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Human-in-the-loop configurations in process and energy industries: a systematic review

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The human-in-the-loop performance evaluation is an area of growing interest in industries where safety-critical systems are in place. Concerns here are due to the increasing complexity of automation, new technologies for control, and safety. Because, unlike a more traditional approach to evaluating the human and the system they work with, human-in-the-loop gives a holistic view of their interaction (human, automation or artificial intelligence) and dynamics. It also emphasizes adapting the technology or automation to the human, being central, considering certain factors like risk. Therefore, there is a need to identify the relevant factors, novel measures and methods or improvements on existing methods that can be adapted for this field of research. This paper intends to present an overview of human-in-the-loop in the process and energy industries by presenting a literature summary highlighting current factors and measures, methods, gaps, solutions and future work. Experimental (13) and observational (11) studies have been reviewed for results. It was observed that new factors, measures and techniques are currently being explored to fill some of the current gaps for the human-in-the-loop, for example, during performance assessment new methods and modalities have been adopted such as eye tracking and electroencephalography methods. The results and open questions from the papers reviewed and possible future research opportunities are presented and discussed in this paper.

Keywords: Human-in-the-loop, safety-critical systems, performance measures and factors, process and energy industries, human-machine interaction, risk

1. Introduction

In safety-critical systems like process plants, safety is known to be of paramount importance. However, this is compromised by many factors, of which human error is considered the leading contributor (Das et al. (2017), Liu et al. (2011), Meshkati (2006)), thus, a driver for the high number of human reliability studies in the safety-critical domain (Nespoli and Ditali (2010)). However, some literature sources have highlighted the importance of estimating human behaviour considering their interaction with their environment as this interaction is the critical point of concern (Meshkati (2006), Boy and Schmitt (2013)). Also considering that in process plants, for example, systems or their controls are becoming even more complex with modern technologies, interaction interfaces, and manipulators that the operator must understand.

In a safety-critical system like control rooms of process plants, for example, despite the increasing levels of automation, operators are still needed to monitor the processes or interact with the system interfaces and take actions when required (Kotriwala et al. (2021), Meshkati (2006), Shi et al. (2021)). Due to automation, the human is more and more placed out of the control loop, impacting their awareness of the process and causing a decline in their knowledge or expertise (Ghosh and Wayne Bequette (2020), Meshkati (2006)). Also, their cognitive ability is known to be impaired with the increasing mental workload during unstable plant states, after a long period of being out-of-the-control-loop.

In cases of process monitoring, the operators are presented with lots of alarms annunciated to them. Dealing with alarms has become even more critical for operators considering the complex state of the plants from automation (Simonson et al. (2022)). Simultaneously, operators might have to take some actions by acknowledging the alarms or changing state parameters. They have to deal with systemic factors like the comprehensiveness of the information from the interaction interfaces or interface usability. The resulting consequence of these different points playing out together is a decline in the operator performance and potentially risking the safety of the process. Nonetheless, there have been positive contributions of automation to the situational awareness and workload of the operators, for example, in using alarm rationalisation as decision support for the operator or model predictive controls (Simonson et al. (2022), Ghosh and Bequette (2019), Hancock et al. (2015)).

The highlighted concerns from the interplay between factors on the human-in-the-loop (HITL) question the more traditional measures or methods for human performance evaluation. By estimating human performance in a more human-centred approach, accurate decisions can be made on resource allocation and safety. A human-centred approach also considers how best these complex systems, when introduced, can be adapted to humans and not vice versa to improve their performance and keep them in the loop. According to Ghosh and Wayne Bequette (2020), the human in the loop concept goes beyond human-machine interaction, which focuses more on the interface designs, but also considers the human dynamics as they interact with their environment.

Recent empirical studies have also shown that cognition is not merely independent of other influencing factors considering the socio-technical nature of the human environment (Boy and Schmitt (2013)). Therefore, advanced methods beyond the first generation Human Reliability Assessment methods like the technique for human error-rate prediction (THERP) and human error assessment and reduction technique (HEART) or second-generation methods like cognitive reliability and error analysis method (CREAM) are needed for this more integrated approach. Some of these recent empirical studies are looking into the cognitive behaviour of the operator and understanding their situational awareness as a proxy for performance using several psychophysiological measures (Das et al. (2017), Shi et al. (2021), Bhavsar et al. (2016)). For example, Ikuma et al. (2014) and Bhavsar et al. (2016) both used eye tracking measures like gaze entropy to asses operators situational awareness.

This review presents an overview of the current state-of-the-art on HITL in the process and energy industries. There is currently no review focusing on HITL for both the process and energy industries. Therefore, through this systematic review, we identify from selected articles, current applicable HITL configurations, performance factors and measures, methods and tools used for performance evaluation, proposed or active solutions, gaps and possible future research points. This paper contributes to the body of knowledge on humans-in-the-loop for safety-critical industries and process safety. It forms a basis for further studies to address the concerns and needs within this field. This first section is followed by Section 2, where the method used for the systematic review is presented. Then, the third section reports the findings, while in section 4, a detailed discussion of the results is presented. The final section concludes the review with the main gaps and opportunities observed.

2. Method

For this review, both empirical and theoretical studies were included. In addition, this review generally considered studies that dealt explicitly with human-in-the-loop or human-machine interaction in process and energy industries. The goal was to understand the current state-of-the-art on HITL within these industries, the factors considered for a more holistic analysis, and the methods used. The review answers questions on

(i) type of configurations in this domain,

(ii) factors and indicators critical for these configurations, and
(iii) current performance measures, technique, solutions, and gaps for the human-in-the-loop inclusion.

Nuclear power plants as an energy industry have been excluded from this review to give some more emphasis to other energy industries. The eligibility criteria were defined based on the goal of the review. Only papers from the past 20 years were included to build the review on recent literature and considering the novelty of the field. The search terms used included the significant topic terms (example, ”Human in the loop, HITL, human-machine interaction, HMI, human factors”) with AND operator connecting industry terms (example, process industry, energy industry). Also, the keywords ”safety-critical systems” and ”control room” were used while searching for the other terms. This search was done in the widely used SCOPUS database. Subsequently duplicates were dropped and all articles were first assessed for eligibility by title and abstract. References from the selected articles were scanned based on the title for potential articles of interest. Their abstracts and a bit of their introduction were read to ensure eligibility. Finally, the full text of all articles selected was reviewed to identify eligible studies.

3. Results

Both observational and experimental studies (Ns=2) have been included in this review. The contributions of the different articles are presented in Table 1. The authors discuss further observations on the studied variables and measures, challenges and solutions, gaps and future work.

3.1. *Search Result*

In total, 141 articles were retrieved from a search in SCOPUS and 17 retained after the process described in section 2. A breakdown is shown in Table 2. The references of these reviewed articles were screened to identify other articles or studies to be included. In total, seven more articles were included. The considered articles and their contributions are shown in Table 1. Finally, by considering both observational and experimental studies, this review considers all contributions from the literature on human performance from a human-in-the-loop perspective in process and energy industries.

3.2. *Human Performance Results*

This paper’s results have been categorized and presented under three configurations: Monitoring and control, Monitoring, and Fault Detection and Isolation. This categorization captures the operators’ role in the loop.

3.2.1. *Monitoring and Control*

For this use case, the articles have studied how multiple display components, level of automation, alarm design, tasks and task complexity affect operator workload and situational awareness (SA) (Simonson et al. (2022), Bhavsar et al. (2016), Iqbal et al. (2020), Sharma et al. (2016)). Das et al. (2017) also studied how the operator’s actions and the information presented through the human-machine interface (HMI) impact the operator’s mental model and consequently his ability to perform correctly. The impact of alarm design and level of automation on workload have been measured subjectively using NASA Task Load Index (NASA-TLX) (Simonson et al. (2022)). Quantitatively, eye tracking and electroencephalogram (EEG) measures like gaze measures, pupillometry, dwell, power spectral density of theta waves with other supporting techniques like directed graph, simulations and more, have been used. These have been used in the articles to analyse the impact of the aforementioned factors on workload, SA and operator mental model. Results from Kodappully et al. (2016) and Bhavsar et al. (2017) showed that these measures are helpful to extract information on cognitive behaviour across different cognitive steps and can be thus helpful in quantifying SA and predicting human error.

3.2.2. *Monitoring*

This category has been considered a lot more in this field. This is understandable from the shift in the role of the human-in-the-loop to that of mon-

Table 1. Contributions from selected articles

Contribution	Experimental	Observational
Background	Shi et al. (2021), Bhavsar et al. (2016) Das et al. (2017), Simonson et al. (2022)	Liu et al. (2011), Meshkati (2006) Nespoli and Ditali (2010) Ghosh and Wayne Bequette (2020) Kotriwala et al. (2021)
Factors	Shi et al. (2021), Bhavsar et al. (2017) Lindscheid et al. (2016), Bhavsar et al. (2016) Kim et al. (2014), Das et al. (2017) Iqbal and Srinivasan (2018), Ikuma et al. (2014) Iqbal et al. (2020), Sharma et al. (2016) Simonson et al. (2022), Kim and Yang (2017) Iqbal et al. (2019)	Meshkati (2006) Liu et al. (2011) Mohammadfam et al. (2019)
Measures	Shi et al. (2021), Kim and Yang (2017) Iqbal and Srinivasan (2018), Ikuma et al. (2014) Iqbal et al. (2020), Sharma et al. (2016) Lindscheid et al. (2016), Kim et al. (2014) Das et al. (2017), Bhavsar et al. (2016) Simonson et al. (2022), Bhavsar et al. (2017) Iqbal et al. (2019)	Mohammadfam et al. (2019)
Method	Simonson et al. (2022), Das et al. (2017) Bhavsar et al. (2016), Sharma et al. (2016) Iqbal et al. (2020)	Mohammadfam et al. (2019) Ghosh and Bequette (2019) Liu et al. (2011)
Tools/ Techniques	Bhavsar et al. (2017), Shi et al. (2021) Iqbal et al. (2019), Iqbal and Srinivasan (2018) Lindscheid et al. (2016), Kim et al. (2014) Shi et al. (2021), Kotriwala et al. (2021) Kim and Yang (2017)	
Solutions/ Future	Simonson et al. (2022), Das et al. (2017)	Kotriwala et al. (2021) Nazir et al. (2013), Meshkati (2006) Deng et al. (2016), Samad (2020) Parsa and Hassall (2018) Ghosh and Bequette (2019)

itoring. Shi et al. (2021), Iqbal et al. (2019) and Kim et al. (2014) have studied the impact of task load or complexity on the operator's workload using eye-tracking and EEG measures. Kim and Yang (2017) also analysed task complexity but generically on the cognitive and physical ability of the operator. The effect of the interface on operators' cognitive ability has been studied a lot more in this category (Shi et al. (2021),Lindscheid et al. (2016), Kim et al. (2014), Ikuma et al. (2014)). Its effect has been evaluated on the operator based on processing ability, trust, detection ability, SA, workload, speed and accuracy, and gaze or attention. Interestingly, from the results found by Ikuma et al. (2014), varying the interface visual-type alone did not affect the workload, speed and accuracy, eye measures and importantly the SA of the participants. However, there was a significant effect when workload and interface-type were varied on SA.

In more recent studies under this category, multi attribute task battery (MATB-II), time window human-in-the-loop (TW-HITL) and eye-tracking techniques have been used. These were in use to analyse the impact of an interface (display type, combinations and more) (Kim et al. (2014)), including that of task load or complexity on the operator (Kim and Yang (2017), Kim et al. (2014)), especially their situational awareness since it is highly correlated to performance. In addition to

Table 2. Search steps and result

Steps		Number of Results
Database search/ abstract review		141
	Excluded (based on criteria)	80
Full text review		61
	Excluded	44
Articles added from references		7
Total included		24
Studies included		2

eye-tracking techniques for assessing HMIs' effect on workload, SA and mental state, Ikuma et al. (2014) used other subjective measures like Situation Awareness Global Assessment Technique (SAGAT), NASA TLX, Subjective Workload Assessment Technique (SWAT). Other measures used here include; the Theta/alpha ratio from EEG to assess the impact of task complexity on cognitive workload (Iqbal et al. (2019)), gaze entropy for the effect of Learning/experience on cognitive workload (Iqbal and Srinivasan (2018)).

3.2.3. *Fault Detection and Isolation (FDI)*

To compare the effect of the interaction between variables in fault detection and isolation, Liu et al. (2011) used the ACP (Artificial systems, computational experiment and parallel execution) theory, FDI track and the VACP (Visual, Auditory, Cognitive, and psychomotor) workload method. Results showed a significant increase in mental workload (perceptual, cognitive, motor, STM and LTM subtasks) within just 80s of physical workload increase. So far, this is the only study found within this use case/configuration.

Furthermore, Meshkati (2006) while observing safety and human performance issues in an oil and gas pipeline control room, identified several relevant human, organisational, and safety factors that impacted the operators' performance were identified. These include some of the factors mentioned from the use cases, alongside others not analysed. To also fill this gap, Mohammadfam et al. (2019) investigated the interaction among individual, situational and organisational variables that affect situational awareness. The authors, however, used expert judgment, through a multi-criteria decision method (Fuzzy DEMATEL and Fuzzy Delphi), for this analysis. The reasons are that the experiments do not entirely address the multidimensionality of the issue, as can be seen from the articles reviewed. Their result showed that organisational factors were most contributory to situational awareness but, more significantly, two human aspects; work and safety knowledge and experience.

Techniques identified that have been employed for the analysis of the data include; multivariate analysis techniques like multivariate analysis of variance (MANOVA), short-time Fourier transform (STFT) (Iqbal et al. (2019)), correlations and Markov's chain (Bhavsar et al. (2017)). A Hidden Markov Model (HMM) has been used by Shahab et al. (2022) to characterise control room operators' mental models. This paper is one, if not the only, study that has worked on characterising the operators' mental model considering the interplay between factors.

The reviewed papers helped in identifying current measures and methods, including the critical factors for safety. However, there are still challenges, as also mentioned in these articles. These challenges, identified solutions and gaps will be discussed in the next section.

4. Discussion

Human performance studies have evolved over the years from methods like THERP, HEART, and CREAM to the use of probabilistic methods. However, there have been gaps identified with the use of these methods. Modern monitoring systems and measures are currently being used to fill some of these gaps during performance evaluation, as seen in section 3. According to Zarei et al. (2021), the use of such systems have been driven by the need for a more holistic overview of how factors interact with each other and consequently influence human performance, which is key to safety. An aspect of this interaction which is also central to HITL applications is the human interaction with automation and their interfaces. An overview of the development of human reliability methods for chemical process industries can be found in Zarei et al. (2021).

Results presented in section 3 show that there is progress in addressing the human-in-the-loop performance assessment concerns, although not as well as in the nuclear power plants (NPP) or other safety-critical domains as also highlighted by Zarei et al. (2021). These articles have so far experimentally and theoretically touched on the effect of automation levels, interface designs or combinations, and task complexities on human performance. Such a consideration is understandable as automation complexity and levels adversely affect the human's situational awareness and decision-making capabilities Lackman and Söderlund (2013), Liu et al. (2011).

4.1. *Challenges and Solutions*

According to Liu et al. (2011), the evaluation of HMI's was limited to the use of checklists, for example, in evaluating the effect of colour, layout and more. Such techniques have left untouched the social and psychological aspects and, notably, the effect on operators. For example, an aspect of interest which has not been very much considered in a collaborative sense is 'trust'. The interfaces contribute to the operators' level of trust in automation and technology Meshkati (2006), Lindscheid et al. (2016). This can be dependent on the information presented, number of interfaces, the grouping of interface information, interface cues or how comprehensible the information is. Addressing their effects together with other factors can potentially make for improved situational awareness, as seen in Ikuma et al. (2014), better human-automation collaboration, and the potential to discover areas for better adaptation for the operators.

To further address the challenges with interfaces and their effect on operators, Meshkati (2006), Deng et al. (2016) recommends matching information displayed to the model the operator has on the dynamics of the problem. Invariably, looking into expertise and knowledge levels, information processing capability or cognitive ability and the interface displays. Deng et al. (2016) in their work used a computation intelligence algorithm, genetic algorithm and ant colony algorithm (GA-ACA) as a solution for the interface layout optimisation. The methods and measures introduced present possibilities to make such assessments quantitatively. Also, the work by Simonson et al. (2022) on state-based alarms can be considered a solution for the HMI studies. This state-based alarming approach can be seen as decision support and an aid for situational awareness.

Another interesting topic of concern in this field is task allocation, assigning tasks between humans and automation Samad (2020), Pretlove and Skourup (2007), Lackman and Söderlund (2013). According to Lackman and Söderlund (2013), this depends on which solution provides the least acceptable risk. The model proposed by Fitts has helped determine function allocation with the limitation that it has been unable to do this considering cases of interaction. This limitations open up an area for further studies in this research field. Samad (2020) proposes that addressing this would include a comprehensive view of the human-in-the-loop and the modelling of their cognition, comprehension and decision-making abilities. Such an approach holds potential for making appropriate decisions on task and cost allocation. Also, Meshkati (2006) and Lackman and Söderlund (2013) in their works have emphasised certain organisational, social and safety factors worth considering for task allocation.

Parsa and Hassall (2018) has proposed an advisory system to support decision making and increase the operator's situational awareness. This system presents the operator with the current state of the operations in the form of an event tracking of paths from real-time event analysis and data processing of abnormal events. Training the operators can be a solution to address situational awareness issues faced by operators in these complex settings Nazir et al. (2013), Das et al. (2017). Using this method enhances the operators' skills and mental models. Also, the digraph technique used by Das et al. (2017) for attention monitoring over time through eye trackers can be resourceful in addressing decision-making issues. Their learning development (knowledge and capability) can be assessed by monitoring their attention. The use of eye trackers and eye-tracking measures is also highlighted by Bhavsar et al. (2016) as useful in training applications.

In line with the attention monitoring solution, real-time performance monitoring has been proposed for proper decision making. This solution has also gained ground in the literature focused on nuclear power plants Singh and Mahmoud (2019). The approach proposed by Bhavsar et al. (2016) holds potential for such application. Ghosh and Bequette (2019) in their work proposed a smart control room (SMC) also employed a similar concept. The SMC solution considers humans-in-the-loop across the different plant-wide hierarchies while understanding the dynamics of this type of system under several components like human factors, safety, ergonomics and more.

5. Conclusion

As can be seen from the results, human performance from a HITL perspective has not been addressed extensively. Generally, though the effects of one variable over the other have been observed, there is no work on a method to integrate more factors using these new measures together to assess human performance. Also, there are gaps so far in terms of the factors assessed and the measures. For example, it would be insightful to compare how different interface variations or components influence other states like stress, fatigue, attention, and other cognitive factors. Also, the suitability of the measures, methods and techniques or tools used in these studies can further be assessed experimentally for different use cases. Further work on the measures can include combining them to identify their potential for measuring other latent factors, e.g. combining more than one eye-tracking measure. Furthermore, although the interplay between some factors has been studied, there is an observed gap in further relating these factors to estimating human error and their impact on safety. This gap can be due to the many factors and the challenge of integrating them for such analysis. Therefore, future work can look at novel methods to integrate or model these factors. An example can be looking into a machine or deep learning technique or combining them with old techniques. Despite these gaps, issues observed or identified open topics, the reviewed articles have set a foundation in this field and opened opportunities for further research possibilities. A subsequent step should be reviewing how other safety-critical domains address the human-in-the-loop challenges. In conclusion, the solutions proposed as reviewed by the paper and possible solutions coming up from future research should be analysed for how they impact the operators' performance.

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