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Improving the Assessment of Human Barriers: an Innovative Methodology for the Energy Industry

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The present contribution aims at providing an innovative method for the assessment of human barriers, specifically addressing the framework of the energy industry, including offshore operations. Introducing a revised framework to analyse human errors, the methodology developed aims at extending the current Human Reliability Analysis (HRA) methods including psychosocial factors and barriers. The new methodology was developed extending and tailoring to the specific context the well-known framework set by two widely used HRA methodologies (SPAR-H and HEART). An innovative holistic framework, dedicated to the wide range of operations of the energy industry, was developed to assess human error probability (HEP). Human factors were considered safety barriers against human error: more specifically, workers were considered having an active role in shaping their own performance. The method developed introduced a revision of the Generic Task Types (GTT). Each GTT was then associated with a Nominal Error Probability (NEP). The NEP is then modified by the assessment of correction factors obtained from the assessment of conditions affecting task performance, in analogy with the Performance Shaping Factors (PSF) approach introduced by SPAR-H. The method proved to be easy to apply and the results obtained clearly show that human factors play a significant role in preventing workers from making errors while performing tasks by reducing human error probability.

1. Introduction

Human error is one of the principal causes of accidents and incidents in several industrial sectors and activities. Statistics show that, among several others, the chemical and petrochemical (Kariuki and Lowe, 2007), the nuclear sector (Reason, 1990) and the marine sectors (Ren et al., 2008) are specifically affected by human error when accident causes are considered. A widely used technique to assess human error probability is human reliability analysis (HRA). HRA is a widely used tools to enhance reliability and safety in industrial activities and complex socio-technical systems. A number of different HRA methodologies are available to assess human error associated to task or work performance (Mosleh et al., 2006). Among the conventional HRA methodologies of general use, Human Error Assessment and Reduction Technique (HEART) (Williams, 1988) and the Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) (Whaley et al., 2012) are two of the most extensively applied tools. Both methods are based on the assumption that human error probability may be estimated starting from specific factors as the working context, the type of task, the working environment and others. Actually, human error probability is effectively assessed by these methodologies, although both do not account for the possible active role of workers and the psychosocial dynamics involved in working performance. Actually, the transformation of tasks and systems in current working environments hinder the application of conventional HRA methods, requiring the development of a new generation of HRA models, able to cope with

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the new problems and issues posed by the modern workplace. The key importance of human factors in determining system failure and safety performance is evidenced by a number of different studies, addressing different activities (Zhen et al., 2020). Thus, the advancement of HRA methods requires to include the cognitive and affective processes and organizational factors that influence the performance of workers. In particular, the safety culture and the safety climate need to be included, considered these ad psychosocial "barriers", contributing to prevent accidents and incidents, also mitigating their consequences.
The present study aims at the development of a specific methodology to analyze human errors and assess human error probability, based on the inclusion of psychosocial factors to determine specific safety barriers affecting human error probability (HEP). Although having general validity, the methodology was developed within an energy company, considering the specific tasks carried out by workforce.

2. Methodology

2.1 Outline

In the model proposed, human error probability is the product of the interaction among three elements: the type of task to be performed (generic task type, GTT), the conditional factors affecting performance (performance shaping factor, PSF), and human factors (human barriers, HB), deriving from the human and organizational factors aimed at preventing errors from the workers.
As shown in Figure 1, the assessment of HEP is carried out in four steps: 1) Determination of task type; 2) Assessment of the performance shaping factors; 3) Assessment of direct and safeguard barriers; and 4) Calculation of integrated HEP. The single steps of the procedure are discussed in the following.

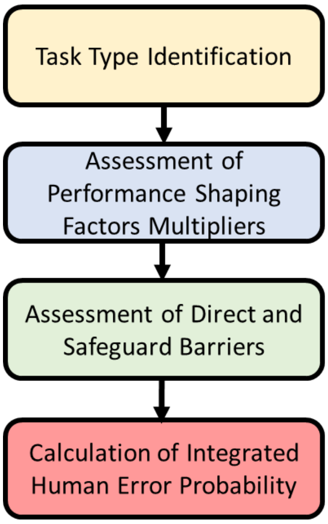

Figure 1: Methodological steps for the calculation of Human Error Probability (HEP).

2.2 Task type identification

In an energy company, carrying out a number of different tasks requiring a high level of complexity and cognitive load is required to workforce. Therefore, the classification of a task as “diagnostic” or “action” might be complex, not allowing to distinguish between the tasks under analysis. Starting from the Generic Task Types (GTT) introduced in the HEART methodology, seven GTT originally proposed by Williams et al. (2016) were revised and modified according to the specific organizational context. As in the HEART methodology, a Nominal Error Probability (NEP) was determined for each GTT. Table 1 shows the GTTs and the NEPs considered in the methodology developed.

2.3 Assessment of Performance Shaping Factor Multipliers

The second step of the proposed methodology consists in the identification and assessment of the factors affecting performance. Also in this case, the methodology developed aimed at building on and improving the SPAR-H and HEART methods. A revised version of SPAR-H Performance Shaping Factors (PSFs) was used, aimed at adapting the original PSFs to the specific context. Coherently with the approach proposed by Laumann (2016), only the more relevant PSFs were considered. The PSFs included in the model are presented in table 2.

Table 1: Definition of Generic Task Types (GTT) and of Nominal Error Probability (NEP)

Definition	GTT	NEP
A totally unfamiliar task, performed at speed	A	$5.5 \cdot 10^{-1}$
Shift or restore the system to a new or original state on a single attempt without supervision	B	$2.6 \cdot 10^{-1}$
A complex task requiring a high level of comprehension and skill CF15	C	$1.6 \cdot 10^{-1}$
Routine, highly practised, a rapid task involving a relatively low level of skill	D	$2.0 \cdot 10^{-2}$
Restore or shift a system to original or new state following procedures, with some checking	E	$3.0 \cdot 10^{-3}$
Respond correctly to system command even when there is an augmented or automated supervisory system	F	$2.0 \cdot 10^{-5}$

In order to assess the influence the different PSFs on human reliability, a score, used as a multiplier of the error probability, was determined for each PSF. These have been identified through the review of SPAR-H methodology carried out by Laumann et al. (2016), and they have been modified according to the contextual needs of the oil & gas industry (Bye et al., 2016). Table 3 describes the multipliers proposed for each PSF. A composite probability shaping factor (PSFC) is then calculated from the multipliers assigned:

$$\mathrm{PSFC} = \prod_{i=1}^{n} PSF_i \tag{1}$$

Where PSF_i is the value of the multiplier attributed to the i-th PSF and n is the total number of PSFs considered.

Table 2: Performance shaping factors (PSF) and multipliers

Definition of PSF	Condition	Multiplier
Available time	Inadequate time	100
	Barely adequate time	50
	Limited time	10
	Nomina	1
	Extra time	0.1
Threat stress	Very threatening	5
	Moderately threatening	2
	Nominal	1
Complexity	Overly complex	50
	Moderately complex	10
	Nominal	1
	Simplified task	0.1
Experience/Training	Mismatch between knowledge or skills and correct behaviour	100
	No experience/training	50
	Low experience/training	15
	Nominal	1
	Extensive experience/training	0.1
Procedures	No procedures available or not used	50
	Very poor procedures	20
	Poor procedures	5
	Adequate procedures	1
	Exceptionally good procedures	0.5
Human-Machine Interaction	Completely inadequate	100
	Inadequate	50
	Barely adequate	10
	Adequate	1
	Specifically designed to ease the task	0.5
Environmental context	Environmental conditions do not allow to perform the task	100
	Adverse condition	10
	Nominal	1
Fatigue	High	100
	Moderate	10
	Nominal	1

2.4 Assessment of Direct and Safeguard barriers

In order to identify the barriers that need to be considered in the model, a first distinction among direct and safeguard barriers is introduced, based on the specific role they have in preventing human error. Direct barriers influence human behavior directly, while safeguard barriers represent the layers of defense that determine the availability and quality of direct barriers. A pool 20 psychosocial dimensions relating to both safeguard and direct barriers were identified through a literature review focused on human factors related to safety in organizations (Hamer et al., 2021, Newaz et al., 2018). The method of Lynn (1986) was applied to assess the content validity of barriers: a specific form was used to consult 5 concerning the identified dimensions. The experts were asked to assess if each dimension could represent a human direct or safeguard barrier. Table 3 provides a list of the dimensions considered as barriers and the related barrier typology.

Table 3: Direct and Safeguard Human Barriers considered in the methodology

Dimension	Type
Safety task performance	Direct
Compliance with safety norms and procedures	Direct
Safety contextual performance	Direct
Safety participation	Direct
Safety teamwork	Direct
Safety communication	Direct
Safety task performance	Direct
Non-Technical Safety skills	Safeguard
Technical Safety Skills	Safeguard
Safety Motivation	Safeguard
Safety organisational citizenship	Safeguard
Assessment and development of safety skills	Safeguard
Safety Leadership	Safeguard
Safety Climate and Culture	Safeguard

To assess the quality of direct and safeguard barriers, an evaluation checklist was prepared. Multiple key indicators representing core aspects and peculiarities of the barriers were identified for each barrier dimension to quantify their quality, concerning their ability to protect operators at work and prevent errors. As an example, the following indicators were defined for safety task performance: "Does the operator work safely while performing the task?"; "Does the operator follow safety norms and procedures related to the task?". In order to assess the quality of the barriers, indicators in the checklist were associated with scores ranging from 0 to 1. The average values calculated by the experts where than associated to a conversion coefficient (CC) estimated as shown in Table 4. As shown in the table, conversion coefficients higher than one are adopted for barriers that have a low performance (conditions that ease the human error). If multiple barriers of the same type (direct or safeguard) are present, the average score is calculated applying a simple arithmetic mean:

$$\mathrm{S} = \sum_{j=1}^{m} \frac{S_i}{m} \tag{2}$$

Where S is the overall barrier score, Si is the score attributed to the single barrier by the evaluation checklist, and m is the total number of barriers (direct or safeguard) considered.

Table 4: Conversion coefficients for barrier scores

Barrier score, S	Conversion Coefficient
S < 0.15	1.80
0.15 ≤ S < 0.35	1.40
0.35 ≤ S < 0.55	1.00
0.55 ≤ S < 0.75	0.60
S ≥ 0.75	0.20

2.5 Calculation of integrated HEP

The final step in the methodology consists in the calculation of the HEP. The HEP is calculated taking into account the composite performance shaping factor, PSFC, and the direct and safeguard barriers by the following expression:

$$P_{HE} = \frac{(NEP \cdot PSFC \cdot CC_{DB} \cdot CC_{SB})}{[NEP \cdot (PSFC \cdot CC_{DB} \cdot CC_{SB} - 1) + 1]} \quad (3)$$

where P_{HE} is the HEP, CC_{DB} is the average value of the conversion coefficient obtained for the direct barriers and CC_{SB} is the average value of the conversion coefficient obtained for the safeguard barriers.

3. Results and discussion

The methodology developed was applied to several case-studies in the energy industry (not described here for the sake of brevity, considering the limitation in the paper length). The results of the case-studies provided useful outcomes and a more detailed insight than that obtained from conventional approaches. Further details are reported elsewhere (Guglielmi et al., 2022).

Human reliability is a significant concern in most organizational contexts. Therefore, assessing which factors may impact human performance has become a priority to identify critical areas of intervention and improve workplace safety. The developed approach provides new insights into the role of human factors as safety barriers. Therefore, the results obtained should be thus considered an evolution of our understanding of how safety performance is shaped by contextual and psychosocial factors. Moreover, it represents a useful analytic tool to assess human reliability, analyzing well-acknowledged factors that can affect human reliability and psychosocial dynamics. This allows us to include the positive role that human factors play regarding safety performance.

The methodology developed addresses the progress and open issues recognized in HRA tools. The method is specifically oriented to the use in the framework of quantitative risk analysis (QRA), in order to assess the importance and possible effects of human factor on safety at work, as suggested by (Zhen et al., 2020). The approach is also coherent with the assessment in terms of HRA of the impact that human factors may have on safety, as suggested in the literature (Aven et al., 2006; Vinnem et al., 2007; Gran et al., 2012).

Most of the models available in the literature focus on errors generated during the performance of specific tasks, or by specific events. In particular, Zhen et al. (2020) evidence that almost all these methodologies are aimed at estimating the expected probability of failures involving the loss of containment from process equipment in offshore installations. The new model proposed is less focused on specific tasks and can be applied to most of the tasks carried out in the energy and in the process industry, offshore and onshore. In addition, it attempts to overcome the main limitations of traditional methods, while retaining some of the basic features of previous approaches. In particular, the model developed is still based on the GTTs, that were used to consider the contextualization of the tasks, providing a general taxonomy of task types and their related nominal error probability. Moreover, also the PSFs were included in the methodology, in order to assess the set of factors that need to be taken into account since having an important influence on the overall safety performance.

Nevertheless, the HRA method proposed still shows some limitations. Since safety barriers were seldom included to date in the analysis of human error, this feature needs further consolidation. In particular, the approach to the scoring of the barriers and the conversion of the scores to conversion coefficient needs in perspective to be further tested and refined. This specific innovation introduced in the methodological approach developed needs testing and validation to assess the accuracy of the HEP values obtained, and the associated uncertainty. Clearly enough, the implementation of the methodology on larger samples will allow its valudation and consolidation on the ground of more robust HEP figures. Therefore, future work needs to be considered for a more extended testing of the model, also considering other working environments and extension beyond the framework of the energy industry.

A further issue concerns the selection of the safety barriers introduced in the analysis. Actually, in the current approach, the safety barriers were selected on the basis of the consultation of a single group of experts. Widening the experts consulted and extending the analysis to other working environments may contribute to identify further human factors affecting the performance and the HEP. Therefore, future work should aim at a further expansion of the model, including different psychosocial factors as safety barriers.

4. Conclusions

An innovative methodology addressing the quantitative assessment of HEP was developed. The methodology was developed extending and tailoring to the specific context the well-known framework set by two widely used HRA methodologies (SPAR-H and HEART). The main innovation proposed is the inclusion of human barriers in the approach, considering both direct barriers and safeguard barriers. The method proved to be easy to apply and the results obtained show that human factors play a significant role in preventing workers from making errors while performing tasks by reducing human error probability. Although developed in the specific framework of the energy industry, the approach has a general validity and in perspective may be extended to other working environments and industrial sectors.

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References

Aven, T., Hauge, S., Sklet, S., Vinnem, J. E., 2006. Methodology for incorporating human and organizational factors in risk analysis for offshore installations. Int. J. Mater. Struct. Rel., 4(1), 1-14.

Gran, B. A., Nyheim, O. M., Seljelid, J., Vinnem, J. E., 2012. A BBN risk model of maintenance work on major process equipment on offshore petroleum installations. In: Berenguer C, Grall A, Soares, CG, (Eds.). Adv. Saf., Reliab. Risk Manag, pp. 1249-57. Boca Raton: CRC Press.

Guglielmi, D., Paolucci, A., Fraboni, F., Cozzani, V., Mariani, M., Pietrantoni, L., 2022. Integrating Human Barriers in Human Reliability Analysis: a New Model for the Energy Sector. Int. J. Env. Res. Pub. Health, submitted for publication.

Hamer, R., Waterson, P., Jun, G. T., 2021. Human factors and nuclear safety since 1970–A critical review of the past, present and future. Saf. Sci., 133, 105021. http://doi.org/10.1016/j.ssci.2020.105021

Kariuki, S. G., & Löwe, K. (2007). Integrating human factors into process hazard analysis. Reliability Engineering & System Safety, 92(12), 1764-1773. https://doi.org/10.1016/j.ress.2007.01.002

Laumann, K., Rasmussen, M., 2016. Suggested improvements to the definitions of Standardized Plant Analysis of Risk-Human Reliability Analysis (SPAR-H) performance shaping factors, their levels and multipliers and the nominal tasks. Reliab. Eng. Syst. Saf., 145, 287-300. https://doi.org/10.1016/j.ress.2015.07.022

Mosleh, A., Chang, J., Chandler, F., Marble, J., Boring, R., Gertman, D., 2006, January. Evaluation of current HRA methods for NASA use. In: NASA HRA Methods Workshop, Kennedy Space Centre, pp. 16-18. Florida, Jan

Newaz, M. T., Davis, P. R., Jefferies, M., Pillay, M., 2018. Developing a safety climate factor model in construction research and practice: A systematic review identifying future directions for research. Eng., Constr. Archit. Manag. https://doi.org/10.1108/ecam-02-2017-0038

Reason, J., 1990. Human Error. New York, NY: Cambridge University Press.

Ren, J., Jenkinson, I., Wang, J., Xu, D. L., Yang, J. B., 2008. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. J. Saf. Res., 39(1), 87-100. https://doi.org/10.1016/j.jsr.2007.09.009

Vinnem, J.E., Haugen, S., Kongsvik, T., Seljelid, J., Steen, S., Sklet, S., Thomasssen, O., 2007. Operational safety condition-concept development. Proc. ESREL 2007; Stavanger, Norway, June 25–27.

Whaley, A. M., Kelly, D. L., Boring, R. L., Galyean, W. J., 2012. SPAR-H step-by-step guidance (No. INL/CON-12-24693). Idaho National Laboratory (INL).

Williams, J. C., & Bell, J. L. 2016. Consolidation of the Generic Task Type database and concepts used in the Human Error Assessment and Reduction Technique (HEART). In: Safety and Reliability 36 (4), pp. 245-278. Taylor & Francis. https://doi.org/10.1080/09617353.2017.1336884

Zhen, X., Vinnem, J. E., Yang, X., Huang, Y., 2020. Quantitative risk modelling in the offshore petroleum industry: integration of human and organizational factors. Ships Offshore Struct., 15(1), 1-18. https://doi.org/10.1080/17445302.2019.1589772