, especially using data sources, has not been available. In this contribution, the quantification of human behavior levels with Rasmussen's SRK model is given based on three databases for the first time. Effects of time pressure and training on human reliability switching are also analyzed based on related publications. To determine the HEP of these three levels, three databases, technique for human error rate prediction (THERP), Savannah river site human reliability analysis (SRS-HRA) and nuclear action reliability assessment (NARA), from human reliability analysis (HRA) methods are used. The procedure contains identifying the tasks including the operator involved and the assumptions the analysts made and classifying the tasks into suitable cognitive behavior mode (CBM). In this case, the relationship between SRK levels and HEP is mapped. The effects of the two in automation context very relevant performance shaping factors (PSFs), time pressure and training/knowledge degradation, on human behavior levels switching are analyzed and the explanations of the SRK switching are presented. In this case, a more general structure is established to illustrate the dynamic behavior of levels switching with six directions under different conditions. From the results we conclude that skill, rule, and knowledge behavior levels are continuous in terms of HEP and therefore allow a new inside into this key aspect of human factor quantification. Based on this analysis the consequences of daily automation in the context of autonomous transport systems in combination with human qualification and reliability degrading are from this specific and in the current automation discussion very intensively discussed. The presented discussion linking SRK levels and HEP gives a new perspective on the foreseeable consequences of further automation in application areas with increasing automation of everyday tasks (like using a highly automated vehicle).

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1. Introduction

Automation has become increasingly common in a wide variety of fields due to the ongoing advancement of technology. Most safety-critical systems or fields such as power plants in energy production [70], guiding or flying aircrafts in aviation [11], or in transportation in general [65], automation is involved. Automation has profoundly influenced human behaviors in human-machine-systems, as many repetitive, many mechanical tasks can now be left entirely to machines, humans mainly are related to supervisory control tasks. While in safety critical fields typical automation side-effects firstly very intensively discussed by [2] are considered and well-known this is not necessarily the case in other fields. At the same time, higher levels of automation are increasingly capable of performing tasks that were previously thought to be performed only by humans. Automation has been varied to different levels, with higher levels representing increased machine autonomy. In [54], the automation of decision and action selection is divided into ten levels where level 1 indicates no assistance from the automation and level 10 presents that the automation decides everything and human is ignored. Humans cannot be excluded except for the automation of level 10. From level 0 of no automation to level 5 of full automation, the society for automotive engineering (SAE) has defined six levels of automation for driving [55]. It demonstrated that, even with fully autonomous vehicles, the human driver cannot be separated from driving activities since driving situations are still required to be monitored and, in some cases, the vehicle needs to be controlled again. In high-risk environment, such as the prediction of air traffic conflicts, decision automation settings should be made to allow for human involvement. While waiting for humans to decide how to react to an automated scenario evaluation, dangerous occurrences could occur. For example, different takeover time is critical to the reliability of automated vehicle drivers in dealing with emergencies [65]. Automation can have both beneficial and negative effects on human performance [44]. When changes in environmental or system states are controlled by another agent, humans tend to be less aware of them indicating the operator's situation awareness of the dynamic features of the working environment is reduced. If the system functions are consistently performed by automation, humans will not be as skilled in performing the functions which means skill degradation. In this contribution, a dynamic system is defined as the outside world of the interacting human in which the relevant variables are dynamic and therefore enforce a dynamic human interaction. This dynamic environment will result in the dynamic interaction, which will further include that the time variant changes are perceived by human cognition. It is known that human cognition is not only strictly linear or serial, but also involves parallel and cyclic processing. Cognition functions occur in a continuous loop and overlap. Operators in realistic contexts often need to accomplish most or all of these functions at the same time. Therefore, task performance normally requires a simultaneous consideration of all three cognitive control levels in the SRK model.

In human-machine systems, human error causes behaviors that can be considered non-optimal or, at worst, undesirable, and unacceptable. The role played by humans is of increasing importance, due to the fact that more accidents are related to human errors. In [72], about 80% of marine casualties are attributed, at least in part, to various types of human error, making human error the primary contributing cause for shipping accidents. Most experts in the field of aviation concur that human error accounts for between 60% and 80% of aviation accidents [52]. The national highway traffic safety administration (NHTSA) stated that human factors are to blame for 94% of traffic accidents [42]. Human error mechanisms are dependent on mental functions and knowledge that are sparked by subjective factors. The characteristics of the task and working environments can be used to infer these mental functions and knowledge, which cannot be directly observed [46]. With the development and refinement of research on human error mechanisms and failure modes, the study of human reliability analysis (HRA) has been formed.

Human reliability is a common used concept in probability assessment context. Human error probability (HEP), which is determined by the ratio of the frequency of errors to the number of possibilities for errors, is calculated using the sophisticated method known as human reliability analysis (HRA). For the analysis, forecasting, and prevention of human errors, methodologies for HRA have been presented. Generations are frequently used to categorize the modifications that HRA approaches have undergone over time. For the so called 'first generation' HRA methods, human is considered similar to a mechanical component, so all aspects of dynamical interactions with the working environment, both physical and social environment are not considered [12]. The basic assumption which has been made in many of these methods such as technique for human error rate prediction (THERP) [34], accident sequence evaluation program (ASEP) [60] and human cognition reliability (HCR) [24] is that humans have natural weakness and logically fail to execute tasks, similar to mechanical or electrical components. With this assumption, based on the operator's task characteristics, the HEP can be assigned by experts and can be modified by performance shaping factors (PSFs).

With the criticism of absence of consideration on the dynamic aspects from the environment, researchers developed some new methods, such as a technique for human event analysis (ATHEANA) [9], and cognitive reliability and error analysis method (CREAM) [27]. These methods are so called 'second generation' HRA methods. The methods in this generation aspire to lean toward conceptual methods as cognitive models are proposed, while the so called 'first generation' methods are often behavioral approaches. The objective of 'second generation' HRA approaches is the qualitative evaluation of the operator's behavior and the search for models that describe the synergy with the production process [12].

The shortcomings and restrictions of the 'second generation' HRA approaches serve as a catalyst for further advancements of the current ones. There are also studies that have concentrated on the lack of empirical data for the development and validation of an HRA model and are intended to define the database HRA. These studies may provide the methodological tools required to more intensively use different types of information in future HRA methods and reduce uncertainties in the information used to conduct human reliability assessments [12]. With the increased development of computer technology, several HRA methods are using artificial intelligence and simulation techniques to predict human error based on cognitive models. The cognitive simulation model (COSIMO) [5] based methods are defined as so called 'third generation' HRA methods [43]. The method now defined as 'third generation' is nuclear action reliability assessment (NARA) [12].

Table 1
Human cognitive process and corresponding HRA methods (adapted from [43]).

Researcher	Year	Cognitive process	HRA methods
Rasmussen	1979	Recognition, identification, decision, and planning	THERP/HCR
Wreathall	1982	Detect, diagnose, and implement	OAT
Woods	1987	Monitoring, explanation building, and response management	CREATE
Reason	1990	Planning, storage, and execution	GEMS
Cacciabue	1992	Cognitive filter, diagnosis, hypothesis evaluation, and execution	COSIMO/DYLAM/HERMES
Wickens	1992	Perception, decision and response selection, and response execution	ATHEANA/CREAM/ADS-IDAC
Cooper	1996	Monitoring, situation assessment, and response	ATHEANA
Hollnagel	1998	Observation, interpretation, planning, and execution	CREAM
Mosleh	2004	Information processing, problem solving and decision making, and execution	ADS-IDAC

ATHEANA: A technique for human event analysis.
ADS-IDAC: Accident dynamics simulator with the information decision and action in a crew context operator model.
CREAM: Cognitive reliability and error analysis method.
COSIMO: Cognitive simulation model.
CREATE: Cognitive reliability assessment technique.
DYLAM: Dynamic logic analysis method.
GEMS: Generic error modeling system.
HERMES: Human error reliability methods for event sequences.
HCR: Human cognition reliability.
OAT: Operator action tree.
THERP: Technique for human error rate prediction.

The HRA methods use different cognitive explanatory models of the human behavioral process to explain the mechanisms by which human errors occur. Cognition is primarily concerned with memory judgment, interpretation, concept formation, decision making, and other mental activities prior to action execution in the environment. To characterize the human cognitive process and explain human thinking and behavioral modes, a cognitive model is developed. With the development on psychology, behavioral science, ergonomics, and other interdisciplinary, the understanding on human cognition becomes more detailed. At the same time, these cognitive models inspire HRA researchers to develop more comprehensive HRA methods on different human cognitive activities. The HRA methods with their adopted cognitive processes are listed in Table 1.

Among the listed cognition models, skill-rule-knowledge (SRK) model proposed by Rasmussen is well-known and wildly used. This model has been applied in many application fields in human-machine system [53]. In 1979, Rasmussen was able to distinguish human behavior into three levels including skill-based behavior, rule-based behavior, and knowledge-based behavior [69]. It is known that skill-based behavior corresponds to highest human reliability and knowledge-based behavior has the lowest human reliability from the consideration of cognition process, but this is only considered qualitatively [36]. Although human error probability (HEP) intervals of SRK model are estimated in [22], and modified in [71], the data are only taken within a THERP context. No quantitative results on the human reliability of these three different levels of behaviors using data from different generation of HRA methods exist in existing research. However, this is of increasing importance as automation in human-machine systems is becoming increasingly important. Human skills are changing from a fundamentally technical understanding of devices to abstract process management skills. The question arises whether humans can control automation in certain challenging situations (takeover situations or when the driving state abruptly changes), whether autonomous driving vehicles make human qualification for vehicle guidance superfluous? In addition to issues of disqualification [64] and training [10], the question arises in practice about the right time for the warning [62] or for suitable interfaces [65].

To answer these questions, the human reliability must be quantitatively evaluated to generate knowledge about the quantitative knowledge about the human reliability within the context of new relations between human and machine. The goals of this contribution include:

1) Quantification of human behavior levels in SRK model;
2) Analysis of the effects of time pressure and training on SRK levels switching;
3) Establishment of a general framework to map the relation between HEP and SRK levels.

To determine HEP of these three levels, three databases (technique for human error rate prediction [34], Savannah river site human reliability analysis (SRS-HRA) [3], and nuclear action reliability assessment [33]) as HRA methods are used.

The structure of this contribution is organized as follows: in Section 2, the framework of SRK model is explained. The quantification of SRK levels is described in section 3 including the introduction of databases, the procedure to determine the HEP of SRK levels. In section 4, the effects of two performance shaping factors (PSFs), time pressure and training, on human reliability is analyzed. Discussion related to a general framework to present the dynamic behavior of SRK levels switching and the expected application of the proposed framework on new assistance system is illustrated in section 5. This work is finally concluded in section 6.

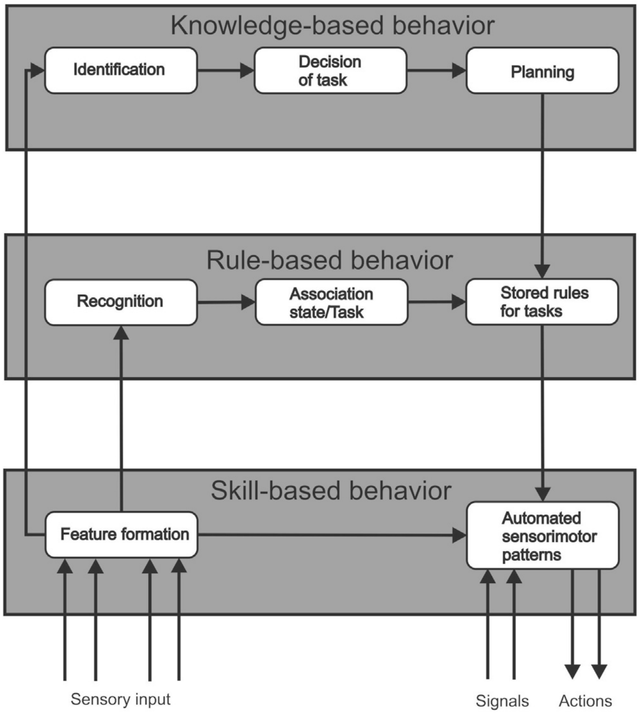

Fig. 1. Rasmussen's SRK (skill-rule-knowledge) model (adapted from [46]).

2. Skill-rule-knowledge (SRK) framework

According to Rasmussen's study [46], human behavior can be differentiated into categories according to different ways of representing the restrains in the behavior of a deterministic environment or system, three different kind of interaction with respect to the integration of human cognitive abilities can be distinguished with related different performance results: skill-, rule-, knowledge-based performance. Whether or not the operator is involved in problem solving at the time an error occurred is the key distinction based on SRK levels [48]. These levels and a brief illustration of their relations are shown in Fig. 1.

2.1. Skill-based behaviors

According to [68] the sensory-motor performance along with a statement of intentional acts or activities, development with noncognitive control as smooth, automated, and highly integrated patterns of behavior is an indication of skill-based behavior. These actions have more or less been trained by repetition, and they thereafter proceed in a continuous stream. The most efficient human behaviors in terms of effort and time are those based on such well-established skills. Routine, repeated works often involve skill-based behavior, even when there is opportunity for ancillary tasks that may not directly connected to the task at hand.

2.2. Rule-based behaviors

In rule-based behavior, a memory-based stored rule or procedure that may have been derived empirically during prior experience or communicated from other operators' know-how as an instruction or a handbook is used to consciously control the sequence architecture of subroutines in a well-known work situation.

From [47], the border between skill-based and rule-based behavior is ambiguous, and depends on the level of training and on individual attention. In general, the skill-based behaviors perform without conscious attention. The individual will be unable to explain how to control the performance and is unable to explain the information based on for the performance. Explicit know-how is referred to in a higher level of rule-based coordination. The rules used can be reported.

2.3. Knowledge-based behaviors

The performance which is goal-controlled during unfamiliar situations, which no know-how or rules for control are available from previous encounters, is known as knowledge-based level. This type of behavior can be described as a mental process in which the operator searches for problem-solving action options based on knowledge that is already known or that has still to be learned. In doing so, the operator checks whether the thought-out action routines are suitable for the goal-oriented management of the situation and finally applies the solution that seems to be the most effective. The process is thus highly individual and is always based on the

Table 2
Equations for HEPs in various HRA methods.

HRA methods	Equations for HEP
THERP [61]	$HEP_{Final} = BHEP_{Diagnosis} \cdot \prod_1^n PSF_{Diagnosis,i} + BHEP_{Execution} \cdot \prod_1^n PSF_{Execution,i}$
SLIM-MAUD [17]	$SLI = \sum(Normalized\,Weight(PSF_i) \cdot State(PSF_i))$; $Log(1 - HEP) = a \cdot SLI + b$
SPAR-H [21]	$HEP = NHEP \cdot \prod_1^8 S_i$; $HEP = \frac{NHEP \cdot \prod_1^8 S_i}{NHEP \cdot (\prod_1^8 S_i - 1) + 1}$
HEART [67]	HEP =Nominal human unreliability$\cdot \prod$Assessed effect$_i$
ATHEANA [50]	$P(HFE\|S) = \sum_j \sum_{i(j)} P(EFC_i\|S)xP(UA_j\|EFC_i, S)$
HuRECA [37]	$HEP_{diag} = Basic_H EP_{diag} x \prod w_i(PSF_i)$; $HEP_{exec} = \sum[Basic_H EP_{exec}(i) x HEP_{rec}(i)]$

THERP: Technique for human error rate prediction; BHEP:Basic HEP.
SLIM-MAUD: Success likelihood index method using multi-attribute utility decomposition; a and b: Constants that can be obtained by two sets of known HEPs.
SPAR-H: Standardized plant analysis risk HRA; S_i: The multiplier associated with the value of corresponding PSF levels; NHEP: Normal HEP, for diagnosis task is 0.01 and for action task is 0.001.
HEART: Human error assessment & reduction technique; Assessed effect = ((Multiplier of EPC-1)xAssessed proportion of effect)+1; EPC: Error producing conditions.
ATHEANA: A technique for human event analysis; $P(HFE|S)$: Probability of the error for the HFE applicable to accident scenario (S); $P(EFC_i|S)$: Probability of accident contexts to the scene of accident including deviations and nominal context; $P(UA_j|EFC_i, S)$: Probability of failure of UA corresponding to each context evaluated; HFE: Human failure event; EFC: Error forcing context.
HuRECA: Human reliability evaluator for control room actions; $Basic_H EP_{diag}$: $f(availabletimefordiagnosis)$; $Basic_H EP_{exec}(i)$: $f(tasktype(i), stresslevel(i))$; $HEP_{rec}(i)$: $f(availabletime(i), MMI(i), supervisorrecovery(i))$.

existing knowledge and cognitive abilities [57]. Otherwise, there will be no action usually because there is not enough time [68]. Successful solutions may be stored as rules for future challenges.

From the description of these three behavior levels, it can be found that these three levels could be interacted in between. The interaction is useful when a task performance needs to be analyzed, because the cognitive activities are not always at the same level, but will shift to another. When a disturbance occurs acting on the skilled performance from the environment, the attentive cognitive apparatus searches for suitable rules to adjust the performance. At knowledge-based domain, the attention is usually planning for future activities or improvement of rules from previous successful applications.

3. Quantification of human behavior levels with SRK model

3.1. Calculation of HEP

Human error probability (HEP) is a variable to characterize the probability of human error occurrence or briefly: the reliability of humans [13]. The definition of HEP could be summarized as the mathematical ratio between the number of errors occurring in a task and the number of tasks carried out with the opportunity for errors. The number of opportunities for error is generally the same as the number of times the task is carried out [66]. The HEP is the indicator for the relative occurrence of errors and subsequently faultless actions. In Table 2, how HEPs are calculated in some representative HRA methods is shown. It can be concluded that performance shaping factors (PSFs), which emphasize human error contributors and change basic human error probabilities, have a significant impact on the final HEP. In general, experience, complexity, stress, adequacy of procedure, human-system interface, and workload are adopted as PSFs in HRA [45].

3.2. Determination of behavior levels

3.2.1. Databases

Three databases, including technique for human error rate prediction (THERP) from so called “first generation”, Savannah river site HRA (SRS-HRA) and nuclear action reliability assessment (NARA) from so called “third generation”, are selected to obtain operation tasks and corresponding HEPs. These three databases are mainly applied in the nuclear power plant (NPP) field. The data are generated from surveys on skilled operators, advice from HRA experts, and site visits. In recent years, SACADA (scenario authoring, characterization, and debriefing application) [73] and HuREX (human reliability data extraction) [32] are often referred within the NPP field. In this study, the three databases are selected which are based on a broad and widely representation of application fields.

The database of THERP is based on studies and observation from various kind of plants in the world. Besides that, it also obtained support and guidance from program managers at nuclear regulatory commission [61]. In THERP, 44 tasks are analyzed. For each task operation, a basic HEP and corresponding error factor (EF) exist, where the basic HEP denotes the probability of human error without considering the conditional influence of other tasks. The error factor is integrated for the variation in estimated HEP due to different operation conditions and modeling uncertainty. For operation at different conditions or environments, HEP will be various. The upper bound of the estimated HEP is the product of basic HEP and EF, while the lower bound of the estimated HEP is the result of dividing HEP by EF.

Table 3
Summarized distinctions between skill-based, rule-based and knowledge-based errors (adapted from [48]).

Dimension	Skill-based errors	Rule-based errors	Knowledge-based errors
Type of action	Routine actions	Problem-solving activities with rules or knowledge	
Focus of attention	On something other than the task in hand	Directed at problem-related issues	
Control mode	Mainly controlled by automatic processors (Schemata)	(Stored rules)	Limited, conscious processes
Predictability	Largely predictable "strong-but-wrong" errors (Actions)	(Rules)	Variable
Ratio of error to opportunity for error	Though absolute numbers may be high, these constitute a small proportion of the total number of opportunities for error		Absolute numbers small, but opportunity ratio high
Influence of situational factors	Low to moderate; intrinsic factors (frequency of prior use) likely to exert the dominant influence		Extrinsic factors likely to dominate
Ease of detection	Detection usually fairly rapid and effective	Difficult, and often only achieved through external intervention	
Relationship to status change	Knowledge of change not accessed at proper time	When and how anticipated change will occur unknown	Changes not prepared for or anticipated

Table 4
The meaning of branches in Hanaman decision tree (adapted from [31]).

Branches	Operation type	Crew's understanding of situation	Requirement of procedure	Availability of procedure	Crew's understanding of procedure	Crew's familiarity of procedure
Upper	Routine	Understanding	Not required	Available	Understanding	Familiar
Lower	Non-routine	Not understanding	Required	Unavailable	Not understanding	Unfamiliar

The SRS-HRA database is developed from generic models and SRS-specific data, surveys from department of energy sites, THERP, human cognitive reliability (HCR), and actual national or regional data for transportation accidents and expert judgment [3]. In this database, 35 human error events with 3 different failure probabilities: low, nominal and high are considered. The nominal or low HEP is chosen for a situation with normal operation, planned process transients, and frequent minor abnormal occurrences. Nominal or high HEP is selected when the situation is less frequent, more significant abnormal occurrence. High HEP is applied when the effects are directed on personnel (e.g., personal well-being threatened).

The database from NARA comes from computerized operator reliability and error data (COREDATA) which are supported by a wide range of information, thus understanding of HEP in its practical and methodological context becomes possible [33]. The generic task types in NARA are divided into four sections including task execution, ensuring correct plant status and availability of plant resources, alarm or indication response, and communication.

With the HEP data collected in these three databases, human behavior levels in SRK framework could be quantified when the potential human errors described in these databases are reasonably identified and classified.

3.2.2. Identification and classification of human errors

The identification of human errors is an important phase in HRA. It breaks down the human activities into a more detailed level by task analysis, so that the identification of human errors becomes possible. It could be either a quantitative or qualitative analysis. The quantitative task analysis requires sufficient data to quantify the probability of errors. The qualitative task analysis could assist in understanding potential human errors.

In [48], the SRK framework combining with human error theory distinguishes human errors into skill-based errors (slips and lapses), rule-based mistakes as well as knowledge-based mistakes. Eight dimensions are discussed to distinguish these three level errors. The distinctions are summarized in Table 3 providing suitable references. Operation errors can be classified from the eight dimensions listed in Table 3. These eight dimensions of errors contribute to the establishment of the generic error modeling system (GEMS), which is a structured map for detailed examination of the types of errors applicable to the task [58].

Furthermore, Hanaman decision tree could be adopted as the joint approach to classify human operation errors into SRK levels [31]. In the Hanaman decision tree, six influence factors (operation type, crew's understanding of situation, requirement of procedure, availability of procedure, crew's understanding of procedure, crew's familiarity of procedure) are selected to determine human operation error levels. The structure of Hanaman decision tree is shown as Fig. 2. From Fig. 2, it is clear that Hanaman decision tree collects the relationship between influence factors and SRK framework. The meaning of the branches in Hanaman decision tree is explained in Table 4. In this case, with Hanaman decision tree, the human error levels could be determined when the states of influence factors are known.

As a short summary, the steps to classify human errors from the three databases into SRK levels are as follows:

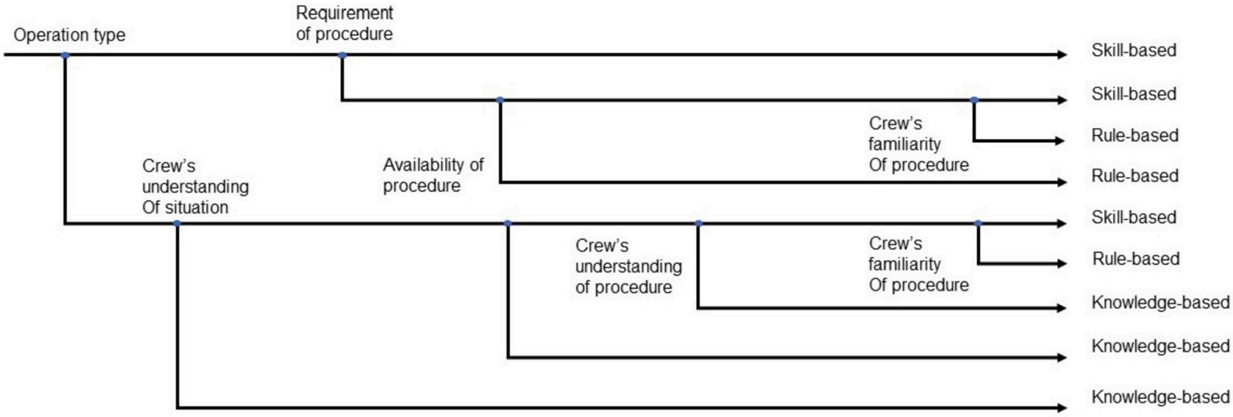

Fig. 2. Hanaman decision tree (adapted from [31]).

Table 5
HEP intervals for three level errors.

Databases	Skill-based error	Rule-based error	Knowledge-based error
THERP	1×10^{-4} - 5×10^{-3}	1×10^{-4} - 5×10^{-2}	1×10^{-3} - 1.0
SRS-HRA	3×10^{-5} - 5×10^{-3}	3×10^{-3} - 3×10^{-2}	3×10^{-3} - 3×10^{-1}
NARA	1×10^{-4} - 6×10^{-3}	1×10^{-3} - 2×10^{-2}	6×10^{-3} - 2×10^{-1}
Mean	7×10^{-5} - 5.3×10^{-3}	1×10^{-3} - 3.3×10^{-2}	3×10^{-3} - 5×10^{-1}

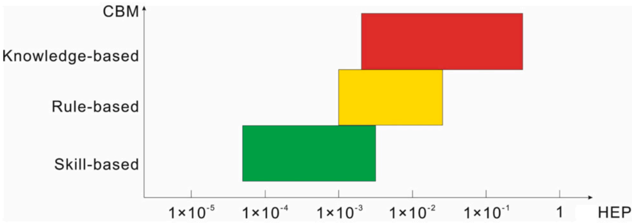

Fig. 3. The relationship between human behavior levels and HEP.

1) Understanding the environment of the operation scenario and the characteristics of the operation behavior, identification of the operation tasks including the specific operation steps, working conditions, the time budget for the task, and number of simultaneous actions, etc.
2) Matching the operation behavior characteristics with the listed dimensions in Table 3 and the influence factors in Table 4
3) Determination of the behavior level of the analyzed task
4) Calculation of the HEP of operation behavior with the consideration of operating environment and working conditions
5) Summarizing the HEP intervals of SRK levels of each database
6) Based on the HEP intervals of SRK levels obtained from the databases, a final HEP intervals table is obtained by calculating the mean HEP of the same level behaviors from the three databases.

The summarized HEP intervals of each task from three databases are listed in the Appendix. With these three Tables A.1–A.3 in Appendix, the HEP intervals for skill-based, rule-based, and knowledge-based behaviors can be summarized as Table 5. Therefore, the behavior levels in SRK framework can be characterized quantitatively. To visually represent the relationship of HEP between different behavior levels, the principal relations based on numerical values from literature based on the HEP (Table 5) are illustrated as shown in Fig. 3, where x-axis is indicating HEP values and y-axis is presenting cognitive behavior mode (CBM).

3.3. Case illustration

For better illustration how human errors are identified and classified into SRK framework and how HEPs of tasks in databases are determined, case illustration from THERP [61] is presented.

For demonstration, the selected task is chosen as administrative plant control. It refers to the extent the plant is run in conformance to the guidelines by which it was designed to operate, reflects the type of structure inherent in a plant, and reinforces the lines of responsibility. The human operators involved are responsible for the performance of certain tasks necessary to reliable and safe plant

Table 6
Estimated HEPs related to failure of administrative control (adapted from [61]).

Item	Task	HEP	EF
(1)	Carry out a plant policy or scheduled tasks such as periodic tests or maintenance performed weekly, monthly, or at longer intervals	1×10^{-2}	5
(2)	Initiate a scheduled shiftly checking or inspection function	1×10^{-3}	3
	Use written operation procedures under		
(3)	Normal operating conditions	1×10^{-2}	3
(4)	Abnormal operating conditions	5×10^{-3}	10
(5)	Use a valve change or restoration list	1×10^{-2}	3
(6)	Use written test or calibration procedures	5×10^{-2}	5
(7)	Use written maintenance procedures	3×10^{-1}	5
(8)	Use a checklist properly	5×10^{-1}	5

Table 7
Determination of error level with eight dimensions for item (1) and its explanation.

Dimension	Item (1)	Explanation
Type of action	Routine actions	Plant policy is described fully in a formal set of written instructions that operators need to follow in the operation procedures.
Focus of attention	On something other than the task in hand	The related errors in item (1) as described include the operator's attention may be drawn away from the tasks at hand by another, more compelling demand for action.
Control mode	Mainly by automatic processors (stored rules)	Operators need to follow the rules for operation. They are not always check the steps with the checklist, most of the steps are memorized.
Predictability of error types	Largely predictable "strong-but-wrong" errors (rules)	The errors of plant policy or scheduled tasks are predictable as the operations are followed by controlled rules and the steps are clear.
Ratio of error to opportunity for error	Absolute numbers may be high, but constitute a small proportion of total number of opportunities for errors	The absolute numbers may be high because they are daily, weekly operations, when considering the error rate, it is low as the operation frequency is high in daily, weekly working.
Influence of situational factors	Low to moderate; intrinsic factors likely to exert the dominant influence	Not following the plant policy or did not have the periodic tests may have low effect on the safety production of plant, but when the error at some part is not detected because lack of periodic tests, which leads to large failures or accidents, it will exert the dominant influence.
Ease of detection	Detection usually fairly rapid and effective	The errors can be detected when checking the taggings and checklists, or discuss with the responsible operators to know his familiarity on the duties.
Relationship to status change	When and how anticipated change will occur unknown	Due to the lack of periodic tests, it is known that status change will happen, but when and how it will happen is unknown.
	Rule-based errors	

operation in both normal and abnormal situations. The possible failures in administrative control with the estimated HEPs are listed in Table 6.

For item (1), plant policy refers to a set of operating requirements that plant management generally expects to be followed. These structured requirements are described in a formal set of written instructions that are available to all operation staffs in relevant positions. The estimated HEP is assigned to be 0.01 (EF = 5). In this case, the upper bound of HEP of task item (1) is 0.05, while the lower bound of which is 0.002. Therefore, the HEP of task item (1) can vary within the range between 0.002 to 0.05. With the description of tasks item (1), the error level of this item could be classified by the joint approaches of eight dimensions in Table 3, and the information from the Hanaman decision tree. The determination of error level with eight dimensions for item (1) and its explanation is presented in Table 7. Next the Hanaman decision tree is applied for the double check. The operation type is 'routine', so it is the upper branch; the requirement of procedure is 'required', so it goes to the lower branch; the availability of procedure is 'unavailable' because operators did not follow the procedures, so it is the lower branch. In this case, the item (1) is 'rule-based error' from the Hanaman decision tree. So the HEP of item (1) belongs to 'rule-based level'. In this study, the effect of EF on HEP is not considered as EF represents the upper and lower bound of HEP for special cases, and the nominal HEP is for most of the common cases.

The results from the eight dimensions approach and Hanaman decision tree are almost identical but have to be adapted in detail in some cases when the results are different. In this case the results from eight dimensions will be mainly adopted because this approach has more degrees of freedom to be adapted.

As a final result, the new introduced Fig. 3 illustrates the relationship between cognitive behavior modes and HEP values. For the first time here the SRK levels are mapped with HEP values. This builds now the base for consideration of additional effects related to time pressure and training levels (chapter 4 following).

4. Analysis of the effects of time pressure and training on SRK levels switching

4.1. Switching between SRK levels

In [63], the effect of switching behavioral levels was investigated. Knowledge-based activities can be executed 'online' and synchronously, which means that the whole process is realized 'online' using skills or rules (or as a tool). For example, a pilot manually controls an aircraft using skill-based behaviors while simultaneously applying knowledge-based behaviors to decide whether the target inclination is appropriate [20].

It should be recognized that the switching between SRK levels can be identified as short or long time scaled. Switching between SRK levels can be realized in short time (some activities mainly refer to the 'online' activities which require real-time feedback). The time scale could be seconds, minutes, or hours, depending on the situations. The skill-based behaviors related to highly routine activities in familiar environment. Rule-based behaviors are involved when attention checks upon progress and detects a deviation from the planned-for conditions. When operators realize that their rule-based solutions are not able to cope with the problem, knowledge-based performance is engaged. The activities of knowledge-based levels can be stopped when adequate plans for problem are acquired, which leads to the rule-/skill-based behaviors again.

When the time is stretched to weeks, months or years, the SRK level of operator behaviors could be switched depending on their experience regarding the situations they encountered. Operators who have continuous training on specific situations will increase their experience, which lead to behavior level switch from knowledge-based to skill-/rule-based. Meanwhile, after a long period of no training, the experience that operators previously occupied may be lost, thereby changing their behaviors from skill-/rule-based to knowledge-based.

4.2. Why time pressure and training are selected?

Two performance shaping factors (PSFs) namely time pressure and training are selected for the analysis of SRK level switching as these two PSFs affect SRK level switching and human reliability of operators significantly from short time scale and long time scale, respectively.

4.2.1. Time pressure

Time pressure has strong effects on human judgment and decision making as the strategies of coping with situations under time pressure are changed comparing with non-time pressure situations [39]. For example, the strategy of acceleration may be adopted with a faster rate of information processing and/or reducing pause and other interruptions in task-related activities. Filtering (processing some parts of the information more, and others less), acceleration, and omission (ignore particular parts of the information) are mostly employed strategies by human operators to deal with time pressure situations [59]. The relationship between time pressure and human performance is in inverted U-shape (increasing time pressure could induce to better human performance up to a certain point). After this point, human performance is decreasing with more time pressure [30]. In different application fields, time pressure is a key factor affecting human reliability, which often cause premature decision making, increased risk tolerance, and impaired cognitive performance and health [26]. In transportation, time pressure is regarded as the most hazardous task characteristics of emergency vehicle driving [29]. In aviation maintenance, time pressure is the most frequently mentioned factor leading to incidents from a survey as maintenance operators tempt to take shortcuts to get an aircraft back into service more quickly [49]. Air traffic control (ATC) is characterized by time pressure, multiple tasks and goals, and high error consequences because continuous increasing in the volume of air traffic imposes more demands on air traffic controller [35].

4.2.2. Training

Training helps to enhance human operator performance, so to reduce human errors. Whenever a human operator's ability to perform a task is limited by lack of knowledge or skill, it is making sense to bridge the gap by training [56]. Training is one of the essential constituents of a quality system process, delivering qualified operators to meet the demands of exacting roles. A significant latent failure in the chain of events leading up to an accident is ineffective or detrimental training [51]. From [4], it can be identified that sub-optimal training is one of the two most critical flight hazards in aviation, with the other one being a shortage of experienced operators. Training of control room operating crews in nuclear power plant consists of two stages: one is a lengthy process of initial training in which acquiring knowledge on appropriately carrying out the tasks to be performed in the control room, the other is a continuous training aimed maintaining and improving the knowledge and skills on operation [14]. Training standards need to be established for partially automated vehicles as driver assistance systems (ADAS) become standard equipment for lower-priced vehicles [7]. Hence, the effects of training on operator performance should be monitored and measured to identify the effectiveness on human reliability enhancement.

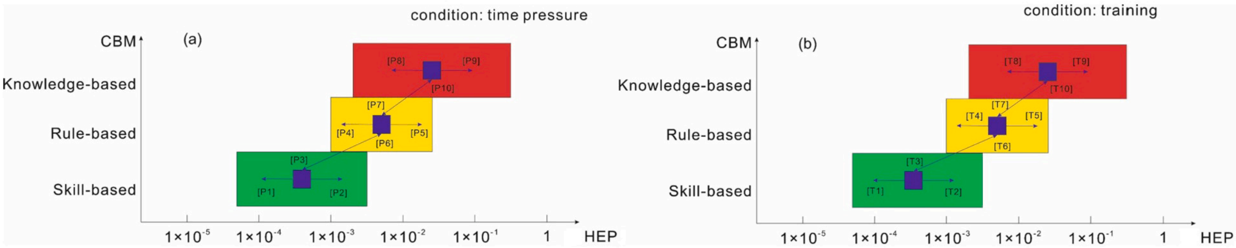

Fig. 4. The effects of time pressure (a) and training (b) on levels switching (in combination with the numerical values for Ti and Pi).

Table 8
Explanation of SRK levels switching with time pressure.

Item	Explanation	References
[P1], [P2]	In routine tasks and very familiar environment, HEP of operator may decrease if time pressure is at less/appropriate degree ([P1]), or it may increase if time pressure is at appropriate/greater degree ([P2]).	[30], [8]
[P4], [P5]	In rule-based tasks, human operator may take the strategies of acceleration or omission with highly time pressure, which will increase HEP ([P5]); when less time pressure imposed, operator has more time to follow the established rules, so to reduce HEP ([P4]).	[30], [23]
[P8], [P9]	In knowledge-based tasks, human operator may not able to search for additional solutions for the problem as there is not enough time ([P9]); when operator is with less time pressure, some solutions may be found ([P8]).	[30], [23]
[P3], [P6]	With appropriate time pressure not exceeding the inverted U-shaped top point, human behavior could switch between skill-based level and rule-based level. For routine tasks in familiar situations, when appropriate time pressure is imposed, rule-based behaviors could move to skill-based as human performance is increasing ([P3]); while skill-based behaviors will move to rule-based with little time pressure ([P6])	[30], [8]
[P7], [P10]	With appropriate time pressure not exceeding the inverted U-shaped top point, human behavior could switch between rule-based level and knowledge-based level. When appropriate time pressure is imposed, knowledge-based behaviors could move to rule-based because of increased performance ([P7]). Rule-based behaviors will move to knowledge-based with less time pressure ([P10])	[30], [1]

4.3. Effects analysis

It is mentioned that time pressure and training as two PSFs deeply affect human reliability. When SRK framework is considered in the effects analysis of time pressure and training on SRK levels switching, the map (Fig. 3) generated in this work could be applied to visualize the effects. In Fig. 4 (a), the effects of time pressure on SRK levels switching are indicated. The detailed explanation of the switching behaviors is presented in Table 8. The effects of training on SRK level switching is presented in Fig. 4 (b). The detailed explanation of switching behaviors is shown in Table 9. It is obtained from Fig. 4 that human performance could be switched not only among the same level, but also between levels with different extent of training.

5. Discussion

5.1. Framework of the SRK levels switching

Although autonomous and semi-autonomous systems are applied to different application fields, human operators are still the center for human-machine systems regarding safety issues. Even the most advanced automated systems still need humans to monitor the situations and takeover or stop the system when emergencies occur. At the same time, high automation may increase boredom and decrease vigilance which affects the ability to takeover control of the system [40]. Therefore, quality of human performance is critical to the reliability of human-machine systems. Many measures have been developed to monitor human performance in human-automation systems, especially human-driving system. In [15], five types (subjective report measures, driver biological measures, driver physical measures, driving performance measures, and hybrid measures) of driver inattention monitoring measures are summarized. In [19], human factors regarding automated vehicles, such as the workload, distraction, situation awareness (SA) and driver trust, are discussed. The ultimate question to be answered by these studies of human factors is the monitoring and evaluation of human reliability. The quantitative study of human behavior reliability of different levels in SRK framework discussed in this contribution provides possibilities for the evaluation of human errors and human reliability. Meanwhile, the study of the effects of

Table 9
Explanation of SRK levels switching with training.

Item	Explanation	References
[T1], [T2]	Human operator may be more skilled on routine tasks with continuous training ([T1]), or the familiarity on skilled tasks decrease because of short time leaving the tasks ([T2]).	[16]
[T4], [T5]	For rule-based tasks, human performance may be improved with more training ([T4]), and may be reduced with less training ([T5]).	[6]
[T8], [T9]	For unknown situations with no know-how or rules for tasks, human reliability is increased with training on knowledge-based tasks ([T9]), and is decreased with less training ([T8]).	[6]
[T3], [T6]	Human performance may be switched from skill-based to rule-based when lack of training ([T6]); with more training, rule-based behaviors could be moved to skill-based ([T3]).	[38]
[T7], [T10]	With more knowledge and training with operation situations, human performance could be moved to rule-based level from knowledge-based ([T7]); when leaving the tasks for long time, human's experience may be lost, so the performance may be switched from rule-based to knowledge-based ([T10]).	[38], [6]

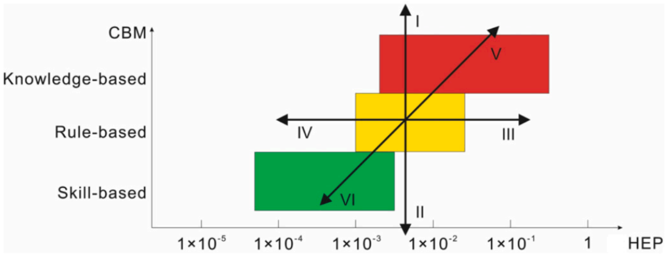

Fig. 5. Analysis of the dynamic behavior of SRK levels switching.

time pressure and training on the levels switching demonstrates the dynamic changes of SRK framework for environment. Hence, a more general structure to illustrate the dynamic behavior of levels switching could be established which is illustrated in Fig. 5.

From Fig. 5, it can be obtained that six directions are used to indicate the relationship between HEP and human behaviors.

Directions I/II mean that the quality of the tasks is different but HEP is identical. The typical example for this case is that a very experienced operator is in process of tasks in familiar environment, although some rules are available or situations need to be diagnosed and new plan should be generated, human reliability is identical as the solutions could be found easily.

Directions III/IV indicate that the quality of tasks is identical, while human operators' experience level is varying. As the experience levels of human operators on situations are different, their human performance ability regarding the same task is also different, which induces the HEP varying.

Directions V/VI present loosing experience (V) and typical learning process (VI). As learning continues, operators become more familiar with the situations and more proficient in the process, so the behavior level switches from knowledge-based level and eventually to skill-based level. Meanwhile, after long time of decoupling from the operation loop (due to automation) or specific tasks (due to tasks changing), human operators will loose abilities for the tasks, so their experience on tasks is gradually fading away (knowledge degradation) and the behaviors finally reach knowledge-based level.

5.2. Expected application

Many approaches and techniques have been developed for human performance assistance to reduce risks in application fields. In [41], the technologies for driver assistance system (ADAS) driven solutions are summarized, the eye-gaze and head pose estimation in vision intelligence are reviewed and the development of learning algorithms makes it possible to develop a real-time recommendation system for autonomous vehicle. In aviation, the human performance model is used to improve predictions of situation awareness of pilots [28]. In [18], the impact of seafarers' emotion on their performance is investigated with electroencephalogram (EEG) and self rating. In the previous work of the authors, human driver reliability is evaluated using a modified fuzzy-based CREAM approach with the data collected from driving simulator [25]. The approach of estimation of human reliability could be developed into a real-time monitoring system for human driver. When the driver displays low human reliability in some situations, the system could issue alerts to bring the driver's attention and ability back to the driving operation. In some critical situation, when human driver reliability is extremely low, and the vehicle cannot be controlled at all, the system could directly takeover the vehicle from the driver. Hence, the work of quantification of human behavior levels regarding SRK model lays the foundation of evaluation between automation and operator's takeover.

The framework of SRK levels switching considering the effects of time pressure and training provides the idea for evaluation of simulator training for daily tasks for individuals. When simulator training data are collected, human operators' reliability could be estimated based on the approach proposed in [25], which could be quantified into points mapping into Fig. 5. In this case, the actual training status of individuals could be recognized and training suggestions for further steps could be made. Meanwhile, the error types could be also identified by the map, which helps to analyze and improve human performance during training.

6. Summary and conclusion

Humans are always somewhere integrated in the loops although the automation level in human-machine systems is getting higher with the development of technology. Human error is causing an increasing proportion of total accidents. With the research on human error mechanisms and failure modes, the study of human reliability analysis (HRA) has been formed. Many cognitive process models have been established to explain human performance. Among these models, skill-, rule-, knowledge-based behavior (SRK) model is wildly used. In this contribution, human behavior levels of SRK framework are quantified and the effects of two performance shaping factors, time pressure and training, on levels switching are analyzed. Based on the analysis a new graphical summary is developed to illustrate the effects. The main work could be summarized as follows:

1. The HRA methods, including the so called 'first generation', 'second generation' and 'third generation', are briefly discussed, the cognition process in these HRA methods are summarized, and SRK model is selected in this contribution to characterize human behavior.
2. Three level behaviors in SRK model are illustrated. With the description of three levels, it could be concluded that skill-based behaviors relate to the higher human performance reliability and knowledge-based behaviors correspond to the lowest, but the defining of HEP values of each level need human reliability data research.
3. Human error probabilities (HEP) from three databases (THERP, SRS-HRA and NARA) are collected to quantify human behavior levels in SRK model. The detailed procedures for the identification and classification of human errors are illustrated. A case study regarding classifying the task of administrative control in plants into SRK levels is presented to explain how the procedure works. Finally, the HEP intervals of SRK levels are summarized and a graphical framework presenting the relationship between human behaviors and HEP is generated.
4. The effects of time pressure and training on SRK levels switching are analyzed and the switching behaviors are explained. Human behavior levels in SRK model can switch in several ways. The switching behaviors could be identified as short time scale and long time scale. Short time scale switching mainly refers to the 'online' activities where real-time feedback is required. Human behavior levels of the SRK framework can be switched depending on experience regarding the tasks and environment for the long time scale. Two performance shaping factors including time pressure and training are selected for analysis of SRK levels switching. It is obtained that human behaviors can be switched between levels with time pressure and training. It can be stated that the established visual connections show the effects with respect to time pressure and additional training. Furthermore, it becomes clear that from the HPE point of view, the SRK levels roughly correlate but in detail overlap.
5. A general map describing SRK levels switching with six different directions is generated, the explanation of each direction is presented. The new graphical illustration allows: i) a human performance reliability monitoring system to be established combining with the fuzzy-based modified CREAM approach from the previous works of authors; ii) the individual recognition and evaluation system of training status to be generated with collected operator training data.

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CRediT authorship contribution statement

Chao He: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Dirk Söffker: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data included in article/supp. material/referenced in article.

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Appendix A

Table A.1
Summary of skill-based errors and corresponding HEP.

Databases	Skill-based errors	HEP
THERP	Preparation of written material	3×10^{-3}
	Initiate scheduled shiftly checking in administrative control	1×10^{-3}
	Using written operation procedures in administrative control	5×10^{-3} - 5×10^{-2}
	Omission of item when procedure with checkoff provision use correctly	1×10^{-3} - 3×10^{-3}
	Recalling oral instruction items ont written down	1×10^{-3}
	Selection of unannunciated displays for quantitative or qualitative readings	5×10^{-4} - 3×10^{-3}
	Reading and recording from various numerical indicators	1×10^{-3} - 6×10^{-3}
	Check-reading from various types of displays	1×10^{-3} - 6×10^{-3}
	Inadvertent activation of a control	3×10^{-2}
	Turn a rotary control or two-position switch with common stereotype in wrong direction	1×10^{-4} - 5×10^{-4}
	Set rotary control to an incorrect setting	1×10^{-3}
	Fail to complete change of state of a component which must be held until change is complete	3×10^{-3}
	Improperly mate a connector	3×10^{-3}
	Selection in changing or restoring a locally operated valve from a group of unambiguously labeled valves which are set apart from similar looking valves	1×10^{-3} - 3×10^{-3}
	Detect stuck locally operated valves with indications are available	1×10^{-3} - 5×10^{-3}
	Resume attention to a legend light within 1 minute after an interruption	1×10^{-3}
SRS-HRA	Communication error	5×10^{-2}
	Incorrect labeling or tagging	5×10^{-3}
	Failure to lock out	5×10^{-4}
	Chemical addition or elution error	3×10^{-3}
	Transfer error	$3 \times 10^{-6}/tank-h$
	Overfilling of a tank	$5 \times 10^{-6}/tank-h$
	Laboratory analysis error	3×10^{-4}
	Random actuation/shutdown of system	$5 \times 10^{-6}/h$
	Vehicle collision with stationary object	$1 \times 10^{-6}/miles$
	Single vehicle accident	$1 \times 10^{-6}/miles$
	Vehicle collision with another moving vehicle	$1 \times 10^{-6}/miles$
	Dropping of load when using forklift	5×10^{-5}
	Puncturing of load when using forklift	3×10^{-5}
	Dropping of load when using crane/hoist	1×10^{-4}
	Crane/hoist strikes stationary object	3×10^{-4}
NARA	Carry out simple single manual action with feedback	5×10^{-3}
	Perform completely familiar, well designed highly practiced, routine task	1×10^{-4}
	Set system status as part of operations using strict administratively controlled procedures	7×10^{-4}
	Calibrate plant equipment using procedure	3×10^{-3}
	Simple response to a range of alarms or indication providing clear indication of situation	4×10^{-4}
	Verbal communication of safety-critical data	6×10^{-3}

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Table A.2
Summary of rule-based errors and corresponding HEP.

Databases	Rule-based errors	HEP
THERP	Rule-based actions by control room personnel after diagnosis of an abnormal event	2.5×10^{-2} - 5×10^{-2}
	Carry out a plant policy or scheduled task	1×10^{-2}
	Use a valve change or restoration list in administrative control	1×10^{-2}
	Use a written test or calibration procedure in administrative control	5×10^{-2}
	Omission per item when procedure without provision are used or incorrectly used	3×10^{-3} - 1×10^{-2}
	Arithmetic calculation errors	1×10^{-2} - 5×10^{-2}
	Selection of control on a panel from an array of similar-appearing controls	5×10^{-4} - 3×10^{-3}
	Turn rotary control or two-position switch with unusual stereotype in wrong direction	1×10^{-2} - 5×10^{-1}
	Select wrong circuit breaker in a group of circuit breaker	3×10^{-3} - 5×10^{-3}
	Selection in changing or restoring a locally operated valve from group of ambiguously labeled and similar appearance of valves	5×10^{-3} - 1×10^{-2}
	Checker checks non-routine task or involve active participation	1×10^{-2} - 5×10^{-2}
	Checking the status of equipment if that status affects one's safety either by checker or maintainer	5×10^{-4} - 1×10^{-3}
	Response to multiple annunciators alarming closely in time	1×10^{-4} - 5×10^{-2}
SRS-HRA	Failure of administrative control	5×10^{-3}
	Failure to verify within control room	1×10^{-2}
	Failure to verify outside control room	3×10^{-2}
	Error in selecting control within control room	1×10^{-2}
	Error in selecting control outside control room	1×10^{-2}
	Incorrect reading or recording of data	1×10^{-2}
	Miscalibration	5×10^{-3}
	Failure to restore following test	1×10^{-2}
	Failure to restore following maintenance	5×10^{-3}
	Failure to verify parameter with calculation	3×10^{-2}
	Excavation error	1×10^{-2}
	Failure of long-term accident recovery	3×10^{-3}
NARA	Start or reconfigure a system from the main control room following procedures, with feedback	1×10^{-3}
	Start or reconfigure a system from a local control panel following procedures, with feedback	2×10^{-3}
	Routine check of plant status	2×10^{-2}
	Restore a single train of system to correct operational status after a test, following procedures	4×10^{-3}

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Table A.3
Summary of knowledge-based errors and corresponding HEP.

	Knowledge-based errors	HEP
THERP	Diagnosis of the abnormal events within certain time	5×10^{-1}
	Rule-based actions by control room personnel after diagnosis of an abnormal event	1.0
	Perform the task without using written maintenance procedures or checklist	3×10^{-1} - 5×10^{-1}
	Written procedures are available and should be used but not used	5×10^{-1}
	Reading and recording from various large number of parameters recorder and graphs	1×10^{-2} - 5×10^{-2}
	Recognize that an instrument being read is jammed without indicators to alert the user	1×10^{-1}
	Detect stuck locally operated valves when indications are not available	1×10^{-2}
	Checker checks routine tasks with or without written materials	1×10^{-1} - 2×10^{-1}
	Checker notices the locally operated valve is not completely opened or closed after the valve is checked	1×10^{-1} - 9×10^{-1}
	Checking the task in a two-man team	5×10^{-1}
	Respond to a legend light if more than 1 minute elapses after an interruption	9.5×10^{-1}
	Respond to a steady-on legend light at initial audit or hourly scans	9×10^{-1} - 9.5×10^{-1}
	Fail to detect unannunciated deviant display	9.5×10^{-1} - 9.9×10^{-1}
	Fail to detect multiple unannunciated deviant displays	1×10^{-3} - 9.9×10^{-1}
	Daily walk-around inspection	5.2×10^{-1}
SRS-HRA	Failure to respond to compelling signal	1×10^{-2}
	Checker verification error	1×10^{-1}
	Supervisor verification error	3×10^{-1}
	Diagnosis error	1×10^{-2}
	Failure of visual inspection	1×10^{-1}
	Failure of manual fire detection	1×10^{-1}
	Failure of manual fire suppression by occupant	3×10^{-1}
	Failure of manual fire suppression by non-occupant	3×10^{-1}
	Failure of long-term accident recovery	3×10^{-3}
NARA	Judgment needed for appropriate procedure to be followed based on interpretation of a situation	6×10^{-3}
	Carry out analysis	3×10^{-2}
	Identification of situation requiring interpretation of complex patter of alarms or indications	2×10^{-1}

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