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Human error contribution to accidents in the manufacturing sector: A structured approach to evaluate the interdependence among performance shaping factors

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ABSTRACT

Since the 1970s, Human Reliability Analysis (HRA) methods have received a great interest for the quantification of the Human Error Probability (HEP) in Nuclear Power Plants (NPPs). To this purpose, the second-generation HRA methods consider contextual and cognitive factors - named Performance Shaping Factors (PSFs) - that may influence the workers' performance during tasks execution. Despite the recent extension of HRA methods to different fields, only few studies refer to the manufacturing sector. In addition, the majority of contributions assume the independence among PSFs, which may result in an over or under estimation of HEP. Therefore, the present paper focuses on the manufacturing sector to propose a Fuzzy DEMATEL (FDEMATEL) based method to support the risk analyst in the quantification of PSF interrelationships and importance, when computing HEP.

As a result, the most influential human factors on which taking priority actions to improve the overall human reliability may be identified accurately. Based on a selected list of PSFs, the methodological approach is implemented in an Italian textile company, where experience and training factors are demonstrated to be the most central ones to increase the human reliability when performing the weaving process tasks. The designed approach is well structured and effortless as well as it allows at considering the uncertainty and vagueness of input data and a group decision context.

1. Introduction

Over the last decades, the technological growth of systems has led to a decrease in the number of accidents due to technical failures, while human factors continue to play a prominent role. In this regard, about 70–90 % of accidents - in different fields - arise from human errors, while the remainder is to be found in technical reasons (French et al., 2011). With this recognition, Human Reliability Analysis (HRA) methodologies address to the quantification of the influence of human factors on workers' performance. The earliest HR studies were carried out in the 1970 s in Nuclear Power Plants (NPPs), and later extended to other fields (Konstandinidou et al., 2006; De Ambroggi and Trucco, 2011; Aalipour et al., 2016; Burns and Bonaceto, 2018; Franciosi et al., 2019; Orzàez et al., 2019; Taylor et al., 2020; Abílio Ramos et al., 2020; Martins de Sant'Anna et al., 2021; Catelani et al., 2021). First-generation HRA methods (e.g. Technique for Human Error Rate Prediction - THERP and Success Likelihood Index Method - SLIM) (Swain and Guttmann, 1983; Embrey et al., 1984) consider the human being alike a mechanical or electronic component, characterized by his/her own failure rate by means of which assigning a probabilistic value to the human error (Swain and Guttmann, 1983; Hannaman et al., 1984). On the other hand, second-generation HRA methods (e.g. Cognitive Reliability and Error Analysis Method - CREAM and Standardized Plant Analysis Risk-Human reliability analysis - SPAR-H) (Hollnagel, 1998; Gertman et al., 2005) introduce cognitive models to characterize the human behaviour in the workplace, searching for the root causes of human errors in the application of mental processes based on perception, thinking, memory and action strategy decision (Hollnagel, 1998). Second generation methods generally begin with the assessment of the Nominal Human Error Probability (NHEP) and afterwards include personal, contextual and cognitive factors (i.e. Performance Shaping Factors - PSFs) that may influence the workers' performance to compute the final HEP (Lee et al., 2011; Di Pasquale et al., 2015a). Last-generation HRA techniques are still in progress and used to model the dynamic evolution of human

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behaviour against critical and/or unusual situations by means of simulation tools (Catelani et al., 2021).

In recent years, numerous PSFs have been proposed in the literature focusing on diverse application fields besides the nuclear one (Swain and Guttmann, 1983; Hollnagel, 1998; Gertman et al., 2005; Li et al., 2018; Franciosi et al., 2019; Kang and Seong, 2020). Nevertheless, there is still a gap in the manufacturing sector, where human errors are often disregarded even if responsible of worse quality and productivity (Elmaraghy et al., 2008; Di Pasquale et al., 2013; Di Pasquale et al., 2015b). In addition, the majority of literature contributions assume the independence among PSFs, although the empirical evidence shows that PSFs can overlap and influence one each other in some circumstances (Boring, 2010; Park et al., 2020; Liu et al., 2021a). As a consequence, an over or under estimation of HEP may occur (Park, et al., 2020). To deal with this issue, only few contributions provide qualitative guidelines (Swain and Guttmann, 1983; Hollnagel, 1998; Gertman et al., 2005) or analytical methodologies (Groth, 2009; Boring 2010; De Ambroggi and Trucco, 2011; Groth and Swiler, 2013; Xi et al., 2017; Park et al., 2020; Liu et al., 2021a; La Fata et al., 2021). While qualitative methods do not provide a well-structured approach, the quantitative ones are very challenging to be implemented (e.g. Analytic Network Process - ANP) and/or statistical-based, so requiring a large amount of data. With this recognition, the present paper focused on the manufacturing sector to propose a structured and easily replicable approach to support the risk analyst in the evaluation of PSF interrelationships when computing HEP. To this aim, a detailed literature review of scientific contributions on PSFs was firstly carried out. In most cases, PSFs had similar or even equal descriptions even if differently named. As a consequence, redundant or similar factors were replaced by single ones. The reduced list of PSFs was then provided to three different Italian textile companies to choose the ones deemed to be meaningful and useful in their work environment. As a result, a final list of eight PSFs was obtained, and the Fuzzy extension of DEcision MAking Trial and Evaluation Laboratory (FDEMATEL) (Lin and Wu, 2008) was then proposed to assess both their mutual influence and relative importance (i.e. weights) (Dalalah et al., 2011; Baykasoğlu et al., 2013). Originally developed by Gabus and Fontela (1973), traditional DEMATEL is able to identify and quantify the dependence among the components of a complex decision problem, owing to its simplicity of application and clear representation of results (Baykasoğlu et al., 2013; Yorulmaz and Karabulut, 2022). In addition, its fuzzy extension (i.e. FDEMATEL) allows at properly dealing with the vagueness and uncertainty of human judgments often occurring in real-world applications, where exact numerical values may be inadequate to characterize the actual available knowledge. As concerns the input data required by the method, group-based decision making processes generally allow to exploit broader information basis, better diversification of the individuals' cognitive restrictions, less evaluation mistakes, increased acceptance of the solution as well as to achieve a sufficient degree of objectivity (Ossadnik et al., 2016). Accordingly, the input data required by FDEMATEL were hence gathered by means of a survey administered to three respondents - one for every textile company involved in the study - differently weighted based on their own expertise in the investigated sector. Afterwards, PSF weights were obtained by FDEMATEL and used to compute the HEP of the weaving process tasks of one of the aforementioned companies. Based on the proposed methodological approach, the most influential human factors on which taking priority actions to improve the overall human reliability when performing tasks were properly identified.

The remainder of the paper is organized as follows. The literature review is reported in Section 2 whereas Section 3 synthetizes the methodological approach, comprising the PSF list proposed for the specific application in the manufacturing field, the FDEMATEL method and the HEP computation. The case study is detailed in Section 4, and Conclusions are given in Section 5.

2. Literature review

A systematic literature review of scientific contributions on PSFs was firstly carried out by means of the Scopus database. Focusing on those papers which mentioned "performance shaping factors" and "human reliability analysis" within their title, abstract and keywords, the database returned a total number of 358 documents, among which the ones written in English and published on journals were only considered. As a result, the number of documents was reduced to 139. Afterwards, a specific search was performed to identify the application sector (Fig. 1). As expected, the highest number of papers referred to NPPs, followed by the medical field. The remaining sectors showed a much lower number of published papers, and only few of them were focused on the manufacturing sector (Cheng and Hwang, 2015; Aalipour et al., 2016; Di Pasquale et al., 2017; Wang et al., 2019).

Afterwards, a further selection was performed by the authors excluding the nuclear field, where a general agreement on the used PSFs already exists (Liu et al., 2017; Park et al., 2020; Kang and Seong, 2020; Liu et al., 2021b). Therefore, the remaining 84 documents were investigated. Among them, the papers proposing a list of PSFs and/or an application case were further selected. In Table 1, the most relevant papers for the authors' purpose are listed, also including the application sector and the list of PSFs adopted.

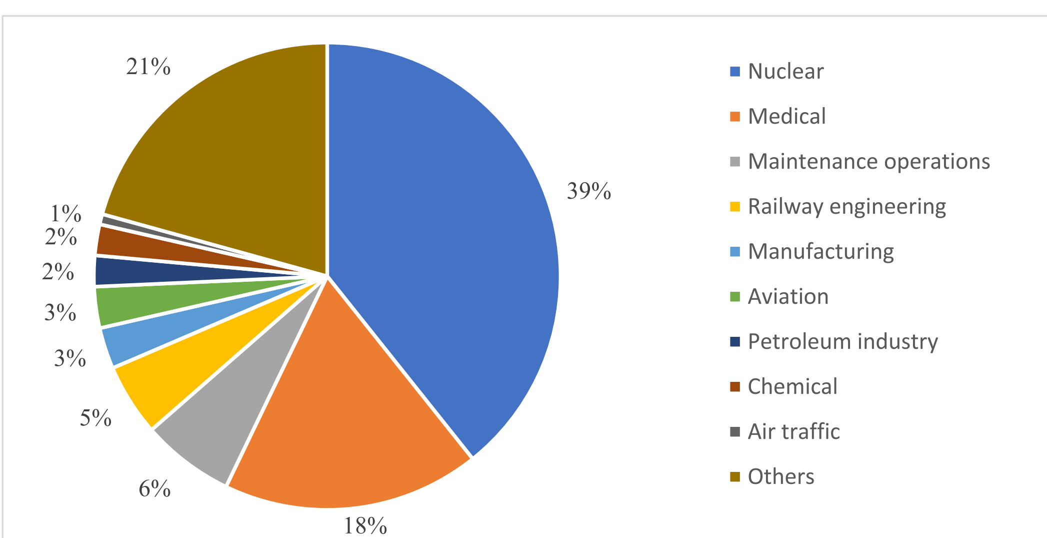

Fig. 1. Literature contributions on PSFs and HRA.

Table 1
Scientific contributions on PSFs in different contexts.

	Paper	Application field	Number of PSFs	PSFs list
1	Setayesh et al., 2022	Generic	8	Available time; Complexity; Skills/Training/Experience; Work procedures; Ergonomics/HMI; Organization management strategy; Fitness for duty; Stress/stressors
2	Jafari Nodoushan et al., 2022	Health care systems: surgical context	9	Available time; Threat stress (Stress/stressors); Task complexity; Experience/Training; Procedures; Working conditions; Human-machine interactions; Fatigue (Fitness for duty); Teamwork (Work processes)
3	Guglielmi et al., 2022	Generic	15	Safety task performance; Safety communication; Safety teamwork; Safety participation; Safety contextual performance; Compliance with safety norms and procedures; Safety non-technical skills; Safety technical skills; Safety motivation; Safety organizational citizenship; Assessment and development of safety skills; Safety leadership; Safety climate and culture
4	He et al., 2021	Generic	11	Patience; Carefulness; Responsibility; Communication and co-operation; anti-fatigue ability; Arm and hand co-ordination; Attention; Reaction ability; Memory; Sentience; Hearing
5	Catelani et al., 2021	Railway engineering	8	Available time; Stress; Complexity; Experience and training; Procedures; Ergonomics; Fitness for duty; Work processes
6	Ghalenoei et al., 2022	Combined cycle power plant control rooms	5	Mental condition; Consciousness at work; Professional competence; Communication skills; Quick reactions and decision-making capabilities
7	Samima and Sarma, 2021	Generic	17	Work process; Work shift; Environmental stressors; Fitness for duty; Experience; Time Pressure; Skill; Perceived task difficulty; Complexity; Type of Task; Available time; Task frequency; Ergonomics; Leadership; Human machine interaction; Procedures; Training
8	Di Bona et al., 2021	Generic	8	Available time; Stress; Complexity; Experience and training; Procedures; Ergonomics; Fitness for duty; Work processes
9	Zhou and Lei, 2020	Railway driving process	16	Resource management; Organizational climate; Organizational process; Inadequate supervision; Planned inappropriate operations; Failed to correct known problems; Supervision violation; Technological environment; Physical environment; Condition of the operator; Crew resource management; Personal readiness; Skill-based errors; Decision errors; Perception errors; Violations
10	Wang et al., 2020	Civil flight crew operations	10	Cognition characteristics; Physiological and psychological characteristics; Personal and social characteristics; Procedures; Task characteristics; Human machine interface; System state; Phenomenological characteristics; Physical working conditions; Team and organization factors
11	Rozuhan et al., 2020	Offshore operations	6	Stress; Task complexity; Training; experience; Time available; Atmospheric factor
12	Wang et al., 2019	Manufacturing	4	Flexibility; Coordination; Memory; Attention
13	Franciosi et al., 2019	Industrial maintenance	9	Available time; Cognitive ergonomics; Complexity; Experience and training; Fitness for duty; Procedures; Stress; Work processes
14	Longo et al., 2019	Generic	11	Attention; Communication; Knowledge; Memory; Reasoning; Health; Motion; Perception; Emotions; Relationships; Self-management
15	Li et al., 2018	Shield tunnel construction	12	Physical factors; Memorized information; Mental state; Society-related factors; Human–machine interface (HMI); Technical system state; Natural environment; Working environment; Construction team climate factors; Construction site organizational factors; Task type; Task attribute
16	Kyriakidis et al., 2018	Railway operations	7	Personal factors (static); Personal factors (dynamic); Task factors; Team factors; Organizational factors; Environmental factors; System factors
17	Di Pasquale et al., 2017	Manufacturing	8	Available time; Stress; Complexity; Experience and training; Procedures; Ergonomics; Fitness for duty; Work processes
18	Rangra et al., 2017	Railway operations	7	Training, Experience, Communication; Situational awareness; Task load; Time load; HSI quality.
19	Petrillo et al., 2017	Industrial plants	8	Available time; Stress/Stressor; Complexity; Experience and training; Procedures; Ergonomics; Human machine interface (HMI); Fitness for duty; Work processes
20	Aalipour et al., 2016	Manufacturing	8	Available time; Stress; Complexity; Experience and training; Procedures; Ergonomics; Fitness for duty; Work processes
21	Aju Kumar et al., 2015	Industrial maintenance	10	Task/Job factors; Workplace factors; Physical design of equipment; Physical environment; Workload; Resource availability; Personal factors; Fitness for duty; Organizational factors; Maintenance documentation
22	Cheng and Hwang, 2015	Manufacturing	10	Time; Shifts; Interface; Training; Experience; Procedure; Organization; Stress; Task complexity; Environment
23	Tu et al., 2015	Lifting operations	5	Experience; Training level; Equipment and tool condition; Environmental condition; Supervision
24	Kyriakidis et al., 2015	Railway operations	7	Personal factors (static); Personal factors (dynamic); Task factors; Team factors; Organizational factors; Environmental factors; System factors
25	Onofrio et al., 2015	Healt care systems: surgical context	10	Noise & background talk not related to the task; Safety culture and safety climate; Standardization; Equipment; HMI and space design; Communication and teamwork; Experience and team training; Fatigue; Leadership; Staffing and team member familiarity; Workload
26	Rangra et al., 2015	Rail transport	6	Training; Communication; Concentration/Distraction; Experience; Task load (Work load); Time load (Work load)
27	Di Pasquale et al., 2015a	Generic	8	Available time; Stress; Complexity; Experience and training; Procedures; Ergonomics; Fitness for duty; Work processes
28	Mindock and Klaus, 2014	Spacecraft operations	8	Organization; Training; Team; Physical environment; Human system interaction; Task specific characteristics; Individual mental characteristics; Individual physical characteristics
29	Calhoun et al., 2014	Spaceflights	11	Crew offloading via ground support; Ground failure response; Crew workload management; Consistency of procedure format; Procedure verification quality; Activity intention; Procedure quantity; Crew prior experience; Applicability of training; Recency of applicable training; Repetition of applicable training
30	El-Ladan and Turan, 2012	Marine and offshore applications	9	Training; Welfare; Logistics; Quality of crew; stress; Procedure; Communication; Supervision; Human contribution to accidents
31	De Ambroggi and Trucco, 2011	Air Traffic Management	10	Traffic and airspace; Weather; Pilot–controller communication; Documentation and procedure; Training and experience; Workplace design and HMI; Environment; Personal factors; Team factors; Organizational factors
32	Bea, 2002	Offshore structures management	7	Interfaces; Environment; Structure; Equipment; Procedures; Organizations; Operators

As highlighted in Table 1, diverse sets of PSFs were proposed in the literature as concerns the same application field, where a general consensus does not exist differently from the NPPs sector. Most of papers (Aalipour et al., 2016; Catelani et al., 2021; Di Bona et al., 2021; Setayesh et al., 2022; Jafari Nodoushan et al., 2022) provided a PSFs list based on the main HRA methods (e.g. SPAR-H and CREAM) and included some industry-specific factors. In this regard, it is widely recognized in the literature that the calculation of HEP should be based on a set of PSFs properly chosen and/or customized, specifically referring to the work environment under investigation to develop suitable PSF taxonomies (Kyriakidis et al. 2015; Franciosi et al., 2019; Li et al. 2018). Accordingly, De Ambroggi and Trucco (2011) developed a PSFs list for the air traffic control room operations, including some factors inspired by the most famous HRA methods (e.g. "training and experience", "workplace design and HMI" and "environment") and a few customized ones related to the air traffic control (e.g. "traffic and airspace", "weather" and "pilot–controller communication"). Referring to maritime and offshore operations, El Ladan and Turan (2012) made use of experts' interviews to propose nine specific PSFs, named Human Entropy Boundary Conditions (HSBC). Since traditional PSFs are terrestrially based, Mindock and Klaus (2014) designed a list of specific PSFs for the spacecraft operations, including the ones that influence human health and performance in spaceflights. A literature review was performed by Kyriakidis et al. (2015) to propose PSFs for railway operations. In particular, 479 railway incidents and accidents over fifteen years worldwide were analysed, and forty-three Railway-Performance Shaping Factors (R-PSFs) were firstly identified and then grouped into seven categories. Based on SPAR-H, a PSFs list for generic industrial operations was proposed by Di Pasquale et al. (2015a) and used within a third generation HRA method named Simulator for Human Error Probability Analysis (SHERPA). Li et al. (2018) developed a PSFs list for shield tunnel construction operations. Eighty-five sub-factors were identified, hierarchically organized, and then categorized in twelve PSF groups. Structured on three hierarchical levels, Longo et al. (2019) developed a PSFs list which encompassed all aspects related to cognitive capabilities, physical skills and psychological attitude of a generic industrial worker. The cognitive, physical and psychological spheres were placed at the top level, and every sphere was then articulated into eleven characteristic traits in the lower level. In the maintenance operations field, Franciosi et al. (2019) provided an extensive classification based on a deep literature review, whereas the final list of PSFs was compared with the one of SHERPA. Focusing on manufacturing, Aalipour et al. (2016) and Di Pasquale et al. (2017) did not propose their own set of customized factors, but made use of PSFs proposed by the SPAR-H method. In particular, Aalipour et al. (2016) referred to the maintenance activities of a cable manufacturing industry to compare the consistency of HEP results arising from three different HRA methods (i.e. SPAR-H, HEART and Bayesian Networks method). On the other hand, Di Pasquale et al. (2017) implemented SHERPA in a manufacturing company to schedule the operators break. Physiological and psychological factors consisting of personal abilities of flexibility, coordination, memory, and attention were considered by Wang et al. (2019). Afterwards, these factors were inserted in a Bayesian Network (BN) model to reduce the system failures in a bulk container manufacturing plant. Referring to the process of changing chemical cylinders in a factory, Cheng and Hwang (2015) analysed the main HRA techniques and then integrated them into a single one, combining PSFs arising from traditional HRA methods and from the literature.

Contributions on HRA methods have also claimed the need to consider the mutual influence among PSFs to avoid both their double counting and estimation errors when computing HEP (Boring, 2010; Park et al., 2020; Liu et al., 2021a). Nevertheless, there is a great shortage from this point of view, and only few technical or scientific contributions have provided qualitative guidelines or analytical methodologies to deal with this issue. In this regard, the PSFs interrelationship issue was mentioned by CREAM but no structured formula was suggested to compute its effect on HEP calculation. SPAR-H proposed the use of linguistic variables (i.e. zero, low, medium, high and complete) to assign a correlation degree between PSFs. Growth (2009) developed a statistical based methodology which combined correlation and factor analyses. Referring to NPPs and considering the eight PSFs of SPAR-H, a correlation analysis was also performed by Boring (2010). The Author demonstrated that a short list of PSFs is preferable to avoid overlaps and double counting. With relation to the aviation field, De Ambroggi and Trucco (2011) proposed ANP to consider the direct and indirect influence among PSFs. Groth and Swiler (2013) used a Bayesian Network model, while Kyriakidis et al. (2018) combined ANP and Success Likelihood Index Methodology (SLIM) techniques to evaluate PSF dependencies in the railway operations field. Park et al. (2020) proposed a statistical approach based on factor and correlation analyses in the NPPs field, while Wang et al. (2020) referred to the civil flight crew operations to quantify PSF interrelationships by a statistical-based approach which combined moderating and mediating effect analyses. Liu et al. (2021a) performed a system dynamics-based approach within the SPAR-H method, and La Fata et al. (2021) combined HEART and SPAR-H to calculate the human contribution to risks in a manufacturing context, also considering PSFs correlation.

3. Methodological approach

As aforementioned in Section 1, the present paper addressed to the proposal of a structured and easily replicable approach to support the risk analyst in the evaluation of PSF interrelationships when computing HEP. As a result, the most meaningful PSFs on which taking primary actions to improve the worker reliability when performing tasks may be identified. To this purpose, the designed methodological approach comprised the steps synthetized in Fig. 2 and detailed in next sections.

3.1. PSFs list

Based on the performed review (§ Section 2), the selection of a limited number of PSFs was deemed to be fundamental to facilitate their understanding and use in the context under investigation. To this purpose, PSFs having similar or equal descriptions even if differently named were replaced by a single PSF, so considerably reducing their number. Afterwards, the obtained list was further reduced by the three textile companies involved in the study, whose respondents selected the most significant PSFs for the evaluation of their workers' performance. For instance, the PSF "available time" (i.e. time available to perform a task) is always considered in NPPs while it was deemed to be negligible in the textile sector. In fact, if the task under investigation concerns the implementation of a whatever NPP emergency procedure to avoid major accidents, the time to perform the task itself is crucial and strongly affects the operator reliability. On the other hand, "available time" could not be so much meaningful in manufacturing, owing that the psychological stress arising from a short time availability does not strongly influence the worker performance. As a result, the eight PSFs listed in Table 2 were chosen.

3.2. Evaluation of PSFs interdependence: Fuzzy DEMATEL method

DEMATEL is a Multi-Criteria Decision making (MCDM) method developed by Gabus and Fontela (1973) to assess and easily visualize the casual relationship degree among evaluation criteria (Dalalah et al., 2011; Baykasoğlu et al., 2013). Later, Lin and Wu (2008) proposed a Fuzzy version of DEMATEL (FDEMATEL) with the aim of properly dealing with the uncertainty, vagueness and imprecision often occurring during the elicitation of input data required by the method. So far, the use of DEMATEL and its enhanced versions have been limited in the field of risk analysis in general (Han and Deng, 2018; Li and Yazdi, 2022; Adelfio et al., 2022). In this regard, Yazdi et al. (2020a) integrated DEMATEL, Best-Worst Method (BWM) and BN to identify the most

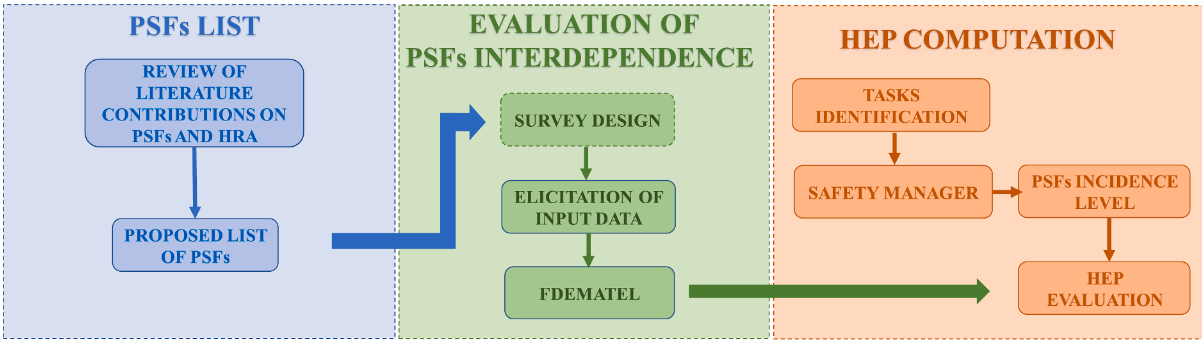

Fig. 2. Methodological approach.

Table 2
PSFs list.

PSF	Description
Experience (PSF_1)	It refers to skills and know-how acquired by the worker over the years by performing the same task and/or working in the same industrial sector. It also considers aspects related to the familiarity with work environment, staff and procedures.
Training (PSF_2)	It relates to the worker training in terms of: teaching/training methods, duration of courses and professionalism and qualification of trainers; contents of training courses (e.g. task to be performed, working department, equipment, maintenance procedures, etc..).
Fitness to work (PSF_3)	Worker personal factors that can influence his/her performance such as: cognitive skills (e.g. reasoning ability, memory, attention and communication skills), physical fitness (e.g. health, age, constitution and agility of the operator): psychic fitness (e.g. state of mental health and work related stress); drug use.
Environmental conditions (PSF_4)	It refers to the environmental conditions of the workplace (e.g. lighting, temperature, humidity, noise, vibrations, etc..).
Procedures (PSF_6)	It refers to both the presence and suitability of operating procedures (e.g. normal plant management procedures, maintenance procedures, emergency procedures, etc..).
Task complexity (PSF_7)	It considers the complexity of the task to be performed. This complexity can be cognitive, physical, or referred to the level of accuracy and presence of simultaneous tasks to be performed.
Organization and working conditions (PSF_8)	It relates to organizational and relational aspects such as: team organization, in terms of definition and composition of the work team, clear definition of roles and responsibilities, leadership; communication level and well-being in the workplace due to cooperation, absence of conflicts, presence of recreational activities; operator satisfaction and gratification in terms of salary, personal recognition, integration with colleagues.

critical factors of Safety Management Systems (SMS). Referring to an offshore facility platform, Yazdi et al. (2020b) proposed a novel Pythagorean FDEMATEL to rank corrective actions with consideration of causal influence of criteria, while Zhou et al. (2017) combined D-numbers and DEMATEL to determine the most critical success factors in emergency management. In the context of the present paper, PSFs are considered as criteria, and FDEMATEL is used to get both the influence degree among PSFs and their weights. Therefore, let k be the k^{th} decision maker (with $k = 1, \ldots, p$) and let C_i (with $i = 1, \ldots, n$) be the i^{th} criterion (i.e. i^{th} PSF). The implementation of FDEMATEL comprises the following steps.

(a) For every decision maker k, determine the direct relation fuzzy matrix $\tilde{Z}^k$ where the generic element $\tilde{z}_{ij}^{(k)} = \left(l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}\right)$ represents to what extent the criterion C_i affects the criterion C_j. Using the five-point linguistic scale of Table 3, $\tilde{z}_{ij}^{(k)}$ is obtained through pairwise comparing the criterion C_i with C_j.

(b) For every decision maker k, determine the normalized direct relation fuzzy matrix $\tilde{X}^k$ where the generic element $\tilde{x}_{ij}^{(k)}$ is computed by the equation (1) (Kuzu, 2021).

Table 3
Five-point scale for pairwise comparison.

Linguistic variable	Fuzzy Number
No influence (No)	(0, 0, 0.25)
Very low influence (VL)	(0, 0.25, 0.50)
Low influence (L)	(0.25, 0.50, 0.75)
High influence (H)	(0.50, 0.75, 1)
Very high influence (VH)	(0.75, 1, 1)

$$\tilde{x}_{ij}^{(k)} = \frac{\tilde{z}_{ij}^{(k)}}{r} = \left(\frac{l_{ij}^{(k)}}{r}, \frac{m_{ij}^{(k)}}{r}, \frac{u_{ij}^{(k)}}{r}\right) \forall k = 1, 2, \cdots, p \tag{1}$$

where

$$r = \max_{i,j}\left\{\max_{i} \sum_{j=1}^{n} u_{ij}, \max_{j} \sum_{i=1}^{n} u_{ij}\right\} \tag{2}$$

(c) Identify the fuzzy aggregate matrix $\tilde{X}$. Being e_k the crisp weight of the k^{th} decision maker (Mzougui and El Felsoufi, 2021), the generic element $\tilde{x}_{ij}$ of $\tilde{X}$ is computed by the equation (3).

$$\tilde{x}_{ij} = \frac{\sum_{k=1}^{p} \tilde{x}_{ij}^{(k)} \cdot e_k}{\sum_{k=1}^{p} e_k} \tag{3}$$

(d) Determine the three crisp matrices X_l, X_m and X_u, whose generic elements l_{ij}, m_{ij} and u_{ij} are the lower, medium and upper bounds of the generic fuzzy element $\tilde{x}_{ij}$ respectively. From the three crisp matrices X_l, X_m and X_u, compute the three total relation matrices $T_s | s=(l, m, u)$ (equation (4)).

$$T_s = X_s \cdot (I - X_s)^{-1} \quad \forall s = l, m, u \tag{4}$$

where I is the identity matrix. The generic element $\tilde{t}_{ij} = \left(t_{ij,l}, t_{ij,m}, t_{ij,u}\right)$

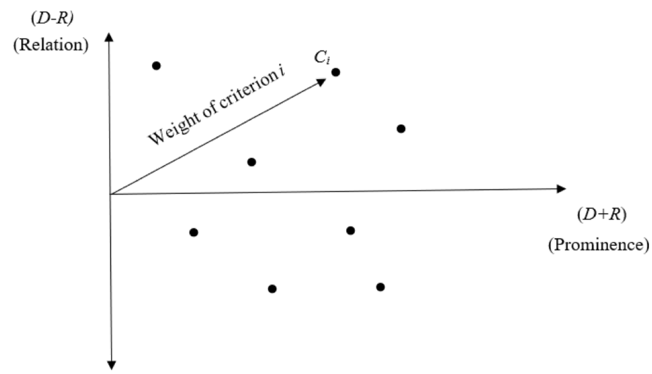

Fig. 3. Causal diagram.

of the total relation fuzzy matrix $\widetilde{T}$ represents the overall - direct and indirect - influence of the criterion C_i on the criterion C_j.

(e) Calculate the crisp vectors (D - R) and ($D + R$). Firstly, the fuzzy numbers $\widetilde{D}_i$ and $\widetilde{R}_j$ are obtained by the equations (5)-(6).

$$\widetilde{D}_i = \sum_{j=1}^{n} \widetilde{t}_{ij} \quad \forall i = 1, 2, \ldots, n \tag{5}$$

$$\widetilde{R}_j = \sum_{i=1}^{n} \widetilde{t}_{ij} \quad \forall j = 1, 2, \ldots, n \tag{6}$$

Afterwards, $\widetilde{D}_i$ and $\widetilde{R}_i$ are defuzzified for every criterion i to get the crisp values of D_i and R_i (equation (7)).

$$R_i, D_i = \begin{cases} u_i - \sqrt{(u_i - l_i)(u_i - m_i)/2} & (u_i - m_i) > (m_i - l_i) \\ \sqrt{(u_i - l_i)(u_i - m_i)/2} - l_i & (u_i - m_i) < (m_i - l_i) \\ m_i \text{ otherwise} & \end{cases} \quad \forall i = 1, 2, \ldots, n \tag{7}$$

Finally, the relative importance of every criterion i (i.e. w_i) is evaluated as follows (equation (8)).

$$w_i = \sqrt{\left\{ (D_i + R_i)^2 + (D_i - R_i)^2 \right\}} \; \forall i = 1, 2, \ldots, n \tag{8}$$

The vector ($D + R$) stands for the strength of influences given to and received by criteria. As a result, the higher ($D_i + R_i$), the higher the degree of received and provided influence by the criterion i. On the other hand, the vector (D – R) provides information about the type of relationship among criteria. In particular, criteria having positive (D_i - R_i) values are defined as net causer in the system, while the ones with negative values of (D_i - R_i) are defined as net receiver in the system, i.e. the net causer group of criteria cause effects or influences on the net receiver group. As a consequence, much attention should be paid on the first group, since by improving cause factors, receiver factors are enhanced simultaneously (Seker and Zavadskas, 2017). The two vectors may be represented in a casual diagram (Fig. 3), where ($D_i + R_i$) (i.e. prominence) and (D_i - R_i) (i.e. relation) values are reported in the x and y axes respectively.

In addition, an influence threshold value may be computed based on the total relation fuzzy matrix to identify interrelationships that can be neglected. To this aim, the total relation fuzzy matrix is firstly defuzzified by the equation (7) on $\widetilde{t}_{ij}$ values, and the mean operator is then used to compute the influence threshold under which interrelationships are meaningless and may be neglected as a consequence.

f) Normalize w_i values by the equation (9) (Baykasoğlu et al., 2013) to get the final weight q_i of the i^{th} criterion.

$$q_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad \forall i = 1, 2, \ldots, n \tag{9}$$

Table 4
Five-point scale of multipliers.

Incidence level	Multiplier
No incidence (NI)	0
Low incidence (LI)	1
Medium incidence (MI)	2
High incidence (HI)	3
Very high incidence (VHI)	4

3.3. HEP computation

According to La Fata et al. (2021) - based on the traditional SPAR-H method - the HEP to perform the generic task a (i.e. HEP_a) may be computed by the equation (10), where $NHEP$ and $PSF_{C,a}$ are the Nominal HEP and the overall impact of PSFs on HEP_a respectively.

$$HEP_a = \frac{NHEP \cdot PSF_{C,a}}{NHEP \cdot (PSF_{C,a} - 1) + 1} \tag{10}$$

In this paper, $NHEP$ was computed by equations (11)-(12), which allow to determine the human failure probability over an eight-hour shift by assuming a Weibull distribution. According to La Fata et al. (2021), Di Pasquale et al. (2015a) and Petrillo et al. (2017), the Weibull function was chosen because it describes systems with variable failure rates over the time. Therefore, it is suitable to describe the HEP trend over the time, with minimum and maximum human unreliability values at the first (i.e. $t = 1$) and eighth hours (i.e. $t = 8$) of shift respectively.

$$NHEP = 1 - f \cdot e^{-\alpha \cdot (1-t)^{\beta}}, \; \forall t \in [0, 1] \tag{11}$$

$$NHEP = 1 - f \cdot e^{-\alpha \cdot (t-1)^{\beta}}, \; \forall t \in [1, \infty] \tag{12}$$

In (11)-(12), the parameters f, α and β depend on the performed tasks based on the classification proposed by the HEART method (Williams, 1988). After the $NHEP$ computation, the obtained value was adjusted to include the overall PSFs contribution to the human error when performing the task a (i.e. $PSF_{C,a}$). Based on the approach used by De Ambroggi and Trucco (2011), $PSF_{C,a}$ was hence computed by (13).

$$PSF_{C,a} = \sum_{i=1}^{n} PSF_{i,a} \cdot q_i \tag{13}$$

In (13), n is the number of PSFs affecting the considered task a, while q_i is the normalized weight of the i^{th} PSF computed by FDEMATEL (§ Section 3.2). As concerns $PSF_{i,a}$, it is a proper multiplier that returns the level of incidence of the i^{th} PSF on the task a (La Fata et al., 2021). In this paper, the incidence level of every PSF on the considered task was assessed by the five-point linguistic scale of Table 4.

4. Application case

4.1. Input data and FDEMATEL

As aforementioned, the methodological approach designed for the estimation of mutual influences among the chosen PSFs (§ Section 3.1) was implemented in the textile industry sector. To this aim, a Google Forms survey was administered to the three Italian manufacturing companies involved. The survey comprised two sections, the first one to collect some general information about respondents, whereas pairwise comparison judgments on the mutual influence degree between PSFs (§ Section 3.2) were expressed in the second section. General information elicited by the first part of the survey were used to weigh the respondents based on their own expertise in the investigated sector. To this purpose, three different criteria $h \mid h = (1, 2,.., H)$ (i.e. $H = 3$) were used, i.e. professional position, years of experience and education level (Mzougui and El Felsoufi, 2021). Accordingly, the overall respondent weight e_k of the k^{th} respondent $\mid k = (1, 2, 3)$ was computed by the

Table 5
Evaluation scale of respondents (Mzougui and El Felsoufi, 2021).

Criterion	Description	Score
Professional position	H&S manager	5
	Corporate	4
	Senior worker with specific roles/responsibilities in H&S	3
	Junior worker with specific roles/responsibilities in H&S	2
	Worker without specific roles/responsibilities in H&S	1
Years of experience	>30 years	5
	20–29 years	4
	10–19 years	3
	6–9 years	2
	<5 years	1
Education level	Ph.D.	5
	Master	4
	Bachelor	3
	High National Diploma (HND)	2
	School level	1

equation (14), where $g_h^{(k)}$ represents the score of the respondent k on the h^{th} criterion (Table 5). The scores of the three involved respondents are synthetized in Table 6 along with the resulting weights.

$$e_k = \frac{\sum_{h=1}^{H} g_h^{(k)}}{\sum_{k=1}^{p}\left(\sum_{h=1}^{H} g_h^{(k)}\right)} \quad \forall k = (1,2,3) \tag{14}$$

As concerns the second part of the survey, the five-point linguistic scale of Table 3 was provided to respondents to answer the question "*how much does the PSF_i affect the PSF_j?*". Fifty-six questions were asked to every respondent k (with $k = 1, 2, 3$), whom answers are synthetized in the direct relation matrix $\widetilde{Z}^k$ (Tables 7-9).

Afterwards, the three normalized direct relation fuzzy matrices $\widetilde{X}^k$ were computed according to the step b) of Section 3.2, while the fuzzy aggregate matrix $\widetilde{X}$ was calculated by the equation (3) (Table 10). By the equation (4), the three crisp matrices X_l, X_m and X_u were hence calculated to get the total relation fuzzy matrix, which defuzzified version is synthetized in Table 11.

After the step d), $\widetilde{D}_i$ and $\widetilde{R}_i$ were computed for every PSF i by (5) and (6) respectively, and then defuzzified by (7) to get D_i and R_i values (Table 12).

Finally, the normalized weights of PSFs were calculated by (9) (Table 13). The resulting causal diagram is shown in Fig. 4.

Based on the defuzzified total relation matrix (Table 11), the influence threshold (§ Section 3.2) was also computed by the mean operator. A value equal to 0.308 was obtained and used to identify the main influence relationships among PSFs, visualized by Fig. 5. In the main influence graph of Fig. 5 every arrow represents the influence direction of those relationships whose intensity is higher than the threshold value.

Referring to Fig. 5, PSF_4 is not linked to the other factors because its relation degree is lower than the threshold value. The latter means that the influence received and caused by PSF_4 is negligible if compared with the others.

Table 7
Direct relation matrix of the first respondent $\widetilde{Z}^1$.

	PSF_1	**PSF_2**	**PSF_3**	**PSF_4**	**PSF_5**	**PSF_6**	**PSF_7**	**PSF_8**
PSF_1	0	H	L	VL	VH	VL	VH	L
PSF_2	VH	0	L	No	VH	VH	VH	VL
PSF_3	VL	L	0	VL	H	L	VH	H
PSF_4	No	No	VL	0	L	No	VL	VL
PSF_5	H	H	VL	No	0	No	No	L
PSF_6	VH	VH	L	No	VL	0	VH	VH
PSF_7	VH	H	H	No	VH	H	0	VH
PSF_8	H	H	L	VL	H	H	H	0

Table 8
Direct relation matrix of the second respondent $\widetilde{Z}^2$.

	PSF_1	**PSF_2**	**PSF_3**	**PSF_4**	**PSF_5**	**PSF_6**	**PSF_7**	**PSF_8**
PSF_1	0	H	H	VL	H	H	VH	VH
PSF_2	L	0	VH	L	H	H	H	H
PSF_3	L	L	0	VL	L	L	L	L
PSF_4	H	H	VH	0	L	VL	L	H
PSF_5	H	H	H	H	0	H	H	H
PSF_6	H	H	H	H	H	0	H	H
PSF_7	L	L	L	L	L	L	0	L
PSF_8	H	H	H	H	H	H	H	0

Table 9
Direct relation matrix of the third respondent $\widetilde{Z}^3$.

	PSF_1	**PSF_2**	**PSF_3**	**PSF_4**	**PSF_5**	**PSF_6**	**PSF_7**	**PSF_8**
PSF_1	0	H	L	VL	VH	H	VH	L
PSF_2	VH	0	VH	L	VH	H	VH	L
PSF_3	VL	L	0	No	H	No	L	H
PSF_4	VL	VL	H	0	L	No	H	VL
PSF_5	L	L	VL	L	0	H	VH	VL
PSF_6	VL	H	No	VL	H	0	H	L
PSF_7	VH	VH	L	VL	H	VL	0	VL
PSF_8	No	No	L	VL	L	H	L	0

By the causal diagram of Fig. 4, net causer in the system group of criteria consists of "experience" (i.e. PSF_1), "training" (i.e. PSF_2), "environmental conditions" (i.e. PSF_4), "procedures" (i.e. PSF_6) and "organization and working conditions" (i.e. PSF_8). On the other hand, net receiver in the system factors are "fitness to work" (i.e. PSF_3), "task complexity" (i.e. PSF_7) and "equipment and MMI" (i.e. PSF_5). As concerns the first group, "training" (i.e. PSF_2) has obtained both high prominence (i.e. 5.502) and relation values (i.e. 0.252), with a final weight of 0.139. Similarly, "experience" (i.e. PSF_1) has high prominence (i.e. 5.220) and relation values (i.e. 0.251), with a final weight of 0.132. As a result, PSF_1 and PSF_2 may be considered as the most central factors in the system, owing to the related received and given influence represented by their prominence. In particular, they strongly influence the other factors as demonstrated by their positive value of relation, also emphasized by Fig. 5. As a consequence, experienced and trained workers are fundamental to reduce the overall probability of human errors in the investigated workplace, increasing workers risk awareness and safe attitudes. A lower prominence value than PSF_1 and PSF_2 is owned by "procedures" (i.e. PSF_6). On the other hand, PSF_6 has the highest impact on the other factors because of a relation value equal to

Table 6
Expert scores and weights.

Expert	Criterion: Professional position	Years of experience	Education level	Score	Weight
1	Senior worker with specific roles/responsibilities in H&S	<5 years	Master	8	0.32
2	Worker without specific roles/responsibilities in H&S	>30 years	HND	8	0.32
3	Corporate	10–19 years	HND	9	0.36

Table 10
Fuzzy aggregate matrix $\widetilde{X}$.

	PSF$_1$			PSF$_2$			PSF$_3$			PSF$_4$			PSF$_5$			PSF$_6$			PSF$_7$			PSF$_8$		
PSF$_1$	0	0	0	0.076	0.114	0.152	0.050	0.088	0.126	0.000	0.038	0.076	0.103	0.141	0.152	0.051	0.089	0.127	0.114	0.152	0.152	0.061	0.099	0.126
PSF$_2$	0.091	0.129	0.141	0	0	0	0.089	0.127	0.139	0.025	0.051	0.089	0.103	0.141	0.152	0.089	0.127	0.152	0.103	0.141	0.152	0.037	0.075	0.113
PSF$_3$	0.011	0.050	0.088	0.038	0.076	0.114	0	0	0	0	0.024	0.062	0.065	0.103	0.141	0.024	0.048	0.087	0.064	0.102	0.127	0.065	0.103	0.141
PSF$_4$	0.023	0.048	0.086	0.023	0.048	0.086	0.062	0.100	0.127	0	0	0	0.038	0.076	0.114	0.000	0.011	0.050	0.039	0.077	0.115	0.023	0.061	0.099
PSF$_5$	0.062	0.100	0.138	0.062	0.100	0.138	0.037	0.075	0.113	0.037	0.062	0.100	0	0	0	0.051	0.076	0.114	0.064	0.090	0.114	0.036	0.074	0.112
PSF$_6$	0.061	0.099	0.125	0.089	0.127	0.152	0.036	0.074	0.112	0.023	0.048	0.086	0.051	0.089	0.127	0	0	0	0.089	0.127	0.152	0.075	0.113	0.138
PSF$_7$	0.091	0.129	0.141	0.079	0.117	0.141	0.079	0.117	0.141	0.011	0.037	0.075	0.078	0.116	0.141	0.037	0.075	0.113	0	0	0	0.050	0.088	0.113
PSF$_8$	0.048	0.073	0.111	0.048	0.073	0.111	0.036	0.074	0.112	0.023	0.061	0.099	0.062	0.100	0.138	0.076	0.114	0.152	0.062	0.100	0.138	0	0	0

0.336. Therefore, developing and detailing work procedures positively and meaningfully affects the other factors simultaneously. "Environmental conditions" (i.e. PSF$_4$) has the lowest prominence value (i.e. 3.418) and is characterized by a positive relation value equal to 0.287. Thus, PSF$_4$ does not play a central role in the system, as also confirmed by Figs. 4-5 and by its weight (i.e. 0.087). Therefore, any corrective measure addressed to improve the environmental conditions is not primary to reduce the human contribution to risks.

As concerns net receiver in the system factors, "task complexity" (i.e. PSF$_7$) is characterized by the highest value of prominence (i.e. 5.474) and has a negative relation value (i.e. −0.286), with a final weight of 0.139. Therefore, "task complexity" is strongly influenced by the other factors, particularly by "experience", "training" and "procedures" as highlighted by the defuzzified total relation matrix (Table 11). Accordingly, providing training and procedures to experienced operators significantly reduces the "task complexity" and the risk of human errors as a consequence. Among the net receiver group, "fitness to work" (i.e. PSF$_3$) has the lowest degree of influence (i.e. 4.683). In this regard, "fitness to work" encompasses individual psychological and physical aspects, so that it is plausible that it is influenced by the other PSFs such as "task complexity" and "training" as highlighted by Table 11. Finally, "Equipment and MMI" (i.e. PSF$_5$) has the lowest relation value (i.e. −0.489), namely it is strongly influenced by all PSFs. In particular, "experience" and "training" exert the highest degree of influence, as skilled and trained workers are more ready and able to use tools and to interact with machineries.

4.2. HEP computation

Among the three companies involved in the previous step, one was chosen to evaluate the human error probability when performing a generic task. Leader in the textile sector, the company mainly produces carpets for both the national and international market. In agreement with the company's top management, the proposed methodology was implemented in the weaving process of the fabric rolls, owing to its criticality for the company productivity. The process under investigation comprises the following tasks Table 14, Figs. 6–10. Based on the classification proposed by the HEART method (Williams, 1988), tasks of the weaving process under investigation were considered as "routine, highly practiced". As a consequence, parameters f, α and β of equations (11) and (12) in an eight-hour shift were the ones synthetized in Table 15.

Assuming the most conservative scenario, NHEP was set equal to 0.045. Afterwards, based on PSF normalized weights computed by FDEMATEL (Table 13), the equation (13) was used to compute the overall PSF_C for every task of the weaving process. To this aim, the company safety manager was questioned on the incidence level of listed PSFs on every task of the weaving process, by using the five-point scale of Table 4. The obtained data are the ones summarized in Table 16, where PSF_C and HEP values computed by (13) and (10) respectively are also reported for every task.

The analysis of PSF multipliers of Table 16 highlights the highest incidence of "experience" (PSF$_1$) followed by "training" (PSF$_2$) and "fitness to work" (PSF$_3$). On the other hand, "environmental conditions" (PSF$_4$) is the least important PSF, whose multipliers range between 0 and 1. Tasks characterized by a prevalent human contribution to risks are weaving (Task 4) and creel loading (Task 1), with HEP values equal to 0.1232 and 0.1133 respectively. As highlighted by the high incidence level (i.e. 4) of "experience" (i.e. PSF$_1$), "training" (i.e. PSF$_2$) and "equipment and MMI" (i.e. PSF$_5$), Task 4 requires a strong interaction between the operator and the automatic loom. In addition, the operator is also asked to be able in performing the quality check, identifying and manually repairing defects if detected. Based on Table 11, PSF$_5$ is highly influenced by PSF$_1$ and PSF$_2$. Thus, taking corrective measures on "experience" and "training" would affect "equipment and MMI", so reducing the HEP in performing the Task 4. With a multiplier equal to 4, "experience" and "task complexity" (i.e. PSF$_1$ and PSF$_7$) are the most

Table 11
Defuzzified total relation matrix.

	PSF_1	PSF_2	PSF_3	PSF_4	PSF_5	PSF_6	PSF_7	PSF_8
PSF_1	0.268	0.383	0.349	0.207	0.424	0.331	0.429	0.346
PSF_2	0.386	0.294	0.387	0.228	0.437	0.369	0.436	0.341
PSF_3	0.259	0.294	0.216	0.167	0.336	0.251	0.329	0.301
PSF_4	0.230	0.241	0.275	0.121	0.279	0.192	0.277	0.236
PSF_5	0.324	0.337	0.306	0.213	0.269	0.293	0.349	0.297
PSF_6	0.345	0.382	0.330	0.215	0.377	0.244	0.405	0.350
PSF_7	0.360	0.367	0.356	0.201	0.391	0.306	0.290	0.324
PSF_8	0.311	0.326	0.311	0.213	0.365	0.328	0.365	0.237

Table 12
D_i, R_i, prominence and relation values.

PSF_i	$\tilde{D}_i$			$\tilde{R}_i$			D_i	R_i	$(D_i + R_i)$	$(D_i - R_i)$
PSF_1	0.754	1.960	5.969	0.656	1.743	5.504	2.736	2.484	5.220	0.251
PSF_2	0.870	2.121	6.111	0.690	1.797	5.879	2.877	2.625	5.502	0.252
PSF_3	0.446	1.400	5.054	0.631	1.757	5.670	2.153	2.530	4.683	−0.377
PSF_4	0.336	1.142	4.488	0.202	0.900	3.972	1.852	1.566	3.418	0.287
PSF_5	0.580	1.588	5.467	0.816	2.058	6.257	2.389	2.877	5.266	−0.489
PSF_6	0.707	1.859	5.859	0.554	1.523	5.324	2.649	2.313	4.962	0.336
PSF_7	0.701	1.850	5.686	0.867	2.101	6.151	2.594	2.880	5.474	−0.286
PSF_8	0.592	1.622	5.646	0.570	1.663	5.522	2.457	2.431	4.888	0.026

Table 13
PSF weights.

PSF_i	Weight (i.e. w_i)	Normalized weight (i.e. q_i)
PSF_1 - Experience	5.226	0.132
PSF_2 - Training	5.508	0.139
PSF_3 - Fitness to work	4.698	0.119
PSF_4 - Environmental conditions	3.430	0.087
PSF_5 - Equipment and MMI	5.289	0.134
PSF_6 - Procedures	4.973	0.126
PSF_7 - Task complexity	5.481	0.139
PSF_8 - Organization and working conditions	4.888	0.124

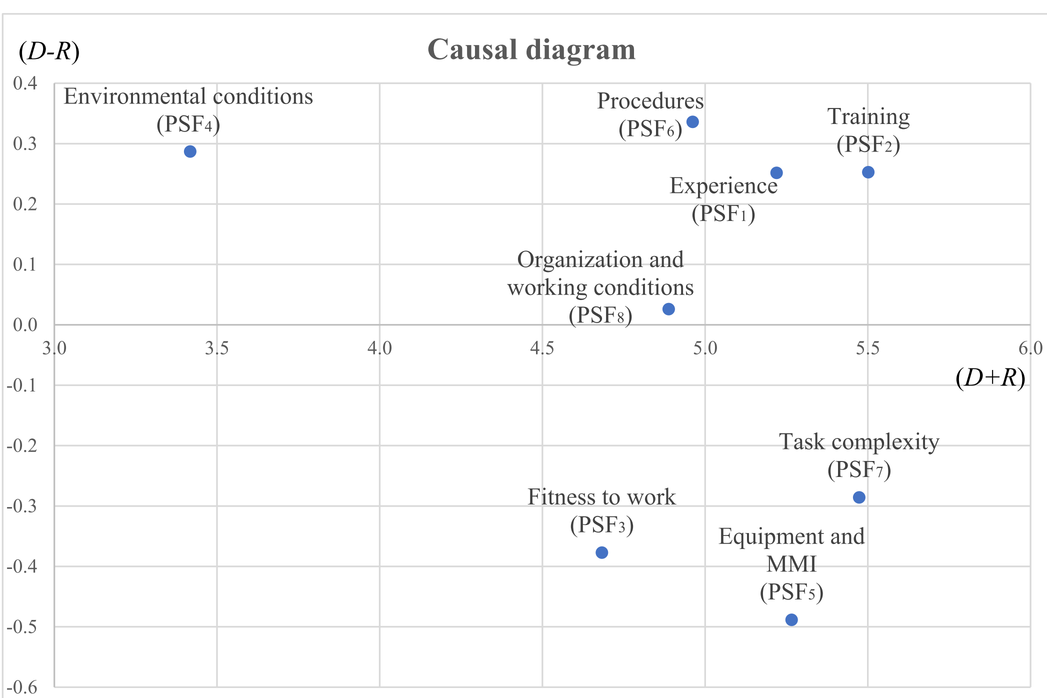

Fig. 4. Causal diagram of PSFs.

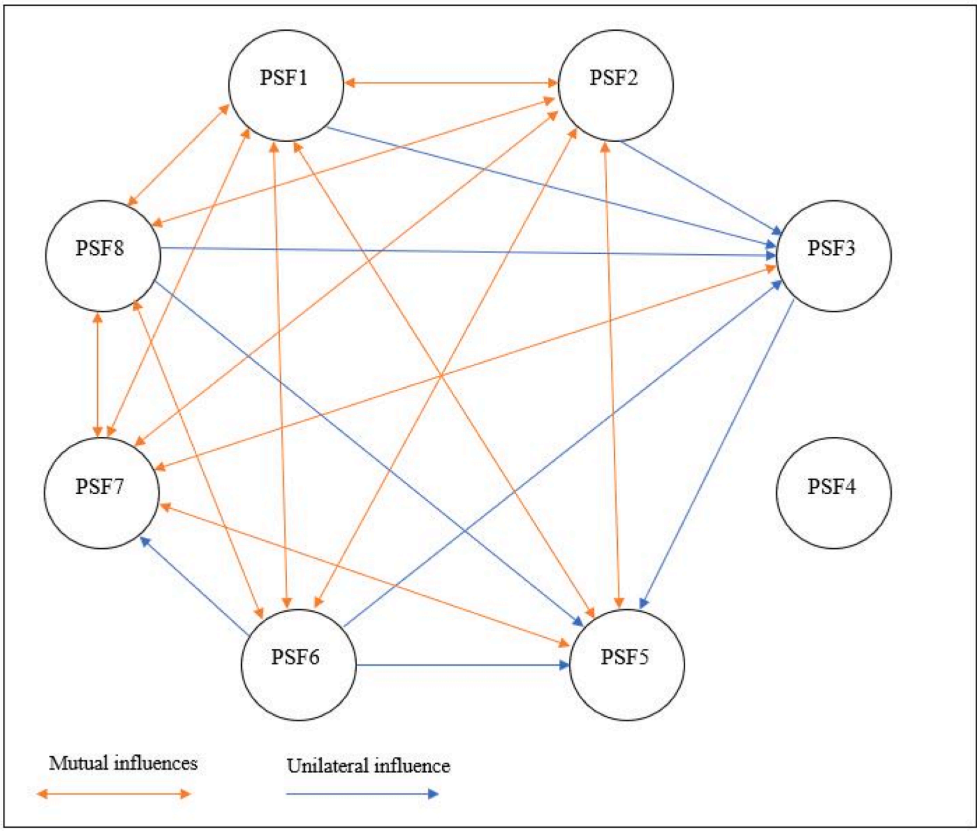

Fig. 5. Main influences graph.

contributing factors to the human error when performing the Task 1, where operators are required to avoid the incorrect positioning of the reels in creel loading. Referring to Tables 11 and 12, "task complexity" is a net receiver factor which receives the highest influence by "experience", followed by "training". Therefore, implementing proper measures to improve workers "experience" and "training" would positively affect "task complexity", reducing the overall HEP in performing the Task 1 as a result. Binding (i.e. Task 2) has a HEP value equal to 0.1079, which is mainly influenced by "training" and "fitness to work" (i.e. PSF_2 and PSF_3). Since the influence of "training" on "fitness to work" resulting from FDEMATEL, the most effective contribution to the operator reliability may be gained by taking actions on his/her training also in this case.

Therefore, the obtained results highlighted the importance to have highly experienced and trained workers to improve the overall operator reliability when performing tasks of the weaving process. As a result, primary actions should be taken on "experience" and "training" whose improvement have a general and positive influence also on the other factors.

5. Conclusions

In recent years, Human Reliability Analysis (HRA) techniques have been widely investigated and implemented in different fields. Despite that, the majority of literature contributions assume the independence among Performance Shaping Factors (PSFs) although the empirical evidence shows otherwise. So far, only few studies have provided not well structured qualitative methods, while others performed quantitative analyses, highly complex or requiring a huge amount of data. In addition, HRA applications are still poor in the manufacturing sector, where human errors are often disregarded even if responsible of worse products quality and productivity. Therefore, the present paper focused on the manufacturing sector to design a structured and effortless approach to support the risk analyst in the evaluation of the PSF interrelationships and importance when computing the Human Error Probability (HEP) to perform a generic task. The study began with an extensive literature review on PSFs. Afterwards, three different Italian textile companies were involved to select a reduced list of PSFs among the ones available from the literature, and the Fuzzy DEMATEL (FDEMATEL) approach was used to evaluate both the mutual influence and the relative importance of chosen PSFs. In this regard, the input data required by FDEMATEL were gathered by means of a survey administered to the three aforementioned companies, whose respondents were differently weighted based on their own expertise in the investigate field. Referring to one of the involved companies, PSF weights obtained by FDEMATEL were finally used in a combined HEART and SPAR-H method to compute the HEP of the weaving process tasks. The resulting HEPs confirmed the importance to have highly experienced and trained workers. In fact, taking actions on experience and training factors was demonstrated to have a general and positive influence on the others, so increasing the overall human reliability.

Properly customized, the designed approach for the quantification of PSFs dependence and relative importance could be implemented in other fields. Compared with the available methodologies, the proposed one is theoretical based on the MCDM framework and provides an easy, structured and replicable way to consider personal, contextual and cognitive factors when computing the human contribution to risks. Nevertheless, the management of a whatever company is not able to focus on all factors which affect the human reliability, owing to the limited availability of resources for instance. Therefore, the proposed one also represents a valid decision aiding support tool for the analyst to decide the corrective measures to be primary taken, mainly focusing on

Table 14
Process tasks.

a) Task 1- Creel loading. Based on the fabric to be produced (e.g. colour, material, etc..), the operator identifies the thread reels to be loaded on the creel and their position (Figure 6). Three reels of thread are loaded at a time.

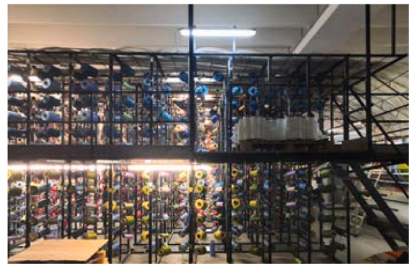

Figure 6. Creel loading

b) Task 2 - Binding. The operator binds each thread of the reels to needles according to three different techniques of binding (i.e. classic knot, compressed air knot, and fusion gun knot) (Figure 7).

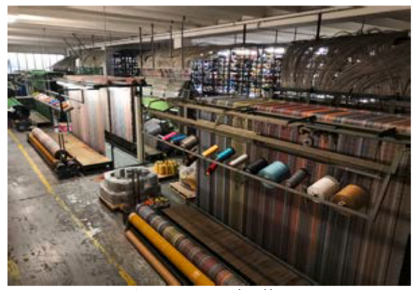

Figure 7. Binding

c) Task 3 - Drawing loading. The fabric drawing to be produced is uploaded in the software that manages the loom operations (Figure 8).

Figure 8. Drawing loading

d) Task 4 - Weaving. The operator activates the automatic loom. By the automatic loom display, a quality check is performed by analysing sequence, drawing and colours of the fabric rolls to be woven. If defects are detected, the operator has to solve them manually by an appropriate sewing gun (Figure 9).

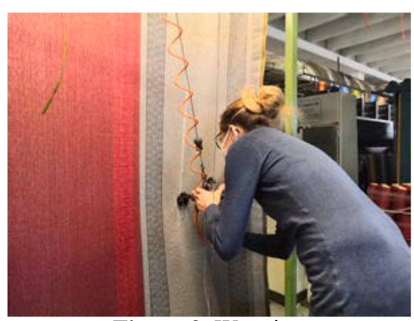

Figure 9. Weaving

e) Task 5 - Fabric roll unloading. Once the weaving task is completed (Figure 10), the fabric roll is unloaded through a cart and labelled.

Figure 10. Fabric roll unloading

Table 15
Parameters values of the generic task "routine, highly-practiced".

f	α	β	Range of NHEP
0.9930	0.0021068	1.5	[0.007; 0.045]

Table 16
PSF multipliers and HEP of the weaving processes tasks.

	Task 1	Task 2	Task 3	Task 4	Task 5
PSF_1	4	3	4	4	3
PSF_2	3	4	3	4	2
PSF_3	3	4	2	3	3
PSF_4	1	1	1	1	0
PSF_5	2	1	1	4	0
PSF_6	2	2	2	3	3
PSF_7	4	3	2	3	1
PSF_8	2	2	1	1	2
PSF_C	2.731	2.57	2.06	2.98	1.80
HEP	0.1133	0.1079	0.0884	0.1232	0.0780

influential factors whose improvement allow at developing the others simultaneously. In addition, the fuzzy version of DEMATEL is able to properly deal with the vagueness and uncertainty of the decision process, where exact numerical values are often inadequate to characterize the expert knowledge.

On the other hand, the design of innovative methods to weigh experts more precisely should be further explored, so representing a possible line of research. In fact, subjective weighting methods have been mainly used in the literature so far, but further efforts are needed to reduce bias or inaccuracy. In addition, a sensitivity analysis could be performed to explore the effects of judgments variations on the robustness of results. Finally, it is noteworthy that the proposed list of PSFs does not presume to represent a taxonomy for the manufacturing sector, which would require a deeper and likely statistical based analysis involving a proper sample size of companies.

CRediT authorship contribution statement

C.M. La Fata: Methodology, Supervision, Writing - review & editing, Project administration, software. **L. Adelfio:** Conceptualization, Data curation, Methodology, Writing - original draft. **R. Micale:** Conceptualization, Methodology, Writing - review & editing, Supervision. **G. La Scalia:** Data curation Formal analysis, Supervision, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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