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Identification and correlation analysis for performance shaping factors in flight crew operation

Lijing Wang[1*], Yanlong Wang[1], Yingchun Chen[2] and Dayong Dong[2]

[1] School of Aeronautic Science and Engineering, Beihang University, 37 Xueyuan Road, Beijing, China
[2] Shanghai Aircraft design and research Institute, Commercial Aircraft Corporation of China Ltd, 5188 Jinke Road, Shanghai, China

*wanglijing505@126.com, wyllaf@sina.com

Abstract. The dependency between PSFs (performance shaping factors) is gaining increasing attention in HRA (human reliability analysis). In this paper, 79 PSFs were identified through literature review and discussion of focus group, which is composed of human factors/HRA specialists and civil pilots. These PSFs were classified into 10 categories as cognitive characteristics, physiological and psychological characteristics, personal and social characteristics, procedures, task characteristics, human-machine interface, system state, phenomenology characteristics, physical working conditions team and organizational factors. Then a survey of 299 pilots was conducted. A self-rate scale was used to investigate how the pilots were influenced by these PSFs. Correlation analysis shows that the correlations between PSF subsets are moderate to strong. The result suggests further research on the dependency between PSFs and PSF interactions need to be included in future HRA efforts.

1. Introduction

The behaviour of human beings in complex systems is affected by many different factors, which may be external factors or some characteristics of human beings themselves. These factors are named performance shaping factors (PSF) [1]. PSFs can influence operator's performance and human error probability (HEP), which may be positive or negative. PSF is an important concept in human reliability analysis (HRA) first proposed by Swan and Guttmann in the THERP method, and has been used in most of the later HRA methods to estimate HEPs. In different HRA methods, PSF might be called different names, including performance influence factor(PIF), common performance condition(CPC) [2], error producing condition(EPC) [3]and error forcing context(EFC)[4].

The use of PSF in HRA can be summarized into the following categories:

- HEP quantification, such as SLIM [5], INTENT [6], STAHR [7] and HRMS [8];
- Analysis of error of commission, such as Macwan's PSF taxonomy [9], Julius's PSF taxonomy [10]and ATHEANA [4];
- Overall context assessment and error analysis, such as CREAM [2], HRMS and INCORECT [11];
- HRA database, such as Taylor-Adams's PSF taxonomy for CORE-DATA [12].

In general, the PSF classification is for specific purposes and application domains. Each HRA method has its own PSF sets. Currently, most HRA methods and PSF taxonomies are developed for the nuclear power sector. There are few PSF taxonomy for aviation transportation. A review of HRA empirical studies called for the identification of a key subset of PSFs [13,14]. The review also asked the question whether HRA methods using a key subset of PSFs and their corresponding qualitative analysis and quantification process can produce reliable and reasonable HEPs for most scenarios. Liu et al argued this vital question should be addressed in future HRA empirical studies [15]. Therefore, in order to ensure a consistent and effective human reliability analysis, it is necessary to establish a key PSF subset for pilots considering the task and context features in flight operation.

Moreover, dependency between PSFs is an important issue in HRA. There are two types of interrelationships, i.e., moderating effects and mediating effects [16]. Although, HRA specialists recommend taking into account for the dependencies and interactions, there is no agreement among methods on how to quantify the effects and interactions of PSFs within a task [17]. Many HRA methods assume PSFs are independent each other (such as SLIM [5], HEART [3], THERP [1]), while some other methods do not consider the correlations among PSFs explicitly (such as HERA)[18].

However, the dependency between PSFs is gaining increasing attention in HRA [19, 20]. This issue is related to the PSF causal model, which is required as an important input by several novel HRA methods, especially those based on Bayesian networks [21, 22]. The PSF dependency model in CREAM [2] was built based on human factors and HRA expert analysis and judgment. Another method for developing the PSF dependency model is gathering the opinions of domain experts and analyzing them through statistics. This is what employed in this paper.

The purpose of this paper is to identify the key subset of PSFs for civil flight crew and to evaluate the correlations among them through a large-scale pilot survey. The other parts of the paper are arranged as follows: The second section describes the process and results of identifying the key PSF subset for flight crew; the third section introduces the survey questionnaire and investigation process briefly; the fourth section provides the correlation analysis results and discussions; and the last section gives the conclusion.

2. Identification of flight crew PSFs

Many HRA methods have already been developed with considerations of various PSF sets. The inconsistence of PSFs selected may lead to some serious issues. First, the use of different PSFs makes the comparison between HEPs calculated by different methods meaningless. Moreover, to reduce human errors, corresponding measures should be taken according to the PSFs selected. The second problem is the number of PSFs used. Some methods use a limited number of PSFs, which can cause analysts to overlook important factors and underestimate the contribution of human error to the overall system safety. The third problem is that the definition and description of each PSF is distinct, which may lead to inconsistent evaluation of the same PSF by different evaluators, and thus different HRA results. Therefore, the above issues should be considered when identifying the key subset of PSFs for flight operation.

Kim and Jung’s [23] review on PSF taxonomy forms the basis of this paper. In their article, they reviewed 18 PSF taxonomies and collected 220 PSFs. Kim and Jung [23] argued that the operator task context model can be demonstrated as Fig.1. According to figure 1, the collated PIFs are classified into four main groups: human, system, task, and environment. The boundary of each group is defined as follows.：

- Human: Personal characteristics and working capability of the operator;
- Task: Characteristics of the procedures and tasks need to be completed;
- System: Human-Machine Interface, plant hardware system and physical characteristics of plant process;
- Environment: Team and organization factors, and physical working conditions.

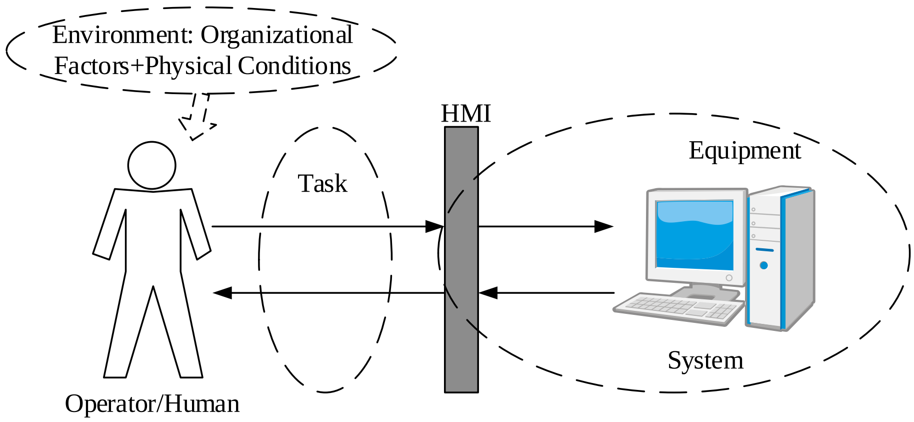

Figure 1. The context model of operator task.

The 220 PSFs collected by Kim and Jung [23] served as the complete set of PSFs for civil flight crew. Then a focus group composed of three human factors/HRA specialists and two pilots was set up to identify the key PSF subset. The below principles were followed during the screening process.

- The PSF selection should include all important factors in the assessed task context as much as possible;
- The selected PSF should not overlap with each other;
- Choose factors that directly affect the occurrence of human error;
- The selected PSF could be reflected in HRA;
- The selected PSF can be evaluated in practice;
- The terms describing PSFs should be as practical as possible and easy to be understood.

Then 79 key PSFs were identified for flight crew through focus group composed of three human factors/HRA specialists and two airline pilots. These PSFs were classified into 10 categories, i.e., cognition characteristics (CC), physiological and psychological characteristics (PPC), personal and social characteristics (PSC), procedures (P), task characteristics (TC), human machine interface (HMI), system state (SS), Phenomenological characteristics (PC), physical working conditions (PWC) and team and organization factors (TOF) (table 1).

Table 1. Key PSF subset for civil flight crew operation.

PSF Groups	PSF Categories	PSFs
Human	Cognition Characteristics(CC)	Attention
		Skill level
		Experience
		Operator Diagnosis
		Perceived Importance
		Confidence in Diagnosis
		Memory of Previous Actions and Accident History
	Physiological and Psychological Characteristics (PPC)	Fatigue
		Discomfort
		Emotion
		Confusion/Perplexity
		Task load
		Fear of Failure/Consequences
	Personal and Social Characteristics (PSC)	Attitude
		Motivation
		Risk Taking

		Self-confidence Sense of Responsibility Role/Responsibility
Task	Procedures (P)	Usability Quality Level of Detail Number of Steps Required Time for Completion Level of Standardization in Use of Terminology Decision Making Criterion Logic Structure Number of Simultaneous Tasks Adequacy of Caution/Warning
	Task Characteristics (TC)	Task Type:Procedure Following, Monitoring, Detection, Verification, Diagnosis, Recovery Required Level of Cognition Dynamic VS. Step-by-Step Activities Number of Required Information Number of Necessary Information to Be Memorized Information Load Task Difficulty Task Novelty Frequency and Familiarity of Task Number of Simultaneous Goals/Tasks Discrepancy between Training and Reality Perceptual Requirements Task Criticality Degree of Manual Operation Precision Requirement on and Type of Feedback Communication Requirement Team Cooperation Requirement
System	Human Machine Interface (HMI)	Availability Discrimination/Distinguishability of Signals Control–Display Relationships Existence of Failed Indicator Reachability Visibility Complicatedness of Control Panel
	System State (SS)	Inherent System Complexity Number of Coupled Components Level of Automation
	Phenomenological Characteristics (PC)	Number of Dynamic Changing Variables Time Available for Operator Performance Time Pressure Degree of Alarm Avalanche

Environment	Physical Working Conditions (PWC)	Temperature/Humidity/Pressure/Illumination Interference in Communication Noise Vibration Narrow Work Space or Obstacles Accessibility of Components Circadian Rhythm Effects
	Team and Organization Factors (TOF)	Clearness in Job Description or Role Definition Adequacy of Distributed Workload Intra/Inter-Team Cooperation Ability/Leadership/Authority of Team Leader Frequency and Training Time Work/Rest Schedule Shift Rotation Maintenance Rewards and Punishments Routine Violations Openness in Communication

3. Questionnaire and pilot investigation

A pilot self-rating scale was developed after identifying the critical PSF subset for the flight crew operation of civil aircraft. In pilots' daily mission, to what extent they were influenced by these PSFs were investigated using the five-degree scale. And the score 1 to 5 represent levels of very little, little, moderate, large and very large, respectively. In addition to these questions, flight hours, flight level, and aircraft types ever piloted were also asked. A total of 299 pilots participated in the survey, producing 231 valid questionnaires, with an effective rate of 77.3%. The flight hours is from less than 100 hours to 30,000 hours, with an average of 6,386 flight hours (SD=6921).

4. Result and discussion

To reduce the amount of analysis, the correlation analysis was only performed at a higher level of PSF subset, i.e. the second level including 10 PSF categories. Each PSF category of the second level was treated as a PSF in the correlation analysis. Each PSF score in the second level is the mean score of each PSF in its lower level. The descriptive statistics result is shown in table 2. The result shows that the influences of the 10 PSFs on pilot performance are between the level of "moderate" and "large". Among them, physiological and psychological characteristics, cognitive characteristics and team and organizational factors exert the greatest impact on pilot performance.

Table 2. Descriptive statistics

	N	Min	Max	Mean	SD
Flight Hours	231	100	30000	6835.92	6921.24
Cognition Characteristics	231	1.00	5.00	3.54	.69
Physiological and Psychological Characteristics	231	1.00	5.00	3.66	.74
Personal and Social Characteristics	231	1.00	5.00	3.29	.82
Procedures	231	1.00	5.00	3.40	.85
Task Characteristics	231	1.00	5.00	3.36	.75
HMI	231	1.00	5.00	3.22	.83
System State	231	1.00	5.00	3.26	.89

Phenomenological Characteristics	231	1.00	5.00	3.48	.87
Physical Working Conditions	231	1.00	5.00	3.23	.83
Team and Organization Factors	231	1.00	5.00	3.50	.78

There are three commonly used correlation coefficients, i.e. Pearson、Spearman and Kendall. Because the degree of influence of PSF on pilot operation performance is a kind of discrete grade data, the Kendall correlation coefficient is selected in this paper [24]. The correlation analysis results are shown in table 3. It can be seen from table 3 that PSFs of team and organizational factors, system states, physical working conditions and phenomenological characteristics are significantly correlated with pilot's flight hours at the level of 0.01 (bilateral), while cognitive characteristics, physiological and psychological characteristics are significantly correlated with pilot's flight hours at the level of 0.05 (bilateral). Taking cognitive characteristics as an example, cognitive characteristics mainly include 7 low-level PSFs, including attention, skill level, experience, diagnosis, perceived importance, diagnostic confidence and memory of previous actions and accident history. These PSFs will be enhanced with the increasing of flight hours, and pilot will have more experience, higher skill level and increased confidence in fault diagnosis. Pilots also tend to be more heavily influenced by this past knowledge. However, due to the extremely weak correlation coefficient, this tendency is not prominent.

Table 3. Results of correlation analysis

			Flight Hours	CC	PPC	PSC	P	TC	HMI	SS	PC	PWC	TOF
Kendall tau_b	Flight Hours	corrcoef	1.000	.107*	.093*	.024	.075	.066	.084	.142**	.125**	.128**	.148**
		Sig.[a]	.	.020	.044	.608	.102	.142	.068	.003	.007	.005	.001
	CC	corrcoef	.107*	1.000	.465**	.454**	.462**	.468**	.424**	.359**	.376**	.341**	.374**
		Sig.	.020	.	.000	.000	.000	.000	.000	.000	.000	.000	.000
	PPC	corrcoef	.093*	.465**	1.000	.448**	.443**	.441**	.399**	.384**	.427**	.432**	.443**
		Sig.	.044	.000	.	.000	.000	.000	.000	.000	.000	.000	.000
	PSC	corrcoef	.024	.454**	.448**	1.000	.556**	.512**	.486**	.439**	.386**	.412**	.418**
		Sig.	.608	.000	.000	.	.000	.000	.000	.000	.000	.000	.000
	P	corrcoef	.075	.462**	.443**	.556**	1.000	.654**	.521**	.517**	.496**	.464**	.446**
		Sig.	.102	.000	.000	.000	.	.000	.000	.000	.000	.000	.000
	TC	corrcoef	.066	.468**	.441**	.512**	.654**	1.000	.625**	.610**	.624**	.470**	.515**
		Sig.	.142	.000	.000	.000	.000	.	.000	.000	.000	.000	.000
	HMI	corrcoef	.084	.424**	.399**	.486**	.521**	.625**	1.000	.701**	.591**	.571**	.544**
		Sig.	.068	.000	.000	.000	.000	.000	.	.000	.000	.000	.000
	SS	corrcoef	.142**	.359**	.384**	.439**	.517**	.610**	.701**	1.000	.640**	.590**	.538**
		Sig.	.003	.000	.000	.000	.000	.000	.000	.	.000	.000	.000
	PC	corrcoef	.125**	.376**	.427**	.386**	.496**	.624**	.591**	.640**	1.000	.522**	.574**
		Sig.	.007	.000	.000	.000	.000	.000	.000	.000	.	.000	.000
	PWC	corrcoef	.128**	.341**	.432**	.412**	.464**	.470**	.571**	.590**	.522**	1.000	.559**
		Sig.	.005	.000	.000	.000	.000	.000	.000	.000	.000	.	.000
	TOF	corrcoef	.148**	.374**	.443**	.418**	.446**	.515**	.544**	.538**	.574**	.559**	1.000
		Sig.	.001	.000	.000	.000	.000	.000	.000	.000	.000	.000	.

*significant at the level of 0.05
**significant at the level of 0.01
[a] Sig.(bilateral)

According to the correlation analysis results, there are significant correlations at the level of 0.01 (bilateral) between all PSFs. This indicates that it is very necessary to consider the correlation between PSFs when evaluating the impact of PSF in the HRA. One of the most relevant PSFs to cognitive characteristics is physiological and psychological characteristics, possibly because cognition is essentially a spiritual activity. Both procedures and task characteristics are significantly relevant to personal characteristics. This can be reflected in the interview where pilots mentioned that if an operation procedure is illogical and there are many steps, the pilot is more likely to risk violation and not following the standard procedures. The most correlated PSF to procedure is task characteristics, since task characteristics such as complexity, novelty, and number of simultaneous tasks all will influence the logical structure, time required and number of steps of procedure. The strong correlations between procedures, task characteristics, HMI, system state and phenomenological characteristics also indicate that these PSFs should be comprehensively considered during the system design process in order to reduce task difficulty and demand. In particular, HMI and system state have the greatest correlation coefficient, reaching 0.7. This is because the complexity and automation level of the system largely determine the way the system is displayed and controlled, as well as the phenomenological features of the system. Physical working conditions and team/organizational factors are moderately correlated with HMI, system state, and phenomenological characteristics (0.4~0.6). This may be because the design of the system to a certain extent determines the working conditions, task assignment and roles of crew.

5. Conclusion

Most current HRA methods lack a sufficient consideration of the dependencies between PSFs. Many scholars in the HRA field have emphasized that PSF dependencies should be included in future HRA method development. In this paper, through literature review and focus group discussion, the key PSF subset for civil flight crew is identified based on the existing PSF taxonomies. The key subset contains 79 PSFs, classified into four group of human, task, system and environment, and further divided into 10 categories as cognitive characteristics, physiological and psychological characteristics, personal and social characteristics, procedures, task characteristics, human-machine interface, system state, phenomenology characteristics, physical working conditions team and organizational factors. Then, the influences of these PSFs on pilot performance were investigated through a pilot self-rating scale. A total of 299 pilots participated in the survey. The survey found that pilots generally believed the PSF had a "medium" to "large" impact on operational performance. Moreover, correlation analysis was performed between PSFs and between PSF and pilot flight hours. The results showed that the PSFs of team and organizational factors, system state, physical working conditions, phenomenological characteristics, cognitive characteristics, physiological and psychological characteristics had a significant but weak correlation with flight hours. While the PSF categories were generally moderately (0.4~0.6) to strongly (0.6~0.8) correlated. This also reflects the complex interaction between the internal elements of civil air transport system as a complex socio-technical system.

This paper is only a preliminary attempt to evaluate the correlations between flight crew PSFs. In the future, we will continue to expand the sample size for a more detailed analysis of dependencies between flight crew PSFs. Furthermore, the specific dependence type between PSFs will be studied through mediating effect analysis and moderating effect analysis. In addition, the aviation accident report data will also be analyzed to explore the PSFs dependencies, providing inputs for the establishment of PSF interaction model, such as Bayesian Network, through the fusion of multi-source evidences.

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