SIMULATIVE ANALYSIS OF PERFORMANCE SHAPING FACTORS IMPACT ON HUMAN RELIABILITY IN MANUFACTURING ACTIVITIES.

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ABSTRACT

In performing Human Reliability Analysis (HRA), the environmental and personal factors impact on human performance and enhance or degrade the human error probability (HEP). Their modelling and quantification is one of the most complex issues in the HRA field, to which many researchers recently are concentrating their efforts. This paper focuses on the eight performance shaping factors (PSFs), used in the Simulator for Human Error Probability Analysis (SHERPA), in order to understand how they affect HEP, considering especially their mutual interactions. The one-factor-at-a-time method was used to assess singularly the levels of each factor, while the analysis of variance allowed to realize if there is more or less dependence between them. The results highlight statistical relevance and interactions between factors when the factors with high multiplier value are combined, like experience, procedures and ergonomics. These outcomes can be useful in the enhancement of work context in order to reduce errors.

Keywords: Human Reliability Analysis, Performance Shaping Factors, Human error modelling and simulation

1. INTRODUCTION

The identification, assessment and reduction of risks are one of the most important elements of health and safety at work (Fera and Macchiaroli 2009). Evidence in the literature shows that human actions are a source of vulnerability for industrial systems (Griffith and Mahadevan 2011, De Felice et al. 2012, Di Pasquale et al. 2013, Iannone et al. 2004). In the workplace human errors can have serious consequences such as accidents, malfunctions and quality defects in the performed task.
Human Reliability Analysis (HRA) is carried out, as part of the Probabilistic Risk Assessment (PRA), to identify and to quantify human actions and the associated impacts on structures, systems, and components of complex facilities, through the forecast of the events that can occur during the working activity. The HRA field aims to identify the causes and sources of human errors and to provide a numeric estimate of the human error probabilities (HEP). HRA typically encompasses three phases (see Figure 1), ranging from identifying error sources, to modelling these errors as part of a systemic analysis including hardware failures, to quantifying the HEPs (Boring 2010).

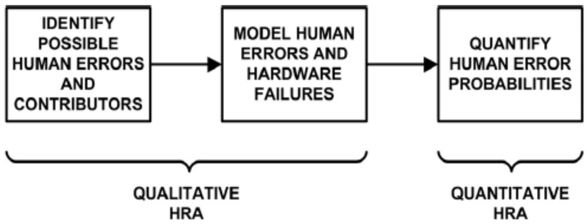

Figure 1: Three Phases of HRA (Boring 2010).

One of the undisputed assumptions in all HRA method is that the human performance depends on the conditions under which the tasks or activities are carried out (De Ambroggi and Trucco 2011). In the HRA methods, conditions that influence human performance are often referred by term performance shaping factor (PSF). They are used in qualitative approaches in order to identify contributors to human performance, while in quantitative ones, they are used to estimate a more realistic HEP. These contextual factors characterize significant facets of human error and they are environmental or personal factors, that have the potential to affect the man performance positively or negatively (Di Pasquale et al. 2013). Therefore, identifying and quantifying the PSF effects are key steps in the process of HRA (Griffith and Mahadevan 2011).
In this paper a simulative analysis of PSFs impact on human reliability in manufacturing activities was carried out thanks to the Simulator for Human Error Probability Analysis (SHERPA), recently proposed in literature. The tool is able to estimate human reliability for different workplaces and to assess the impact of context via several performance shaping factors, as described below (Di Pasquale et al. 2015).
Such factors require an evaluation to understand how they affect human reliability, above all considering their mutual interactions. The influence of every PSF level considered both in singular way and combining with the others factors, was quantified through numerous simulations in SHERPA. The one-factor-at-a-time

(OFAT) method was used to evaluate singularly the levels of each factor, while the analysis of variance (ANOVA) allowed to realize if there is more or less dependence between them.
The simulation outcomes can be useful in the enhancement of work context in order to reduce errors. The main conclusion is that the consideration of the factors influencing human performance is very important in the identification of the corrective action to reduce the risk (Farcasiu and Prisecaru 2012).
The paper is organised as follows. Section 2 summarises the state-of-the-art on performance shaping factors. Section 3 describes the SHERPA model and the PSFs using in it. Section 4 describes the methodology issues related to the simulative analysis. Section 5 shows the simulation results and analyses them. Finally the last section summarises the main findings and the conclusions.

2. STATE-OF-THE-ART PERFORMANCE SHAPING FACTORS

The PSFs are determined by the individual characteristics of the human being, the environment, the organization or the activity that enhances or decreases human performance and increases or decreases the likelihood of human error. Their goal is to provide measures to account for human performance. Performance shaping factors (PSFs) encompass those influences that enhance or degrade human performance. PSFs are used within human reliability analysis (HRA) methods to identify contributors to human errors and to provide a basis for quantifying those contributors systematically. While completing an HRA, an analyst may review a list of possible PSFs to identify possible sources of human error. The analyst may subsequently use predefined error rates associated with specific PSFs to determine a human error probability for a given task or situation (Boring et al. 2007). The PSFs are an integral part of the modelling and characterization of errors and play an important role in the HRA process.
The first-generation HRA methods are less concerned with what people are likely to do than with whether they will succeed or fail (Lee et al. 2011). None of these approaches consider explaining how the PSFs exert their effect on performance. PSFs such as managerial methods and attitudes, organizational factors, cultural differences, and irrational behaviour are not adequately treated in the first-generation. On the contrary, the second-generation considers the context in which humans make errors and derives PSFs based on these contexts. PSFs in the first-generation HRA methods were mainly derived by focusing on the environmental impacts on operators, whereas in the second one they were derived by focusing on the cognitive impacts on operators (Lee et al. 2011).
Within HRA, PSFs are often categorized as internal or external, corresponding to the individual vs. situational or environmental circumstances, respectively, that brings to bear on performance. The research literature divides the PSFs into two other categories: direct and indirect measures of human performance (Boring et al. 2007). While some popular PSFs such as “time needed to complete a task” are directly measurable, other PSFs, such as “fitness for duty,” can primarily be measured indirectly through other measures and PSFs, for example through fatigue measures.
Their definition and classification, although complex and variable, have been carefully detailed by researchers who have proposed over time numerous taxonomies. There has been a greater emphasis recently to catalogue ways in which PSFs might also enhance performance and to develop taxonomy of performance influencing factors for HRA of emergency tasks (Lee et al. 2011, Kim and Jung 2003, Boring 2010).
On the other hand, the interrelationships between PSFs gain much attention from the HRA community. Despite continuing advances in research and applications, one of the main weaknesses of current HRA methods is their limited ability to model the mutual influence among PSFs, intended both as a dependency among the states of the PSFs dependency among PSFs influences on human performance, as shown in Figure 2 (De Ambroggi and Trucco 2011).

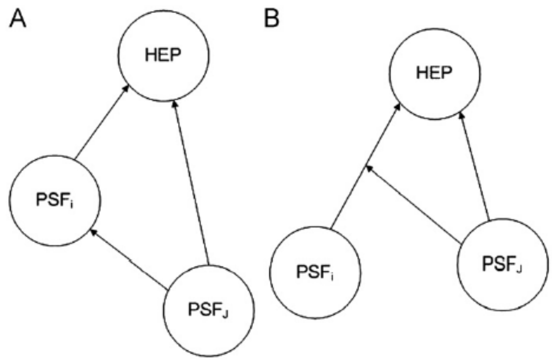

Figure 2: Possible types of dependency between PSFs: (A) dependency between the states/presence of the PSFs and (B) dependency between the state of PSFj and the impact of PSFi over the HEP.

Very different conceptual and analytical models are proposed for describing how these factors exert their influence on the human error probability; indeed if a PSF has an effect on human performance it is crucial to account for how this influence comes about. Several studies argued that the dependency between PSFs should be included in the quantification of HRA and suggested that the Bayesian network (BN) would be a promising technique because it can describe the casual relationship between PSFs (Groth and Swiler 2013, Groth and Mosleh 2012).
The study of De Ambroggi and Trucco (2011), instead, deals with the development of a framework for modelling the mutual influences existing among PSFs and a related method to assess the importance of each PSF in influencing performance of an operator, in a specific context, considering these interactions.

3. PERFORMANCE SHAPING FACTORS IN SHERPA

Di Pasquale et al. (2015) proposes a new use of HRA methodologies for human behaviour modelling and simulation through the implementation of a Simulator for Human Error Probability Analysis (SHERPA), which aims to predict the likelihood of operator error, for a given scenario, in every kind of industrial system or other type of working environment. SHERPA exploits the advantages of the simulation tools and the traditional method HRAs and it is able to estimate human reliability and the impact of context via PSFs.

Unlike many existing HRA methods, that are deeply qualitative and include excessive levels of detail for many assessments, SHERPA focuses on the quantitative aspect in order to obtain a significant numerical result in terms of HEP.

Furthermore SHERPA is suitable for any environment and working conditions, without limitations related to a particular sector or activity; while first and second generation HRA methods have been developed for specific contexts (e.g. aviation or nuclear power plants) and applications (e.g. single operator or crew simulation). Methods such as THERP (Technique for Human Error Rate Prediction), CREAM (Cognitive Reliability and Error Analysis Method) or SPAR-H (Standardized Plant Analysis Risk-Human Reliability Analysis method) were born and are used mainly in the nuclear field and so much effort needs to be applied in different fields, such as manual assembly or manufacturing systems (Di Pasquale et al. 2015). SHERPA can be used in the preventive phase, as an analysis of the possible situations that may occur and for the evaluation of the percentage of scraps or noncompliant processing due to human error and in post-production to understand the nature of the factors that influence human performance in order to reduce errors (Di Pasquale et al. 2015).

The working environment and the operator conditions in SHERPA are taken into account considering the performance shaping factors of SPAR-H method. While many HRA methods have often proposed a large number of PSFs, even as many as fifty, SPAR-H attempts to provide a reasonable coverage of the influence spectra of human performance in a reasonable minimum number of PSFs. The eight PSFs are:

- available time;
- stress;
- complexity;
- experience and training;
- procedures;
- cognitive ergonomics;
- fitness for duty;
- work process.

The decision to use only eight PSFs in SPAR-H is based on a review of the available HRA methods and the behavioural sciences (Boring 2010). In SHERPA this number is increased because of the sub-factors modelled for stress, complexity and work processes (see Table 1).

Table 1. Sub-factors modelled in SHERPA.

	PERFORMANCE SHAPING FACTORS		
	Stress	***Complexity***	***Work processes***
Sub-factors	- Circadian rhythm - Mental stress - Pressure time - Workplace - Microclimate - Lighting - Noise - Vibrations - Ionizing and non-ionizing radiations	- General complexity - Mental efforts required - Physical effort required - Precision level of the activity - Parallel tasks	- General work processes - Communi-cation and integration in team work

The effects of PSF on the HEP are summarized in the following equation (Boring 2010):

$$HEP_c = HEP_n \cdot PSF = \begin{cases} 0 < PSF < 1 \rightarrow HEP_c < HEP_n \\ PSF = 1 \quad\;\; \rightarrow HEP_c = HEP_n \\ PSF > 1 \quad\;\; \rightarrow HEP_c > HEP_n \end{cases} \quad (1)$$

Where HEP_c and HEP_n are respectively the contextual and nominal HEP. Each PSF can have both positive and negative effects on performance. When the PSFs represent a positive effect, the different levels of effect for the PSFs correspond to a value less than one. Multiplying a nominal HEP by this fractional value associated with the PSF serves to decrease the overall HEP. When the PSFs represent a negative effect, the different levels of effect for the PSFs correspond to a value greater than one. Multiplying the nominal HEP by this positive integer serves to increase the overall HEP. When the PSFs are thought to have no effect, the PSF multiplier is set to one, thereby neither increasing nor decreasing the overall HEP.

The tool proposed quantifies the contextual HEP as following:

$$HEP_{\;contextual} = \frac{HEP_{nominal} \cdot PSF_{composite}}{HEP_{nominal} \cdot (PSF_{composite} - 1) + 1} \quad (2)$$

Where $PSF_{composite}$ is calculated as:

$$PSF_{composite} = PSF_1 \times \ldots \times PSF_x \times \ldots \times PSF_8 \quad (3)$$

Where PSF_x is the multiplier for each PSF considered in SPAR-H (Table 2). The multiplier values were attributed by analysts of the method, on the basis of several studies carried out on nuclear power plants. In order to align the evaluation of PSFs in SHERPA model, the multipliers were standardized assigning corrective coefficients for different kind of simulated task (Di Pasquale et al. 2015).

The SHERPA model was implemented in an Arena template that allows doing easily and without time consuming a lot of simulations. The tool is suitable for assessing the PSFs influencing on HEP, having regard to all the possible combinations. Figure 3 shows the main dialogue from that the PSF levels can be clearly selected.

Table 2. Performance shaping factors in SHERPA and corresponding multipliers (Di Pasquale et al. 2015).

SPAR-H PSFs	PSF Levels	Multipliers Action	Multipliers Diagnosis
Available Time	*Inadequate Time*	HEP=1	HEP=1
	Barely adequate time	10	10
	Nominal time	1	1
	Extra time	0.1	0.1
	Expansive time	0.01	0.01
Stress/ Stressors	*Extreme*	5	5
	High	2	2
	Nominal	1	1
Complexity	*Highly complex*	5	5
	Moderately complex	2	2
	Nominal	1	1
	Obvious diagnosis	-	0.1
Experience/ Training	*Low*	3	10
	Nominal	1	1
	High	0.5	0.5
Procedures	*Not available*	50	50
	Incomplete	20	20
	Available, but poor	5	5
	Nominal	1	1
	Diagnostic/ symptom oriented	-	0.5
Ergonomics	*Missing/ Misleading*	50	50
	Poor	10	10
	Nominal	1	1
	Good	0.5	0.5
Fitness for Duty	*Unfit*	HEP=1	HEP=1
	Degraded Fitness	5	5
	Nominal	1	1
Work Processes	*Poor*	5	2
	Nominal	1	1
	Good	0.5	0.8

4. METHODOLOGY

The influencing factors play a key role in the modelling of human error and many theoretical studies have been carried out to define, to classify and to model these factors as above. The aim of this paper is the study of parameters that affect the human performance in workplace, considering how they increase or decrease the human error probability. The simulative analysis focuses the attention on factors previously described and used in SHERPA.

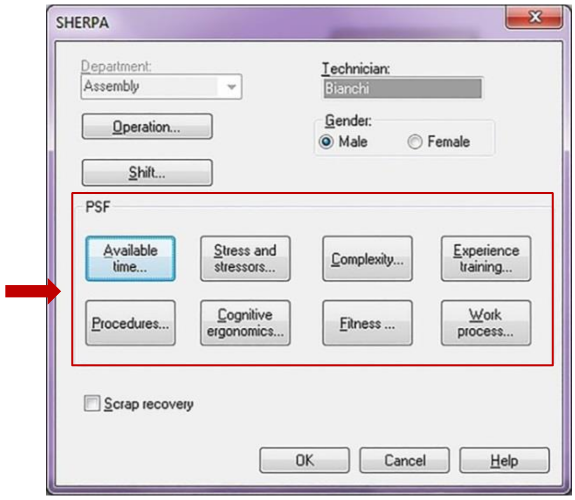

Figure 3. Main dialogue SHERPA.

The influence of every PSF level considered both in singular way and combining with the others factors, was quantified through numerous simulations with the SHERPA template. The following briefly describes the basic steps used in the simulation process:

1. Problem definition: description of the case study.
2. Experiment planning and system definition: identification of the system components to be modelled and the performance measures to be analysed.
3. Experiment execution.
4. Results analysis: list of results and discussion of study implications.

4.1. Problem definition

A manufacturing activity was simulated in an Arena model for the research purpose of this study. The construction of the simulation model takes hint from the description of different assembly stations proposed in literature (Falcone et al. 2010, Falcone et al. 2011). In particular, the Arena model reproduces the operator work station involved in manual assembly on an eight-hour shift, considering 235 working days (Figure 4).

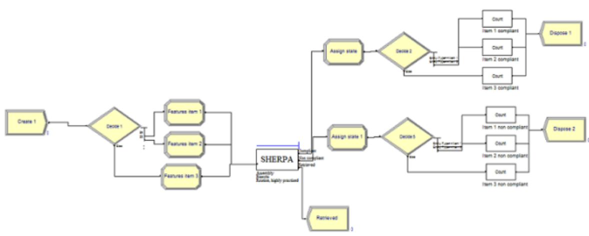

Figure 4: Simulative model used in the study.

A 30-minute break after 4 hours for the shift start is scheduled. The simulations were performed considering the assembly activities belonging to the action category: routine, highly-practiced, rapid task involving relatively low level of skill. The assembly operation was simulated for three different items with random arrival sequences based on a production mix and with processing times characterized by a triangular distribution, with vertices corresponding to the mean ±10%. For each item, processing times, fixed and variable costs and selling prices, as well as overall production mix, were defined and are shown in Table 3.

Table 3. Features of simulated items in the case study.

Features	Item 1	Item 2	Item 3
Mean processing time (min.)	25	36	45
Setup time (min.)	5	5	5
Price (€)	115	155	200
Fixed cost (€)	52	65	78
Variable cost (€)	18	24	32
Productive mix	25%	35%	40%

4.2. Experiment planning and system definition

The SHERPA template allows to model the context and the psycho-physical condition of the operator through 21 PSFs, both main and secondary.

Every PSF impacts in a different way on nominal HEP. SPAR-H method, in fact, uses a nonlinear levels classification and the levels classes are different for every PSF. In the case of available time, for example, there are four levels in addition to the nominal case, while stress or work processes have only two levels. Consider all these factors with a full factorial analysis, would be to make 2^{21} = 2097152 simulations, taking into account just two levels per factor. For this reason in the experiment planning a selection of the potentially most significant PSFs was been necessary.

Firstly, all factors have been classified (as reported in Table 4) compared to the experiment context in:

- Controllable: you can manage and define values in advance, as the input of the experiment itself.
- Uncontrollable: are out of hand when they appear; may change during operation of the product or process.
- Measurable: able to be measured; not subjective, perceptible or significant.
- Unmeasurable: not able to be measured objectively.

The proposed classification has been useful in the subsequent selection of the most relevant factors for the goal of simulative analysis. The choices of the factors have taken into account this classification, considering at least a factor by category.

In the second step a common method of investigating the effects of parameters on a process has been applied. The one-factor-at-a-time (OFAT) method allows to change only one factor at a time, to assess the impact of factors considered one at a time instead of all simultaneously and to notice its influence on a given response. Although this method has the advantage of being simple, it requires a large number of trials and does not point out the possible interactions between several factors.

Table 4: Factors classification in terms of measurability and controllability.

	Measurable	Unmeasurable
Controllable	Available time Parallel tasks Microclimate Lighting	Workplace Procedures Precision level Physical effort Mental effort Cognitive ergonomics
Uncontrollable	Circadian rhythm Experience Noise Vibrations Radiations	General complexity Work processes Mental stress Fitness for duty Pressure time Communication

In our study the PSF levels have been modified one at a time keeping the others at nominal level. The contextual HEP value and the PSF composite were calculated for every simulation. Some factors have been set to scenario: microclimate, lighting, circadian rhythm and physical effort, the last one is related to the performed task). Downstream the simulations, the results were analysed and for each factor the ratio between the percentage variation of contextual HEP and PSF composite was considered (Table 5). It can be clearly seen that the increase of the PSF level determines an increase of the PSF composite and a consequent increase in the probability of error.

The negative changes, such as extra and expansive available time or good cognitive ergonomics, represent the positive effect of the factors on the performance, as seen above. A special factor is the experience. This factor, in fact, determines a very high increase of HEP (ΔHEPc=97.85%) with a modest increase in PSF composite (ΔPSFc=20.63%). Factors with similar changes in their PSF composite, for example the general complexity (ΔPSFc=15.25%) or mental stress (ΔPSFc=26.47%), respectively determine increments of HEP equal to 1.89% and 3.57%. This exception will be thorough better later.

Previous evaluations have been used to select the factors for the next step considering the factors with more impact on HEP and mainly representative of a manufacturing context.

With the aim of reducing the number of runs the parameters *available time*, *state of workplace*, *vibrations*, *radiations*, *pressure time*, *precision level*, *mental efforts* and *communication and integration in team work* were excluded. All these factors were set to the nominal level in the experimental stage and they have not had their influence on HEP.

Table 5: PSF effect on contextual HEP.

SPAR-H PSFs	PSF Levels	ΔHEPc%	ΔPSFc%	ΔHEPc%/ ΔPSFc%
Available Time	*Inadequate*	98.73	not available	not available
	Barely adequate	84.09	85.29	0.9859
	Nominal	0	0	-
	Extra	-1355.27	-1370.59	0.9888
	Expansive	-14409.55	-14605.88	0.9865
Mental stress, Pressure time and Noise	*Extreme*	18.96	70.59	0.2687
	High	3.57	26.47	0.1348
	Nominal	0	0	-
Radiations and Vibrations	*Extreme*	10.39	54.54	0.1904
	High	1.89	15.25	0.1236
	Nominal	0	0	-
Workplace	*Extreme*	10.39	70.59	0.1472
	High	1.89	26.47	0.0713
	Nominal	0	0	-
General complexity, Precision level, Mental efforts, Parallel tasks	*Highly complex*	30.67	70.59	0.4346
	Moderately complex	6.24	26.47	0.2356
	Nominal	0	0	-
Experience/ Training	*Low*	97.85	20.63	4.7421
	Nominal	0	0	-
	High	-191.72	-1.94	0.9877
Procedures	*Not available*	95.72	97.06	0.9862
	Incomplete	91.37	92.64	0.9863
	Available, but poor	69.67	70.59	98.69
	Nominal	0	0	-
Cognitive Ergonomics	*Missing*	95.72	97.06	0.9862
	Poor	84.09	85.29	0.9859
	Nominal	0	0	-
	Good	-191.72	-194.12	0.9877
Fitness for Duty	*Unfit*	98.73	not available	not available
	Degraded Fitness	69.66	70.58	0.9869
	Nominal	0	0	-
Work Processes and Communi-cation	*Poor*	53.95	77.27	0.6981
	Nominal	0	0	-
	Good	-48.71	25.37	-1.92

Based on this assessment and taking into account the classification of the factors in terms of measurability and controllability were chosen the most significant factors:

- noise;
- mental stress;
- general complexity;
- parallel tasks;
- experience;
- procedures;
- work processes;
- fitness for duty;
- cognitive ergonomics.

For the chosen factors have been considered only two levels from those available for the analysis:

- Noise: Extreme and Nominal levels;
- Mental stress: Extreme and Nominal levels;
- General complexity: High and Nominal levels;
- Parallel tasks: High and Nominal levels;
- Experience: Low and Nominal levels;
- Procedures: Incomplete and Nominal levels;
- Work processes: Poor and Good levels;
- Fitness for Duty: Degraded and Nominal levels;
- Ergonomics: Poor and Good levels;

4.3. Experiment execution
In the system definition, nine factors were selected with two levels for each one. In this condition we can define the number of simulations to be performed to analyse the scenarios provided by all possible combinations of PSFs and to evaluate their effect on the likelihood of operator error; they are $2^9 = 512$ simulations. The experiment was conducted simultaneously changing the levels of selected factors until you cover the entire experimental plan.

5. RESULTS ANALYSIS

5.1 Discussion
Analysis of variance (ANOVA) was used to examine the effect of significant PSFs on the HEP (Gelman 2005, Scheffe 1999). This method, developed by Fisher, is at the basis of many designs of experiments and is used to compare differences of means among more than two groups. It does this by looking at variation in the data and where that variation is found. Specifically, ANOVA compares the amount of variation between groups with the amount of variation within groups. It can be used for both observational and experimental studies.
In performing ANOVA the experimental factors and the dependent variable or response are identified. The experimental factors are the source of variability whose effect is to be determined based on the results of a dependent variable or response. In the case of study, experimental factors are therefore the PSFs, while the dependent variable is the contextual HEP.

The simplest experiment suitable for ANOVA analysis is the experiment with a single factor, used in a first time to assess the impact of each factor on HEP. Table 6 lists the one-way ANOVA results. The SS stands for Sum of Squares; F-ratio is test statistic used for ANOVA, the p-value is the probability of being greater than the F-ratio. The F is a ratio of the variability between groups compared to the variability within the groups. The F-ratio will always be at least 0, meaning that it is always nonnegative. The p-values in the last column are the most important information contained in this table. The statistical significance of the effect depends on the p-value, as follows:

- If the p-value is larger than the significance level you selected, the effect is not statistically significant.
- If the p-value is less than or equal to the significance level you selected, then the effect for the term is statistically significant.

Usually, a significance level (denoted as α or alpha) of 0.05 works well. A significance level of 0.05 indicates a 5% risk of concluding that an effect exists when there is no actual effect.
Figure 5 shows the results for all the chosen factors and it underlines graphically the different impacts on error likelihood. Each graph represents the average value of HEP when the factor is set to level one or two. The vertical bars indicate the level of confidence at 95% that is the probability that the calculated values fall in this range. It is to be noted that when the bars are large the possible values are very different from each other and fluctuate around a mean value. The most influential factors (experience, procedures and cognitive ergonomics) have a very tight confidence interval, a sign of their strong impact in the calculation of the error probability.

Table 6: One-way ANOVA results.

FACTORS	SS	F-ratio	p-value
Mental stress	0.046	0.362	0.548
Noise	0.046	0.362	0.548
General complexity	0.128	1.013	0.315
Parallel tasks	0.128	1.013	0.315
Experience	*25.196*	*327.178*	*0.00*
Procedures	*11.565*	*111.289*	*0.00*
Work processes	*2.073*	*16.942*	*0.000045*
Fitness for duty	*1.746*	*14.199*	*0.000184*
Cognitive ergonomics	*18.061*	*198.465*	*0.00*

Through this first analysis the greatest difference of average HEP is easily observed for those factors that have the two multipliers more distant from each other, like procedures and ergonomics. The experience is an exception, because it has a strong impact on the

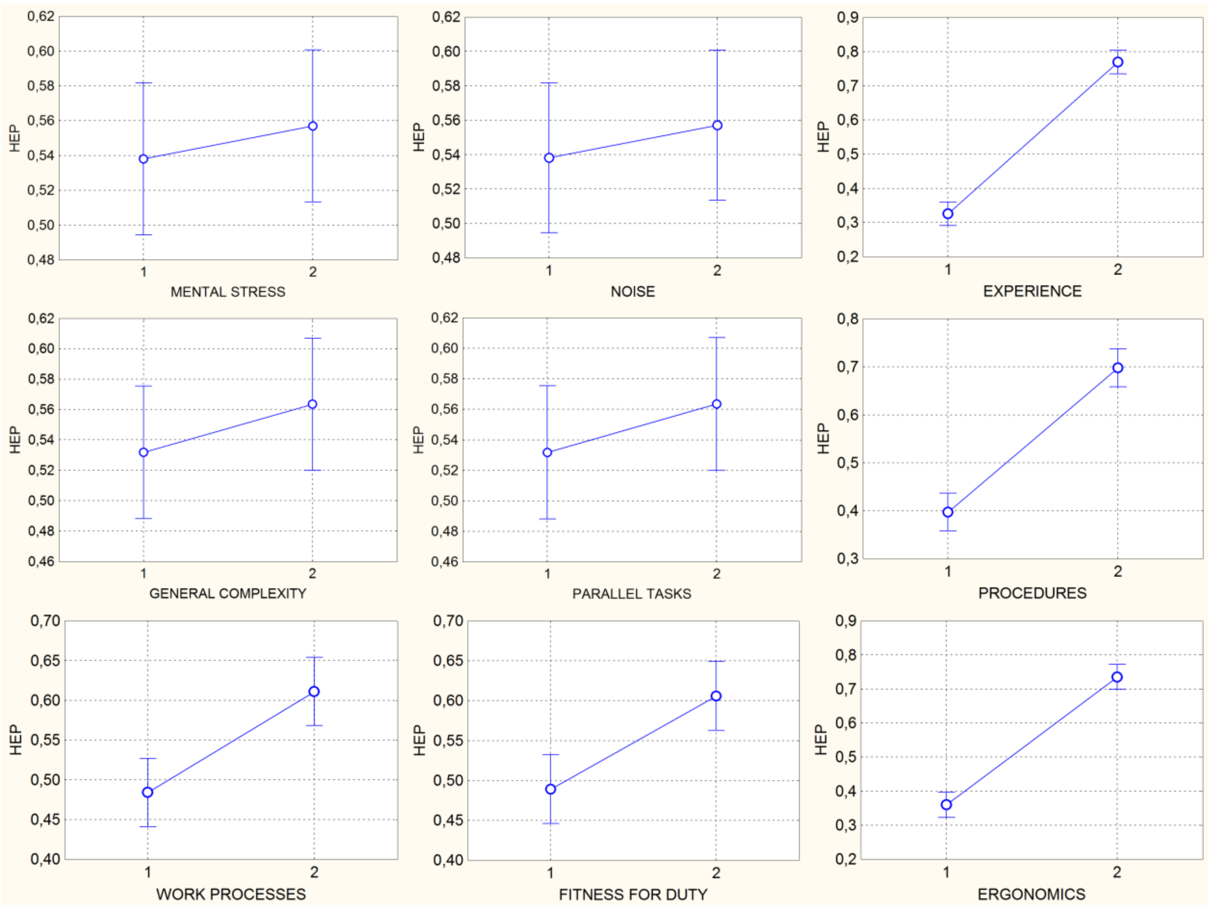

Figure 5. Single factor Analysis of Variance.

probability of error despite its multipliers are comparable to those of stress and complexity. Such behaviour is also clear in the two-way ANOVA.
The two-way analysis of variance is an extension of the previous one-way, which examines the influence of two different factors and aims at assessing if there is any interaction between factors and how the contemporary presence of two factors affects the variable result. Through this second step of analysis, the interrelationships between multiple PSFs were examined. Also in this case the p-value is used as an indicator to determine if the two factors have a significant interaction when considered simultaneously. If one factor depends strongly on the other, the F-ratio for the interaction term will have a low p-value.
The two-way ANOVA table is structured just like the one-way. Table 7, in fact, shows the SS, the F-ratio and the p-value for all factors combinations.
There is a statistically significant interaction between the effects of experience and procedures on HEP (p-value= 0.021<0.05), so the effect on the mean outcome of a change in one factor depends on the level of the other factor (Figure 6). The significant relationship between these factors depends also on the high impact on HEP of single factors. For all the other combinations there is not statistical dependence. In fact their p-values are included between 0.135 (experience x cognitive ergonomics) and 1.000 (mental stress x work processes). For example, in Figure 7 the interaction between mental stress and noise (p-value=0.976) shows clearly the statistical independence: the effects of a change in one factor on the outcome do not depend on the value or level of the other factors.

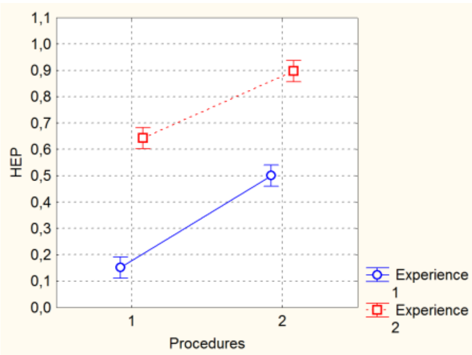

Figure 6. Procedures x Experience ANOVA results.

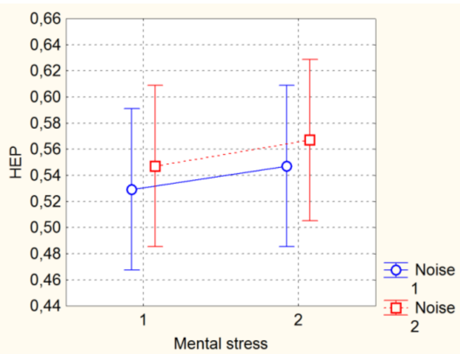

Figure 7. Mental stress x Noise ANOVA results.

Table 7: Two-way ANOVA results.

FACTORS			SS	F ratio	p-value
Mental stress	x	Noise	0.0001	0.001	0.976
Mental stress	x	General complexity	0.0006	0.004	0.946
Mental stress	x	Parallel tasks	0.0006	0.004	0.946
Mental stress	x	Experience	0.0107	0.138	0.710
Mental stress	x	Procedures	0.0007	0.007	0.934
Mental stress	x	Work processes	0.0000	0.000	1.000
Mental stress	x	Fitness for duty	0.0003	0.002	0.963
Mental stress	x	Ergonomics	0.0021	0.022	0.881
Noise	x	General complexity	0.0006	0.004	0.946
Noise	x	Parallel tasks	0.0006	0.004	0.946
Noise	x	Experience	0.0107	0.138	0.710
Noise	x	Procedures	0.0007	0.007	0.934
Noise	x	Work processes	0.0000	0.000	1.000
Noise	x	Fitness for duty	0.0003	0.002	0.963
Noise	x	Ergonomics	0.0021	0.022	0.881
General complexity	x	Parallel tasks	0.0008	0.006	0.937
General complexity	x	Experience	0.0162	0.211	0.646
General complexity	x	Procedures	0.0013	0.012	0.912
General complexity	x	Work processes	0.0001	0.001	0.976
General complexity	x	Fitness for duty	0.0002	0.002	0.965
General complexity	x	Ergonomics	0.0028	0.031	0.860
Parallel tasks	x	Experience	0.0162	0.211	0.646
Parallel tasks	x	Procedures	0.0013	0.012	0.912
Parallel tasks	x	Work processes	0.0001	0.001	0.976
Parallel tasks	x	Fitness for duty	0.0002	0.002	0.965
Parallel tasks	x	Ergonomics	0.0028	0.031	0.860
Experience	**x**	**Procedures**	**0.2884**	**5.348**	**0.021**
Experience	x	Work processes	0.0534	0.731	0.393
Experience	x	Fitness for duty	0.1571	2.135	0.145
Experience	x	Ergonomics	0.0926	2.237	0.135
Procedures	x	Work processes	0.0000	0.000	0.992
Procedures	x	Fitness for duty	0.0012	0.012	0.913
Procedures	x	Ergonomics	0.0075	0.109	0.742
Work processes	x	Fitness for duty	0.0001	0.001	0.973
Work processes	x	Ergonomics	0.0021	0.024	0.876
Fitness for duty	x	Ergonomics	0.0002	0.003	0.960

The experience is the most interesting factors. As already highlighted by the OFAT and one-way ANOVA analysis, the experience has one of the major impact on the error probability. This effect is further confirmed by the interactions between factors (Figure 8). The level two of experience determines a considerable decrease of human reliability and consequent increase in error probability when it is combined with every factor (i.e. mental stress, general complexity, cognitive ergonomics and procedures). The strong impact does not depend exclusively from the multiplier, but it derives also by the logic experience evaluation used by the model. The lack of knowledge of the processes, of the machines and of the procedures modifies the nominal HEP, because it impacts on the category of performed task, which can no longer be regarded as routine and highly-practiced.

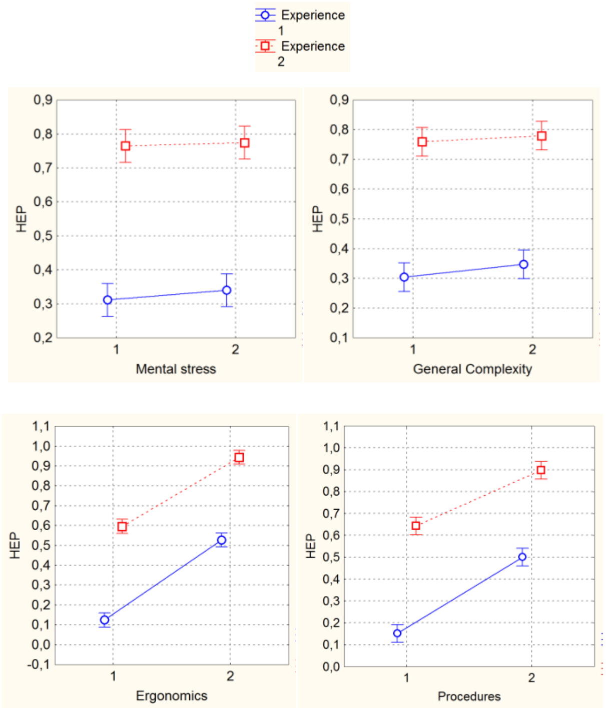

Figure 8. Comparison of the interactions with experience.

6. CONCLUSION

The performance shaping factors are an integral part of modelling and characterization of errors and they affect the productivity and the efficiency at work. Their modeling is a problem for each HRA method. Many HRA approaches introduce widespread PSF taxonomies and complex modeling of their mutual influence. Despite the efforts of HRA experts, the PSFs have not explicit role both in error identification and in probability estimation yet. The goal of this paper has been to analyse the PSFs, used in the SHERPA model, and to assess their impact on HEP in order to improve the model and to make it more responsive to working reality.

Thanks to the simulative analysis and to the results obtained from one and two way ANOVA, the influence of every PSF level, considered both in singular way and combining with the others factors, was quantified and evaluated, allowing to realize if there is more or less dependence between them.

Several useful considerations can be made downstream of the study. First of all, through the preparatory OFAT analysis the different PSF impacts on HEP in relation to the value of its multiplier is evident. It is certainly useful as a starting point for the improvement of PSF modelling, that is currently under investigation.

The one-way ANOVA underlined the higher or lower impact on HEP of individual factors. While the results of two-way ANOVA highlight few interactions between factors. There is significance of impact only when the experience is combined with the procedures. As regards the experience, its special behavior requires further investigations and studies.

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