Stepping Stone to Smarter Supervision Systems: A Human-centered Multidisciplinary Framework

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For many years, industries have been seeking to increase their productivity and competitiveness in an environment that is increasingly uncertain and complex. The use and massive integration of new technologies appears to be one of the paths chosen by industries to achieve these goals that mark the fourth industrial revolution (see Alcacer & Cruz-Machado, 2019 and Zheng et al., 2019 for recent reviews on technologies for manufacturing systems). Overall, new technologies are used to increase the level of digitalisation and automation throughout the development of digital solutions able to increase (or maintain) the productivity of the manufacturing system (Oesterreich & Teuteberg, 2016; Lu, 2017; Perruzini et al., 2017). The rise of new technologies and associated digital solutions are making the industrial environment increasingly intelligent and adaptive. Industry 4.0 particularly promotes the use of agile, flexible, and collaborative digital systems to solve complex problems and make better decisions (Perales et al., 2018; Peruzzini et al., 2017). In some cases, digital systems become so central that they begin to take on the role of a decision board member, with in extreme cases, a real decision-making authority (Oztemel et al., 2020).

Digital systems such as Decision Support Systems (DSS) aim to help decision makers to cope with the increasingly complexity and uncertainty of the manufacturing system (see Felsberger et al., 2016 for a review of DSS for manufacturing systems, voir aussi Manzey et al., 2012; Zikos et al., 2018; Onnasch & Hösterey, 2019). Particularly, the objective of a DSS is to assist or replace the decision makers in most of their tasks especially those of information gathering and processing, planning and decision-making, and supervision of job execution (Guérin et al., 2019). For instance, a DSS with high capacities of information gathering and processing (e.g., allowed by Internet of Things) combined with high capacities of calculation and learning (e.g., allowed by Big Data and machine learning) could quickly provide an accurate diagnosis of the current situation as well as prognoses on its evolution. It could also be possible for such a DSS to infer from a large database (i.e., history of unexpected events) new rules and automatically propose adjustment to the system. Consequently, the aim of digital and technological revolution that underpin Industry 4.0 is twofold: (i) improving the decision makers' performance and working conditions (Wang et al., 2016; Rauffet et al., 2018) by providing adapted technological and digital solutions such as DSS (Frank et al., 2019) and (ii) increasing the agility of the manufacturing system and its productivity. Beyond the understanding of how DSS can improve the productivity of the manufacturing systems, it seems particularly interesting to characterize their impact on the decision-makers' working conditions, especially at the operational level.

DSS type, their positive effects and those more discutable

DSS are technological and digital solutions able to support or handle a wide range of complex tasks. Particularly, DSS are "an interactive computer-based system or subsystem intended to help decision makers use communications technologies, data, documents, knowledge, and/or models to identify and solve problems, complete decisions, process tasks, and make decisions. DSS is a general term for any computer application that enhances a person or group's ability to make decisions" (Power, 2002 cited by Power, 2008). DSS' capabilities, functionalities and autonomy are very varied, which gives them multiple applications ranging from the simplest spam filter or a function able to classify a list of words in alphabetical order, to the most complex such as a DSS capable of generating a production schedule. Haettenschwiler (2001; cited by Felsberger et al., 2016) has highlighted three types of DSS (i.e., passive, active, and collaboratif). DSS can be passive meaning that they operate only as a support for the decision-making process that is they do not offer any recommendations or solutions to decision makers. For instance, it may be a DSS that highlights a conflict between two resources in the production schedule. In the case where the DSS proposes recommendations or solutions to solve this conflict, the DSS is active. Particularly, the DSS can, once the conflict between the two resources has been highlighted, modify the production schedule to resolve it. In this situation, the decision maker cannot modify the solutions proposed by the DSS. In the case where the DSS allows the decision makers to modify, complete, or refine the recommendations or solutions provided, the DSS is cooperative. Consequently, DSS can range from a digital system offering simple support to the decision-making process to a more autonomous system able to make and implement a decision (Nunes & Jannach, 2017). With the advancement of new technologies, it stands to reason that DSS are very useful for decision makers to help them to cope with the increasing complexity of the manufacturing environment and the multitude of information (Herrmann, 2006) associated with operational tasks (e.g., scheduling, monitoring, rescheduling). Particularly, operational tasks require a detailed description and knowledge of the production process, which inevitably require gathering and processing of a very large amount of information (Rossit et al., 2019). Several authors describe such tasks as “complex cognitive processes that comprise a considerable amount of interrelated subtasks” (Dimopoulos et al., 2012; p. 8-9; see also Cegarra et al., 2008). As information systems, DSS are supposed to support decision making by facilitating the gathering, access, processing and analysis of available information (Alter, 1977; Keen & Scott-Morton, 1978). For instance, it has been shown that participants understand and identify potential errors in the supervision of a nuclear power plant more easily when assisted by a DSS than when they have to process and analyze all available information on their own (Lee & Seong, 2009).

In broad terms, DSS are supposed to support operators’ cognitive processes (Keen, 1980). Specifically, DSS are expected to significantly increase the effectiveness, efficiency and quality of the decisions (see e.g. Riveiro et al., 2014; Todd and Benbasat, 1992), not least because they relieve decision makers’ cognitive (Lee and Seong, 2009; Onnasch and Hösterrey, 2019) and emotional workloads (Hung et al., 2007). Decision makers’ cognitive workload would be relieved because DSS are able to automatically and very quickly handle complex tasks such as scheduling (see e.g., Onnasch and Hösterey, 2019) or rescheduling when unexpected events seriously challenge the initial schedule. These tasks are very stressful and highly cognitively demanding for the decision makers performing them without the assistance of a DSS. Several studies have shown that decision makers’ cognitive workload increases when they perform a set of tasks by themselves compared to those using fully automated tasks (Navarro et al., 2018; see also Röttger et al., 2009). A meta-analysis corroborated these findings by showing that the higher the degree of automation, the less operators’ workload (Onnach et al., 2014). From an emotional perspective, DSSs’ use significantly reduce users’ post-decision regret, particularly in tasks involving low user satisfaction (Hung et al., 2007). It has also been argued that DSS would decrease decision makers' stress since it would automatically and very quickly provide optimal solutions in a highly time-pressured environment (Mailliez et al., 2021). However, to our knowledge, only few studies have directly tested this assumption and more generally, the influence of DSS use on the decision makers' emotional state (Mailliez et al., 2021). Taken as a whole, DSS therefore meet all the Industry 4.0 objectives by trying to improve both decision makers' performance and working conditions (e.g., by reducing cognitive and emotional workloads) and the flexibility and the productivity of the system (Wang et al., 2016).

Interestingly, DSS do not necessarily imply either improvement in decision makers' performance or working conditions. For example, in several studies, the decision makers' performance and situation awareness decreased when using a DSS compared to those who do not (see e.g., Kaber, Onal, & Endsley, 2000; Manzey et al., 2011). Particularly, it has been reported that the higher the level of automation, the lower situation awareness (Onnasch et al., 2014). DSS' users may then take longer to decide as they have to recover situational awareness (Lee and Seong, 2009; van der Kleij et al., 2018). They also need minimal stimulation during supervision to stay engaged in their task. Decision makers then tend to prefer manual task completion over automation to reduce their boredom (Navarro & Osiurak, 2015) and stay engaged in production supervision. It has also been shown that DSS reliability and decision makers' trust in automation considerably influences their decision to use it (Madhavan & Wiegmann, 2007). Particularly, the less reliable the DSS and the less decision makers' trust in automation, the less they intend to use DSS in their tasks. A recent qualitative study highlights that the use of digital solutions does not necessarily reduce the emotional demands arising from the manufacturing environment. Particularly, the analysis of a series of semi-structured interviews suggest that technical problems, poor usability, and low situation awareness are stressors caused by the interaction with digital systems like DSS (Korner et al., 2018). Technical issues such as breakdows were highlighted as major stressors in this study especially when users were unable to manage these issues on their own, which slows down workflows and adds time pressure (Korner et al., 2018). Consequently, while it is self-evident that DSS are useful and can significantly improve decision makers' performance and working conditions especially in their operational tasks, it is necessary to deepen the understanding of the origin of DSS' unexpected, and at worst deleterious, effects to counteract them.

Understanding of the DSS' undesired effect

We suggest that one of the explanations for the DSS undesirable effects lies in the approach used to design them. The vast majority of the approach to design DSS in manufacturing systems are based on a "techno-centered" approach (MacCarthy, 2006; Trentesaux, Dindeleux, & Tahon, 1998) as evidenced by one of the current DSS' taxonomies (see Hasan et al., 2017, for a recent review): DSS can be model-centered, data-centered or knowledge-centered. Model-centered DSS are autonomous systems allowing the analysis of available data according to pre-established models. Data centered DSS are digital systems facilitating the decision-making process by providing the user to manipulate and extract data from large databases, whether internal or external to the manufacturing system (Power, 2008). Finally, knowledge centered DSS are digital solutions incorporating artificial intelligence and thus giving it effective problem solving and prediction abilities useful to support decision-making processes (Chung et al., 2016). Based on a literature review in the manufacturing environment, Hasan and colleagues (2017) have shown that 49% of the DSS developed is model-focus and closely followed by knowledge-focus. However, given recent advances in technologies and artificial intelligence, especially big data, it is possible that development based on model-focus is superseded by DSS' developpement based on knowledge-focus (Shi, 2018). Broadly speaking, the techno-centered design (TCD) primarily focuses on the technical specifications of the DSS by seeking to provide a set of efficient and effective problem-solving techniques (e.g., fast information retrieval techniques) to decision makers (i.e., end-users). It is thus clear that the philosophy of the TCD is to automate as many functions as possible in a given context and that it assumes that decision makers must perfectly act and behave in their environment under all circumstances (Pascaux-Lemoine et al., 2017). Consequently, this approach completely neglects the decision makers' strengths and weaknesses in designing DSS (Trentesaux & Millot, 2016). Particularly, in the TCD, the decision makers' role is only taken into account once the DSS is completed, i.e., at the end of the design process (Pascaux-Lemoine et al., 2017). This tendency to relegate the decision makers to the background is particularly present in the modern manufacturing environment. In this context, DSS are responsible for providing intelligent production control systems that manage production goals and constraints (e.g., deadlines), while collecting key performance indicators (e.g., delays, tasks completion levels). Such DSS would ultimately provide more autonomy, improve responsiveness, resilience and overall system robustness. From this perspective, the decision makers are mostly considered as a global DSS supervisor (Gaham et al., 2015; Zambrano et al., 2013). It is interesting to note, that designers embedded in such approach consider, most of the time, that they involve the decision maker in the design process (i.e., “human-in-the-loop” perspective) as soon as the decision maker have to determine the DSS’ objective and parameters constraints. However, as wisely pointed out by Pascaux-Lemoine and colleagues (2017), this approach is more about keeping the decision makers in the "decision/responsibility loop" but not in the control one. The decision maker is totally excluded from the DSS decision-making process and thus relegated to the mere role of spectator. Being unaware of the DSS’ functioning, decision makers would be unable to choose the optimal parameters for the functioning of such a system, except that, in reality, decision makers are expected to react and manage perfectly all the events they are confronted with. Ironically, Trentesaux and Millot (2016) refer to such end-users as ‘magical humans’. Indeed, TCD has exaggerated the ability of end-users’ to behave perfectly and accurately and, of course, within acceptable response time, as well as react perfectly when facing unexpected events (Pascaux-Lemoine et al., 2017). Such an overestimation of the end-users’ capabilities, as well as the fact that this approach incorporates only limited knowledge of the tasks performed by the end-users, their needs, their constraints and their cognitive specificities could account for the undesired effects sometimes observed when using DSS. In line with this hypothesis, several authors suggest that decision makers’ characteristics influence their DSS’ use and their performance (e.g., Fuerst & Cheney, 1982). For instance, it has been shown that as the level of automation increases, decision makers’ performances increase and situational awareness decreases (Jipp & Ackerman, 2016). However, this would depend on decision makers' characteristics. When the level of automation is high, participants with good information processing skills and good working memories skills have better performance and situational awareness than participants with low information processing skills and low working memory skills (Jipp & Ackerman, 2016). Thus, the authors suggest that participants with high information processing and working memory abilities benefited more from high levels of automation compared to participants with low information processing and working memory abilities (Jipp & Ackerman, 2016). Focusing solely on technologies will therefore result in unsustainable and unused systems, and in the case they are, will not have the desired effect on performance and working conditions of decision makers' (Gasseau, 2013).

In the recent decades, it has been proposed that rather than focusing on technologies, it is necessary to focus on individuals. In 1980, Daniel Norman proposed a series of guidelines for DSS designers based on a novative philosophy. In this approach the end-user (i.e., the decision maker) is at the heart of the DSS development process. Within Industry 4.0, this human-centered design (HCD) approach is brought to the forefront to allow for a certain symbiosis between decision makers and automation. Therefore, the HCD is used to promote the cooperation of machines and individuals in their workplaces (Zarte et al., 2020). In HCD, it is important to note that machines or digital systems are not designed to replace decision makers' skills and abilities but to coexist and assist them, especially to improve their working conditions (Romero et al., 2016; Romero et al., 2020). In 2010, users' consideration within the process of digital solutions development was endorsed by the ISO standard 9241-210. This standard defines the HCD as " an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques." This ISO standard also suggests that designing "usable systems can provide a number of benefits, including improved productivity, enhanced user well-being, avoidance of stress, increased accessibility and reduced risk of harm'. Broadly speaking, HCD aims to make accessible digital systems to a specific group of users (Astbrink et al., 2003) or to a larger group of users regardless of their physical or cognitive abilities (e.g., Meyer, 2000 cited by Harte et al., 2017). The HCD would therefore constitute a new engineering philosophy for adaptive solutions, emphasizing the approach of automation as a means to enhance human physical, sensory, and cognitive abilities through the integration of human cyber-physical systems (Zarte et al., 2020). In HCD, users are invited to express their needs by placing them at the center of the design process of digital solutions (e.g., Gill, 1981). Such an approach is expected to reduce the reliance on the magical-human assumption (Pascaux-Lemoine et al., 2017).

HCD are, at first glance, accessible, intuitive, and simple to implement. The ISO standard suggests that HCD is organized around four predefined phases of activities: (1) identification of the user and specifying the context of use; (2) specification of the user's requirements; (3) generation of design solutions; and (4) evaluation of the design solutions against the users' requirements. The first two phases allow us to understand the project objective, the problem and the users' requirements. The results of these two first phases are implemented in the third one, in which the architecture of the proposed solution will be designed, developed and deployed. Once the solution has been deployed, during the fourth and last phase, designers gather feedback from users to improve (or replace some parts) the proposed solution through an iterative process. In addition to the four predefined phase of activities, the ISO standards point out six requirements that design and development processes must meet to be considered as a HCD: "(1) The design is based upon an explicit understanding of users, tasks, and environments; (2) Users are involved throughout design and development; (3) The design is driven and refined by user-centered evaluation; (4) The process is iterative; (5) The design addresses the whole user experience; and (6) The design team includes multidisciplinary skills and perspectives" (Harte et al., 2017). The use of such design methodology can thus considerably reduce the undesired effect of DSS since it focuses only on the end-users needs and demands. The design and development of the solution is therefore not driven by the integration of new technologies in the manufacturing environment as it seems to be the case with TCD. Furthermore, the design process must be multidisciplinary. Such an approach is necessary to acquire the complexity of the design as well as the complexity of the end-users and their socio-technical environment, from the very first steps of designing a DSS (Skoberla et al., 2017). A multidisciplinary approach allows for the use and the integration of knowledge from very different fields (e.g., cognitive ergonomics, social psychology, human-computer interaction, operational research, industrial systems and informatics) that are seemingly unrelated (Lozano, 2008; Miliken, 2003). The integration of such different fields would optimize the design process (Shen & Hao, 2008). The multidisciplinary approach is particularly appropriate because an expert in one domain does not know what information is useful to another expert in another field (Strauss, 2011 cited by Skoberla et al., 2017). For example, for experts in industrial system and operational research, the mental and emotional workload associated with a task is not an information to which they pay attention, whereas experts in cognitive ergonomics are sensitive to this information and integrate such information in the design of digital solutions. In conclusion, the type of approach that designers choose to embed the design process of a DSS and domains included in the multidisciplinary team are determining parameters in the effectiveness and acceptability of the future developed digital system. It would also be a key parameter in the effects the developed solution will have on end-users' performance and working conditions. This is a significant challenge, as developing a human-centered DSS requires a multidisciplinary approach that involves the gathering and integration of many information, requirements, and constraints from many different scientific domains (Skoberla et al., 2017). Although it is clear that the HCD and multidisciplinary approaches are the most appropriate for developing effective DSS, and although designers are increasingly using it, the TCD and its associated single-discipline perspective remain the majority especially for the development of DSS at the operational level. We suggest that one of the explanations lies in the lack of clear guidelines to consider what are the different phases to design and develop a human-centered DSS for the operational level and how multidisciplinary can really be implemented in such an approach.

Towards a Human-Centered Design (HCD) multidisciplinary framework for DSS

The modern manufacturing environment is constantly changing and evolving towards an increasingly complex and uncertain environment. Industry 4.0 seems to bring a relevant answer to this phenomenon by developing digital solutions integrating new technologies aiming to improve decision makers' performance and working conditions (e.g., by reducing their cognitive and emotional workload). As a result, decision makers seem to be at the center of Industry 4.0's concerns. This hypothesis is corroborated by the growing and exponential interest found in the literature for approaches allowing to develop DSS focus on decision makers' needs. For example, Harte and colleagues (2017) propose a detailed methodology and standardized structure to frame the development of digital solutions in healthcare. In the industry 4.0, although interest in HCD is just as strong as in healthcare, the evidence in the literature is much sparser. A growing number of researchers, particularly in ergonomics and human factors, are interested in the design of human-centered supervision systems. In general, they propose to analyze the prerequisites for the acceptance and use of such systems. Particularly, the conditions underpinning algorithms aversion (e.g., Jussapow et al., 2019), the prerequisites facilitating human-machine cooperation (see e.g., Chugunova & Sele, 2020 for a review of the literature), and what are the optimal degree of automation of the solution (Navarro et al., 2019; Romero et al., 2016) have largely been investigated. However, efforts to integrate humans into the DSS' design process, especially at the operational level, mainly focuses on their technical aspects. It appears that designers, usually from the same domain (e.g., informatics, industrial systems) are more guided by the integration of new technologies within a digital system than by meeting decision makers' real needs. Decision makers' activities are therefore only weakly described and taken into account during the design process, which may explain the undesirable effect of DSS. In light of all these elements, we therefore suggest that there is a real need to make explicit a detailed methodology and a reproducible structure for the design of DSS within a multidisciplinary perspective. Particularly, to design DSS for operational decisions such as scheduling or production supervision. The remainder of this chapter therefore describes a proposed three-step methodology inspired by and adapted from the one proposed by Harte and colleagues (2017) in healthcare. We do not intend to provide an absolute solution, but rather to raise questions and solutions to improve the design and the implementation of DSS in the modern manufacturing system. Consequently, the methodology we propose does not claim to be innovative but rather (i) to make explicit and promote a better integration of the decision maker in the design of DSS especially for the operational level and (ii) to facilitate the cooperation and coordination of a multidisciplinary team in the design of DSS.

Phase 1. Identification of decision makers' needs and specification of the context

This phase is divided into four steps (cf. figure 1). The first one (i.e., pre-diagnosis) aims to identify the decision makers' real needs and to specify the socio-technical system in which they evolve. It would therefore lead to a formalization of all decision makers' characteristics, activities, and needs as well as a formalization of all the characteristics of the socio-technical environment. We strongly believe that it is important that researchers do not have any *a priori* hypothesis on the decision makers' needs so that they do not bias this first step. Particularly, individuals tend to favor information that supports their hypothesis and to give much less weight to hypothesis and information that goes against their hypotheses (Klayman, 1995). This well documented confirmation bias can lead designers to a reluctance to change their mind even in the presence of information that clearly contradicts their initial hypothesis (Jones & Sugden, 2001). Consequently, we suggest that if the analysis of decision makers' needs, during the pre-diagnosis, is based on assumptions or preconceived ideas about the functions to be developed in the future DSS, it is possible that the latter will not be adapted to decision makers' real needs. In a second step (i.e., diagnostic), the designers focus their analysis on the particular issues that were identified during the cross-sectional analysis of the data collected during the pre-diagnostic. As a result, the diagnostic would lead to a formalization of decision makers' characteristics, activities as well as the specificity of their socio-technical environment related to specific issues. At the end of these two first steps, the design team is able to identify the decision makers' needs and to elaborate recommendations in order to meet them (i.e., the third step). In a fourth step, a clear and unambiguous discussion made possible by the formal modeling of the decision makers' characteristics and of the socio-technical environment must be carried out with all the stakeholders involved in the project (e.g., researchers/designers, decision-makers, hierarchical superiors). The aim of this discussion is twofold: (i) validate the results of the analysis of the decision-makers' tasks and needs, and of the socio-technical environment and (ii) identify the situations and needs that meet two conditions: (1) it is a real decision makers' need and (2) it can be met by the development of a decision support tool. Taken as a whole, the four steps proposed here help designers to acquire an explicit knowledge of the decision makers, their needs, the tasks they perform and the environment in which they make them before even defining the function that the DSS should have (standard requirements 1 - 3). In line with Skoberla and colleagues (2017) and the ISO standard 6, we promote that the understanding of the complexity of both the design, the end-users and their socio-technical environment should be carried out through a multidisciplinary perspective from the very first steps. One advantage of this first phase is that it would allow, if correctly carried out, to stop the DSS' design process in the very beginning of it and thus save a lot of resources if none of the identified needs can be solved by developing a DSS.

Suggested activities, methods and analyses

In order to study the decision makers' needs and to specify the socio-technical context in which they evolve, we suggest that a researcher with expertise in cognitive ergonomics (also known as human factors) and/or social psychology conducts firstly an analysis of operator activity. This analysis of the operator activity relies on methodological tools (e.g., interviews, questionnaire, and observations) allowing to explore and describe the end-users behavior in its socio-technical environment (Leplat, 2008). The objective of such an analysis is to define and understand what are the tasks the decision makers perform and the socio-technical context in which they perform them, in order to highlight their needs. According to Romero and colleagues (2020), the analysis of operator activity and the modeling of its context can be carried out by normative or descriptive methods. However, most of these methods are unsuitable for HCD (Pascaux-Lemoine et al., 2021). Normative methods tend to focus on specifying the ideal way in which decision makers should work (i.e., the Prescribed work) whereas in reality there is, most of the time, a gap between the Prescribed work and the way in which individuals actually do their work (i.e., the Real work) (Leplat, 2008). As a result, focusing on work as it is prescribed and not as it is performed could lead to the design of unadapted DSS. In contrast, descriptive methods are based on the analysis and description of familiar and recurring conditions, which would make the DSS developed more adaptable than those developed using normative methods because it takes into account the real work done by the decision makers (Romero et al., 2016). Consequently, descriptive methods would allow designing satisfactory DSS under nominal conditions. However, normative and descriptive methods do not allow to take into account uncertainties (e.g., unexpected events) (Pascaux-Lemoine et al., 2021). This is very problematic for designing DSS suitable for Industry 4.0 especially for the operational level, which is particularly affected by uncertainties. Pascaux-Lemoine et al. (2021) also point out that normative and descriptive methods "may forbid the correct evaluation of design choices in terms of human awareness of the situation or mental workload when designing intelligent manufacturing systems integrating the human. Indeed, increasing the intelligence and autonomy of industrial systems and their composing entities (resources, products, robots, etc.), as fostered by Industry 4.0, reduces the ability to understand the behaviors of these systems and increases their overall complexity, leading to the difficulty for human beings, supervisors or operators, not only to elaborate alternative decisions when required, but also to make effective decisions and understand their consequences."

To prevent limitation of normative and descriptive methods, we suggest organizing the first phase of analysis around four steps: pre-diagnosis, diagnosis, recommendations, and selection. In line with Fantini and colleagues (2020), the pre-diagnosis phase aims to identify and understand the decision makers’ tasks as well as their social and technical environments in which they operate. For example, in the context of the design of a DSS for the operational level, it is important to determine the nature of each of the tasks that the decision makers undertake to identify whether these tasks are related to the simple application of procedure, scheduling, planning, or supervision. Within the framework of DSS design, we therefore propose, in line with Pascaux-Lemoine and colleagues (2021), to organize the pre-diagnosis phase around three preliminary analysis which make it possible to describe the activity of the end-users (analysis of the activity), to describe the social environment in which the end-users evolve (analysis of the social environment), and to to describe the tools (i.e., technical environment) with which they work (analysis of the existing). Particularly, in order to develop a DSS for the operational level, we suggest that, during these analyses, it is of relative importance to gather as much as possible information and data allowing us to characterize both the end-users' and their socio-technical environment. Moreover, we suggest that it is also very important to gather as much as possible information and data allowing us to characterize the sources of uncertainties. In line with Romero and colleagues (2016), such recommendations would prevent limitations from descriptive methods that are not suitable to take into account uncertainties. The objective is therefore to be able to (i) determine the nature of the uncertainties, (ii) their impacts on the decision makers' tasks, (iii) specify, if it exists, the procedure for managing them and (iv) specify how the current systems allow to manage this type of events. A particular attention must be paid to the analysis of the socio-technical system. Particularly, the researchers have to identify all the interlocutors with whom decision makers interact, the nature of information they exchange, and the frequency and manner in which these exchanges take place. It would also be important to qualify the type of relationships the decision makers have with their interlocutors in order to be able to integrate, if relevant, the hierarchical and collective decision problems in the design of the DSS. In line with the recommendations of Leplat (2008), the analysis of the activity and the one of the social environment should be carried out using non-directive interviews, observations and survey of data. The third analysis is more specifically devoted to the understanding and specification of the technical environment, especially the digital one, through an expert analysis. This analysis can be done, for example, by using the well-known heuristic criteria of Bastien and Scapin (1995). These criteria are supposed to allow a better understanding of the interfaces already present in the environment. The objective of such an analysis is to characterize their usability issues and to propose solutions able to solve them. Finally, in these three preliminary analysis, the researcher will have to specify the decision makers' characteristics especially in identifying how the activities and tasks they perform influence their cognitive (e.g., mental workload and mental fatigue) and emotional (e.g., stress and frustration) state and which activities or tasks are the most cognitive and emotionally demanding.

We suggest that one formalized method allowing for accurately modeling the socio-technical context and for identifying the decision makers' real needs is the cognitive analysis of work (CWA). This method allows to (i) combine social sciences' contributions with that of engineering, especially those related to industrial system engineering and operational research, (ii) take into account contingencies in the decision makers' tasks and (iii) address the specificity of human-machine interaction within Industry 4.0, especially in the DSS design process (Guérin et al., 2019; Pascaux-Lemoine et al., 2021). Decision makers cannot always rely on pre-established procedures to cope with unexpected events. They must demonstrate flexibility and high problem-solving skills to manage such situations. Therefore, rather than analyzing specific sequences of activities and tasks that occur during typical events, CWA is particularly relevant to design flexible and complex systems that will support decision makers' performance even when unexpected events occur (Jenkins et al., 2017). CWA is classically performed in five steps, each of them focusing on a specific type of constraints: (1) work domain analysis which identifies the goals, priorities, functions, and physical resources of the system, (2) control task analysis which highlights the problem solving or decision making processes required by the system, (3) strategy analysis which identifies the different ways the end-user (i.e., the decision maker) performs these tasks, (4) the analysis of social organization and cooperation which focuses on the way in which work is coordinated and distributed between the different actors of the system and (5) the analysis of workers' competences which allows to identify the skills required by end-users to effectively perform the required tasks (see e.g. Naikar et al., 2006 for comprehensive guidelines).

The fine analysis of decision makers' activities and tasks as well as the identification of their characteristics require the identification, the definition and the understanding of a set of theoretical concepts borrowed from the individuals' cognitive and social functioning (e.g., mental load, emotional load, attention, memory, leadership). Furthermore, we suggest that this data can be completed and processed by means of a CWA carried out jointly by the social sciences and humanities' team and the one specialized in industrial systems and operational research. In line with the guidelines proposed by Naikar and colleagues (2006), we suggest that for achieving the most complete CWA, it's possible for the teams to perform additional studies (e.g., interviews, observations, card sorting) to complete the data collected during the preliminary analyses. Taken as a whole, this pre-diagnosis phase of analysis will allow (i) a fine description of the decision makers' tasks and of the socio-technical environment, (ii) a first mathematical modelisation of these elements, (iii) the creation of a set of use case representing each of the decision makers' activities and tasks, (iv) and the identification of a set of cognitive and physical issues. Here, mathematical modeling has to be considered in its descriptive function. It allows to define the set of variables and parameters present in the decision makers' environment and will be used as a basis for the development of the DSS in the following design phases. At the end of the pre-diagnosis step, several documents are available to describe the decision-makers and their socio-technical environment: analysis of the activity, of the social environment and of the technical one, CWA's report, mathematical model allowing to define all the variables at stake in the situation and a set of use cases generally composed of flow diagrams, storyboards, screenshots, interface mock-ups, paper prototypes, and description of users' profiles. Based on these documents, the design team identifies the cognitive and physical problems. Once the pre-diagnosis is established, the design team proceeds a second time with the three analyses, focusing on the issues identified in order to refine its diagnosis. For example, if the pre-diagnosis step highlights the tasks inducing the higher cognitive and emotional workloads is to cope and manage unexpected events, the diagnosis phase should focus on those issues and specify the end-users' profile and socio-technical environment related to the management of unexpected events. As the CWA framework is particularly relevant to design complex systems (Jenkins et al., 2017) and to embed the design process into a multidisciplinary perspective (Guérin et al., 2019; Pascaux-Lemoine et al., 2021), we suggest processing the data collected during the diagnosis step through this frame. Like at the end of the pre-diagnosis step, several document are available at the end of the diagnosis step: analysis of the activity, of the social environment and of the technical one, CWA's report, mathematical model allowing to define all the variables at stake in the situation and a set of use cases generally composed of flow diagrams, storyboards, screenshots, interface mock-ups, paper prototypes, and description of users' profiles. However, in contrast to the pre-diagnosis step, documents arising from the diagnosis step are focused on the specific issues identified during the pre-diagnosis step. Based on all of these documents, the design team, especially members specialized in cognitive ergonomics and/or social psychology, is then able to provide recommendations to enhance working conditions of the decision makers. It is important to note that the ergonomics recommendations must be established in concert between all areas represented on the design teams (i.e., cognitive ergonomics, social psychology, industrial systems, operational research, human-machine interaction) to facilitate their integration in the final DSS (see e.g., Bjerg Hall-Andersen & Broberg, 2014 for an example of how to integrate ergonomics recommendations into the engineering design process).

Finally, the purpose of all of these documents is to serve as a basis for a clear and unambiguous discussion between all the stakeholders involved in the project (e.g., researchers/designers, decision-makers, hierarchical superiors). This discussion (i.e., selection step) allows (i) to validate the results of the analysis of the decision-makers' activities and environment and (ii) to select the needs of the future users on which the project will focus in the next design phases. To ensure that DSS design is based on a real decision makers' needs, we suggest that the needs on which the design team will focus should be selected according to two criteria: (i) the need must be real (i.e., arising from the proper analysis of decision makers' activities and socio-technical environment rather than from the analysis of Prescribed work or *a priori* hypothesis), and (ii) all the stakeholders involved in the project agree that the development of a DSS is necessary, relevant and feasible to meet this need . The selection of the needs according to these two criteria leads to the selection of use cases allowing to cover them. The following phase of DSS design will then focus on these use cases. Taken as a whole, this phase (cf. figure 1) allows this methodology to meet most of the requirements of the ISO standards (i.e., requirements 1-3 and 5-6).

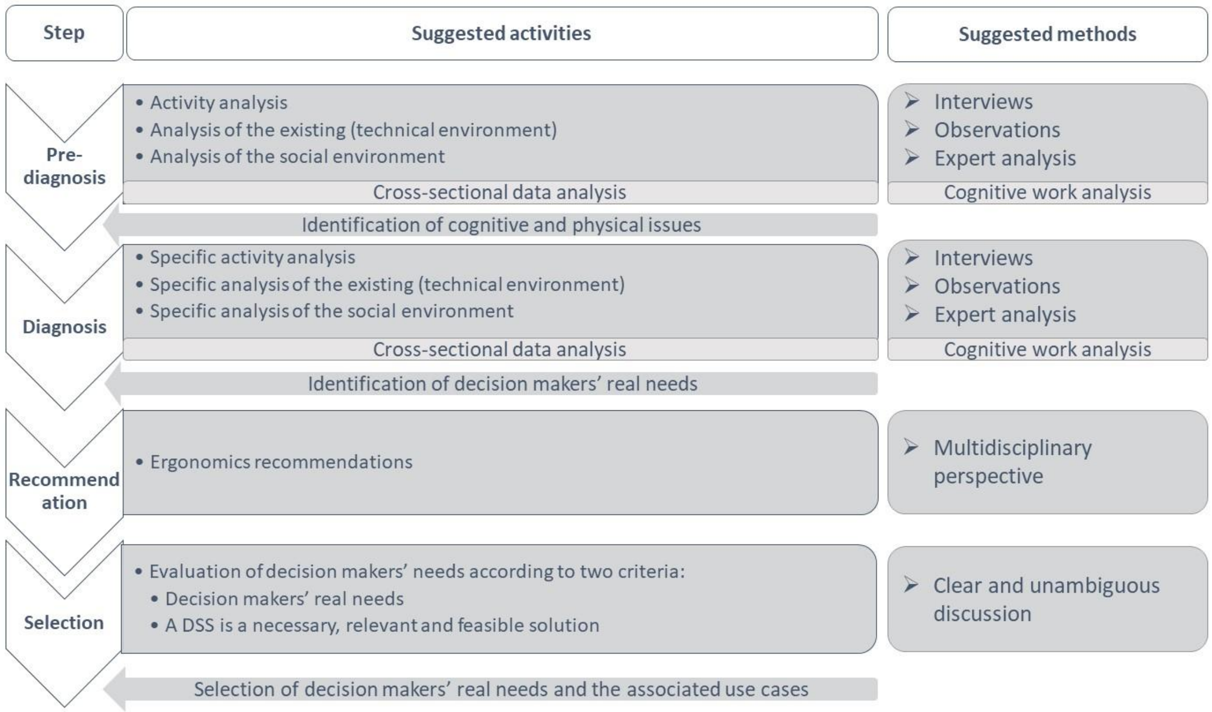

Figure 1. The first phase of our methodology is composed of four steps. The pre-diagnosis step proposes a solution to the well-known confirmation bias by suggesting to conduct exploratory analysis of activity, social and technical environment of the decision makers. The second step (i.e., the diagnosis) allows us to focus on specific issues identified during the pre-diagnosis step using exploratory and descriptive methods. The third step consists of elaborating the ergonomics recommendations in order to enhance decision makers' working conditions. Finally, the fourth step consists of the selection of decision makers' needs according to two criteria to ensure that the decision support systems' design process is centered around decision makers' real needs and not driven by functionalities of technologies to develop.

Phase 2. Prototypes and usability testing

Two steps composed this phase. The first one consists in setting up an iterative process from the selected decision makers' needs using the use cases selected in the previous phase. The objectives are to update and specify the requirements of the decision makers (thereafter called the end-users), and develop the DSS's skeleton and its interface (i.e., developing the first DSS's semi-functional prototype). The second step of this phase consists of testing the prototype, in particular its usability, functionality, user experience, acceptability and acceptance (standard requirements 3, 5 and 6). It is important to carry out as many tests (i.e., iterative process) as necessary so that the DSS developed is as centered as possible on the users' experience (standard requirement 4). We suggest that these tests should be carried out taking a multidisciplinary perspective (i.e., cognitive ergonomics, social psychology, industrial systems, operational research, human-machine interaction) to guarantee that all the human and technical (e.g., interface and functionalities) aspects of the DSS are taken into account and tested. Taken as a whole, this phase must allow the development of an advanced prototype with almost all the functionalities. It is also necessary that at the end of this phase, the prototype as well as the user manual be ready for testing the DSS with end-users (Harte et al., 2017).

Suggested activities, methods and analyses

Although usability research is not new (e.g., Sagar and Saha, 2017 for a review), interest in understanding end-users' subjective experience when interacting with digital solutions is much more recent (e.g., Stein et al., 2015; Jung et al., 2017). In line with Harte and colleagues (2017), we suggest performing usability testing to conduct expert analysis. This methodology has the advantage of being part of a multidisciplinary approach since a multidisciplinary group of experts is required to inspect the functionalities and the interface of the prototype. The experts try to identify usability and human factors issues (e.g., bad emotional experience). During usability testing it is of particular importance to consider users' emotional experience since it could be the main dimension of the user experience (e.g., Thüring and Mahlke, 2007; Bargas-Avila and Hornbæk, 2011; Saariluomaand and Jokinen, 2014; Jeon, 2017). Expert analysis can take the form of an evaluation of the DSS and its interface according to the heuristic criteria of Bastien and Scapin (1995) or to the study of use cases. The groups of experts then perform a given task using the DSS and its interface, focusing on the cognitive processes required and documenting the problems encountered. These tests are commonly used upstream of the final tests because they allow the tools and interfaces developed to be adjusted easily and at a lower cost. Indeed, they provide quick and concise feedback (Nielsen, 1994; see Bastien, 2010 for a review of available usability tests).

Phase 3. Final tests and evaluation

The processing of the results of all tests carried out in the phase 2 should enable the multidisciplinary design team to produce a mature prototype of the DSS. Therefore, the objective of this phase is to test this prototype. Particularly, in this phase the prototype is refined based on an end-user centered evaluation (requirements 2 an 3). Another objective is to evaluate the process undertaken to design the DSS in order to ensure that it really meets (i) the decision makers' real need and (ii) all the ISO standard requirements. This phase is then composed of two stages (cf. figure 2). Usability testing performed during the first stage can be conducted either in a highly controlled environment such a laboratory where the end-users are invited to come or directly in the final socio-technical environment where the DSS will be implemented (i.e., field studies). Field studies seem to be more relevant to capture the real structure in which the DSS will be used. Broadly speaking, the objective of usability testing with end-users is to identify usability problems that have not been highlighted during the previous phase. The usability problems must be prioritized and addressed one after the other to propose a more and more complete and adapted version of the DSS. As in the previous phase, it is essential to carry out as many tests (i.e., iterative process) as necessary so that the design of the DSS is truly centered on users' experience (requirement 3). However, we would like to point out that if usability tests are based on use cases, it is important to consider a possible learning effect that could mask certain usability problems. For example, if the DSS support tool addresses the end-users' need to be helped in re-scheduling production after the occurrence of an unexpected event, it is important to diversify the scenarios used to investigate usability of the DSS. Particularly, if the design team ask the end-users to always resolve exactly the same scenario (or a quasi-similar version), it will be not possible to distinguish if the absence of usability problems is due to the actual improvement of the DSS's interface or to the increasing end-users' familiarity with it. As a solution, we propose to use different end-users' in each new set of usability tests and if it is not possible to use similar but different scenarios (e.g., change in the cover story). In line with Harte and colleagues (2017), we suggest that these usability test cycles should be as numerous as necessary and as short as possible including only a few end-users in each cycle. However, encouraging the inclusion of only a small number of end-users in each of the test cycles does not allow for robust results. Moreover, statistics used (when they exist) are often not appropriate. Designers mostly use descriptive statistics and do not compare the results obtained to those they would have obtained when the end-user performed the same task but in another condition (e.g., without a certain function or even without the DSS). Furthermore, when designers compare two (or more) situations with inferential statistics, they mostly use parametric statistics such as analysis of variance, which are not suitable for small sample size. Therefore, in line with Harte and colleagues (2017), we suggest that designers perform a first set of cycles of classical usability testing as short as possible to reach a final version of the DSS. However, in line with Kelley and Alender's work (1995), we recommend to conduct another cycle of experimental tests to both identify interface design problems that the other methods do not allow to detect and achieve a higher level of results' robustness. In line with Mailliez and colleagues' recommendations (2021), this second cycle of tests particularly allows investigating the effect of the DSS' use on the final user's cognitive and emotional state. Finally, once this first step is carried out, we suggest to the design team to evaluate the whole process undertaken. The objective is to ensure that the process undertaken has been well articulated around the real decision makers' needs and that it fulfills all the ISO 9241-210 standards.

Figure 2. The third phase of our methodology is composed of two steps. The usability tests' phase proposes a solution to the classic problem of small sample size observed in usability tests by suggesting to conduct both usability tests and experimental ones. Moreover, according to Kelley and Alender (1995) experimental tests would allow to identify other types of interface design problems than the ones identified by classical usability tests. The second step (i.e., evaluation) consists of the evaluation of the process undertaken to design the DSS to ensure that it is really end-users' centered and that it meets the ISO standards requirements.

Suggested methods and analysis

Usability testing has been widely described in the literature (see Bastien, 2010 for a review). These tests classically consist of observing end-users while they interact with the advanced DSS prototype. As previously highlighted, it is possible to conduct these tests either in a highly controlled environment such as a laboratory or directly in the socio-technical environment where the DSS will be implemented (i.e., field studies). Each of these environments has advantages and disadvantages. Laboratory-based experiments allow for better control of the experiment and the resulting data are of higher quality and more robust. However, this type of environment results in a loss of fidelity to the end-users' socio-technical environment (Harte et al., 2017). Field studies have the advantage of better fidelity to the end-users' conditions and result in richer data, but these can be difficult to process especially from a quantitative perspective. During these tests, whether conducted in a research laboratory or in the final socio-technical environment, end-users are usually asked to think aloud while using the advanced prototype of the DSS. The observer can then gain insight into the processes (e.g. cognitive) involved in the use of the DSS and in particular those involved in handling problematic events and how it tries to overcome them (requirements 1 and 5). Most of the time, usability tests use subjective measures such as audio or video recordings, observer's note taking, end-users' response to questionnaires allowing them to indicate, for example, their satisfaction with the DSS's interface. In addition to subjective measures, behavioral measures such as the time required to complete a task and the error rate can be used. In this cycle, designers are encouraged to perform as many tests as necessary in order to arrive at a final prototype focused on the user experience. To make this cycle as fast as possible, designers are sometimes advised to include only a small number of end-users. Designers mostly use descriptive statistics and do not compare the results obtained to those they would have obtained when the end-user performed the same task but in another condition (e.g., without a certain function or without the DSS). Therefore, everything happens as if the DSS necessarily improves end-users' performance and working conditions (e.g. cognitive and emotional workload). In the absence of such comparison, it is difficult, even impossible, to conclude on the effect of DSS on the users' performance and working conditions (e.g., reduction of the cognitive and emotional workload). Therefore, in line with Kelley and Alender (1995), we suggest that, in addition to the usability test cycle, the designers carry out an experimental test cycle to draw more robust conclusions about the effect of DSS use on the end-users' performances. The objective of this test cycle is to evaluate the effect of DSS use, or of one (or more) of its functionalities, on the end-users' performance and working conditions. For example, an experimental protocol can be conducted to evaluate the influence of DSS use on the reduction of stress and workload during the supervision of a production system (Mailliez et al., 2020). Particularly, the authors designed an experimental protocol able to test the reduction of stress and workload with the use of a DSS to cope with unexpected events. Furthermore, we suggest that designers should cross the indicators of a phenomenon to obtain a more reliable measure. The subjective experience of users is considered as private and immediate and the use of questionnaires to capture it has been debated for a long time (Schorr, 2001) since it would be very difficult for users to put their experience in words (Dennett, 1988). Moreover, in a recent literature review, Charles & Nixon (2019) point out that there is no single measure of mental workload but a variety of physiological and behavioral measures. Thus, we suggest that, when possible, experimental tests should be part of a multidisciplinary perspective by involving, for example, researchers from experimental psychology, cognitive ergonomics and neuroergonomics. Experimental psychology is a particularly interesting approach because it gives an expertise in processes involved in the interaction between the decision makers and its socio-technical environment, as well as knowledge on decision makers' cognitive and social functioning. Cognitive ergonomics is a particularly interesting approach interested in the adaptation of systems, such a DSS to the decision makers regarding their internal characteristics. Moreover, cognitive ergonomics is definitively centered on the identification of the factors (internal or external) that impact the utility, usability, and the acceptability of a system. Neuroergonomics is a particularly interesting approach because it allows to complement the classical approach based on subjective and behavioral measures by using ocular activity or physiological measures such as cardiac and brain markers (Mailliez et al., 2021). In contrast to classical usability tests, the number of participants to be included in the experimental test should be determined by power analysis prior to data collection. To draw appropriate conclusions, the number of observations must be sufficient. However, in some cases, especially when conducting experimental tests with end-users, the number of observations required to obtain reliable conclusions may be greater than the number of end-users available. In such a case, designers should conduct experimental tests according to single case methodology (see for example, Ledford & Gast, 2018 for a detailed description) as well as statistics adapted to small sample size such as bayesian statistics for single case (e.g., Rindskopf, 2014; Jones, 2003). The use of a rigorous methodology and statistical strategy allow us to increase the robustness of the observed effects. Furthermore, to increase confidence in the observed results, we suggest that this experimental test cycle should be embedded in an open science perspective. Open science practices imply online recording on dedicated website (e.g., OpenScienceFramework), before data collection, of the hypothesis to be tested, the power analysis justifying the necessary sample size, the experimental protocol planned to be used, the statistical analyses envisaged and the expected results (e.g., Kathawall et al., 2020; Gilroy & Kaplan, 2019). Another advantage of embedded design processes, especially experimental tests in an open science perspective, would enhance publication in high ranking academic journals.

Finally, in a second step, we suggest that the designers of DSS evaluate the whole process undertaken with respect to the ISO 920-210 standards. Indeed, Nebe and Baloni (2016) highlight that there is a gap in many design processes between the HCD recommendations and real practices. As a result, an *a posteriori* evaluation of the process would ensure that the DSS is really centered on end-users' needs and experience and that it fulfills all of the Human Centered Design (HCD)'s recommendations. To do so, in line with Nebe and Baloni (2016), we propose to use the HCD checklist provided by the ISO 920 210 standards. Particularly, this checklist describes how HCD can be planned and integrated at each stage of the design process. Therefore, such a checklist can be used to analyze how well the process is in line with HCD. However, as pointed out in the standard, the checklist should be used as a guide and not as a substitute for the standards. It is also possible to use other HCD checklists such as the one provided by Nebe and Baloni (2016) to assess agile HCD.

Discussion and conclusion

In order to cope with the increasing complexity and uncertainty of the modern manufacturing environment, Industry 4.0 promotes the massive use of new technologies (e.g., Decision Support Systems [DSS]). Particularly, DSS are supposed to improve the working conditions (e.g., well-being) and performance of their users by reducing their cognitive and emotional workloads. However, it has been found that DSS do not always improve the users' working conditions and performance (e.g., Manzey et al., 2011). It could be explained by the approach in which the design of the DSS is embedded. Particularly, Techno-Centered Design (TCD) focusing on the integration of new technologies rather than the needs and constraints of human-being in work (e.g., Pascaux-Lemoine et al., 2017) seems to be at the roots of these unexpected effects of DSS' use. In contrast to Human-Centered Design (HCD), TCD therefore overestimated the users' physical and cognitive capacities which may explain that DSS do not systematically improve their working conditions and performance. Taking into account the end-users' capacities (physical and cognitive), their needs, their demands and the constraints associated with their activity could considerably reduce the undesirable effects of DSS' use on their working conditions and performance, and ease their acceptability. According to the ISO standards, a HCD allows the designers to take into account the users' experience.

Moreover, such an approach must be multidisciplinary. This is another key advantage of HCD over TCD which, most of the time, relies on the contribution of a single discipline (e.g., operational research, industrial systems, or informatics). A multidisciplinary perspective allows designers to pay attention to both technological (e.g.,operational research, industrial systems, informatics) and human aspects (e.g., cognitive ergonomics, psychology, neuroergonomics). However, the implementation of a multidisciplinary perspective is a significant challenge as it requires the gathering and the integration of many information, requirements, and constraints from many different scientific domains (Skoberla et al., 2017). Such a challenge may explain why the use of HCD is not widespread in the design of DSS at the operational level. The objective of this chapter was therefore to propose and describe a three-step methodology (adapted from Harte et al., 2017) aiming to promote a better integration of the end-users within a multidisciplinary perspective. We strongly believe that guidelines are very important as poorly managed multidisciplinary teams can negate the benefits of such an approach (Skorberla et al., 2017).

In this perspective, we then proposed to organize the design process around three phases (see Figure 3). First (phase 1), the Multidisciplinary Design Team (MDT) has to identify and understand the users' activities, tasks and characteristics as well as the one of their socio-technical environment to provide a detailed description of them. A detailed knowledge of the users and their socio-technical environments will allow the design team to select the users' real needs around which the following design phases will focus. In order to overcome the well-known confirmation bias, exploratory studies should be conducted (i.e. activity analysis, analysis of the socio-technical environment, analysis of the existing situation). In line with the ISO standards' requirements, the users' real needs have to be discussed and selected on the basis of a clear and unambiguous discussion involving all the stakeholders (i.e. designers/researchers, users, supervisors). A multidisciplinary perspective is then required from the very beginning of the design process. Indeed, if this first stage is conducted exclusively by experts in humanities, it is possible that a significant amount of information is missing for experts in the other fields (e.g., operational research, industrial systems), and vice versa. Particularly, an expert in one field does not know what information is relevant and useful to another expert in another field (Strauss, 2011 cited by Skoberla et al., 2017). It is of particular importance that during this phase, the multidisciplinary experts agree on the vocabulary used for the rest of the design process. We strongly believe that is a necessary condition for the design process to be successful. A term may not have the same meaning between two disciplines involved in the design process and can lead to misunderstanding. Some recommendations made by a discipline may be difficult to understand by the other (Bjerg Hall-Andersen & Broberg, 2014). We therefore suggested that exploratory studies be conducted by one or more experts in the humanities (e.g., cognitive ergonomics, psychology) to ensure that data is collected with a focus on the users and their cognitive and affective functioning. These data will then be processed in concert between experts in humanities and those in engineering sciences (e.g., operational research, industrial systems, human-machine interaction) to ensure that human and technical aspects are taken into account in the analysis and the definition of the users' characteristics and those of their socio-technical environment. At the end of this analysis, and in consultation with the end-users, their real needs will be selected and the characteristics of the interface defined.

Based on these elements, the engineering experts will develop semi-functional prototypes (phase 2). These semi-functional prototypes will be improved throughout an iterative process using usability testing (phase 2). An iterative process is particularly recommended to focus the design of the DSS on the user experience. It is also of particular importance to conduct this iterative process within a multidisciplinary team to ensure that the human aspects are taken into account as much as the technical ones. The iterative process leads to a mature prototype that will then be tested with end-users throughout another iterative process (phase 3). In line with the ISO standards' recommendations, this iterative process involving end-users ensures the design of a DSS centered on their experience. However, such tests seem to have some methodological and statistical limitations. We therefore proposed to complement them with experimental studies investigating whether the use of the DSS really addresses the issues (and needs) identified at the beginning of the design process. For example, a series of experimental studies can investigate whether the use of the developed DSS effectively reduces the users' cognitive and emotional workload. Although all experts of the design team can be involved in such experimental investigation, it is necessary to rely on the skills of experts in humanities (e.g., cognitive ergonomics, neuroergonomics, psychology), especially those who have skills in open science practices (e.g., pre-registration, power calculation). Once the design process completed, we suggest that the MDT evaluate the whole design process in order to ensure that it (i) meets all the ISO standards' requirements, (ii) is centered on users' real needs rather that on the integration of new technologies, (iii) and that the multidisciplinary perspective has been implemented at each stage of the design process.

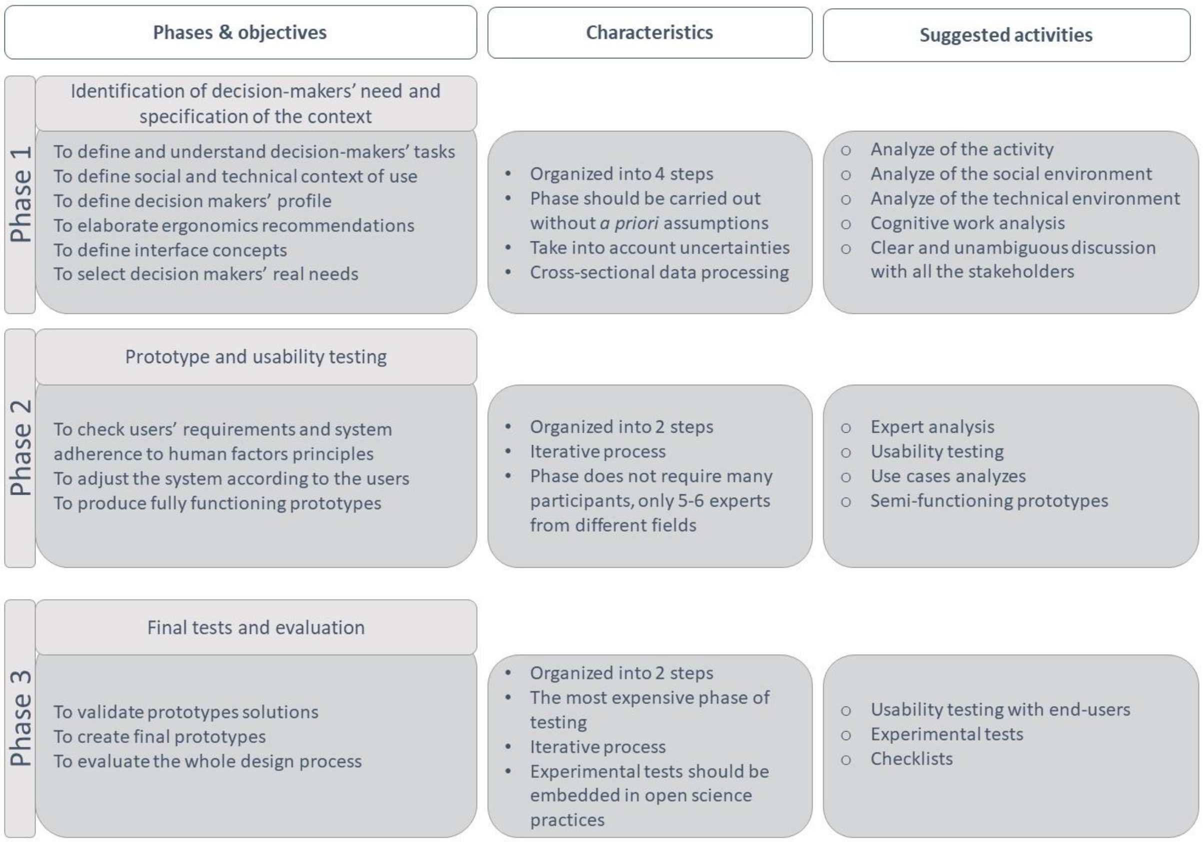

Figure 3. Summary of the three phases of our methodology. The first phase aims to identify and select the users' real needs. The second phase to produce a mature prototype. The third and final phase aim to adjust the mature prototype to the users' experience. This final phase also aims to experimentally evaluate the effectiveness of the DSS in addressing the issues identified in the phase 1 and to evaluate the whole design process to ensure that it is (i) focused on real user needs, (ii) developed according to the users' experience and (iii) part of a multi-disciplinary design process.

Taken as a whole, the methodology we have proposed in this chapter is not intended to be innovative but rather to raise questions and propose answers to improve the design process of DSS at the operational level. However, several limitations can be mentioned. In phase 1, contrary to what Harte et al. (2017) propose, the process of identifying, understanding, analyzing and selecting user needs is a fairly costly process in terms of resources, particularly time-consuming. However, this phase is essential because it makes it possible to identify whether there are real needs that can be met by the design and the implementation of a DSS. If so, it permits to stop the design process at the very beginning of the design so as not to commit more resources to the design of a DSS that will turn out to be useless, unusable and/or unacceptable. Another limitation is that it is difficult to know whether this methodology provides a real improvement over the use of other methodologies. As Harte et al. (2017) point out, the advantage of one design methodology over another can only be assessed if we apply different methodologies to the design of the same type of DSS. Although there is a real desire to place the operator at the center of Industry 4.0 (Guérin et al., 2019, Pascaux-Lemoine et al., 2021), TCD remains the majority (Hasan et al., 2017). We have identified that one of the explanations for this may be the lack of clear and structured guidelines to identify how to implement HCD, especially its multidisciplinary perspective. We therefore proposed a methodology adapted from the one proposed by Harte and colleagues (2017) and guided by the principles and steps described in the ISO standards 9241-210. Our aim was to explicitly describe the steps and activities that designers can follow by making explicit the role of each of the disciplines involved in a multidisciplinary design process. If this methodology is used in the future and adopted by several MDT, we can begin to measure its effects and its shortcomings, which will allow for its improvement. The application of the methodology at the operational level of a large French aerospace company is showing promising results and will be exploited further.

In conclusion, the methodology we propose is far from being completely innovative but offers a multidisciplinary framework for the design of DSS at the operational level. It makes explicit the implication and the necessity of opting for a multidisciplinary design team so that the human aspects are considered at the same level as the technical ones. We have described the activities and involvement of each of the disciplines in each of the phases. We have also presented the rationale for this methodology and why we consider it to be a flexible and useful methodology, particularly for improving the effect of DSS on users' working conditions and performance at an operational level.