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Analyzing resilient performance of workers with multiple disturbances in production systems

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ABSTRACT

With the emergence of Industry 5.0 and an increasing focus on human-centric approaches in manufacturing, the analysis of workers in production systems has gathered significant interest among researchers and practitioners. Previous studies have explored the impact of various aspects, such as skills, fatigue, and circadian rhythms, on human performance. However, the cumulative effect of these aspects as disturbances on work performance has yet to be fully elucidated. This study introduces an approach using the Functional Resonance Analysis Method (FRAM) to investigate the impact of multiple disturbances on workers' performance. Furthermore, this approach explored how the resilience-related skill aspects of workers affect their performance under multiple disturbances. A case study on engine test and repair processes was conducted, employing qualitative data collection and semi-quantitative simulation studies examining the impact of combined disturbances across 4,094 scenarios. The results show that a larger number of compounded variabilities expressed in Common Performance Conditions (CPCs) made it significantly challenging to recover work performance, and CPCs with particularly critical effects were identified. In addition, the FRAM model of skilled workers was shown to sustain higher performance across more scenarios. The approach of this study has demonstrated its ability to provide insights for effectively and safely managing production systems while considering complex disturbances.

1. Introduction

Industry 5.0 has been proposed as an essential concept for next-generation production systems. While Industry 4.0 focuses on technological aspects, such as the Internet of Things (IoT) and Cyber–Physical Systems (CPS), Industry 5.0 places emphasis on the cooperation between humans and machines (Maddikunta et al., 2022; Ivanov, 2023). According to the European Commission, the paradigm of Industry 5.0 consists of three central policies, i.e., resilience, sustainability, and human-centricity (EC, 2021). In particular, resilience highlights the importance of production systems that flexibly adapt to various disturbances, and human-centricity is a concept that contributes to resilience by leveraging the flexibility of workers. In line with this background, many studies have examined the impact of critical aspects of workers on production systems (Greasley and Owen, 2018). Human characteristics significantly impact work performance, so production system models that ignore this can overestimate the system's productivity. If these aspects of workers are incorporated into simulation models appropriately, it will contribute to more effective design, implementation, and evaluation of production systems (Sgarbossa et al., 2020).

Considering human factors in production systems is also consistent with the socio-technical systems perspective (Sgarbossa et al., 2020; Alves et al., 2023). From this perspective, multiple factors, including technical and human factors, may have a combined effect based on their interaction with the system's performance. Previous studies have only examined several aspects of human performance independently, so the compound effects of various disturbances exposed to workers remain to be elucidated. It has also been noted that worker skills are one of the most crucial aspects of human performance in production systems (Abubakar and Wang, 2019). However, the impact of workers' skills on operational performance under complex disturbances has yet to be sufficiently elucidated. Thus, the focus of this study includes how worker skills contribute to maintaining production performance against compound disturbances. The two main research questions of this study are described as follows:

- How do multiple disturbances affect human performance in production systems?

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- How do workers' skills contribute to resilient work performance under multiple disturbances?

This study developed a method to evaluate the effects of various disturbances combined in production systems, considering workers' skills, using the Functional Resonance Analysis Method (FRAM). FRAM is one of the leading methods in resilience engineering suited to analyze non-linear interactions between the system and multiple factors in the environment (Hollnagel, 2012). This study extended the previous simulation method based on FRAM to estimate human performance, given a scenario of what skill level the worker is assigned and what disturbances occur in the environment. Thus, this study contributes to practical managerial insights to maintain resilient production performance in factories subject to various disturbances.

The remainder of this paper is organized as follows. Section 2 provides background on human factors in production systems. Section 3 describes methods, including FRAM and the simulation method. Section 4 shows the implementation of the methods in a case study. Section 5 shows the simulation results examining the effects of multiple disturbances. Sections 6 and 7 present the discussion and conclusions of the paper, respectively.

2. Background

2.1. Human factors and ergonomics in production systems

Modeling workers in production systems is a research field in ergonomics and human factors (IEA, 2019). Within this research field, modeling human work in production systems, including interaction with the surrounding environment, aims to improve productivity and reduce ergonomic risks. Furthermore, human-centricity has been gaining attention in industry in recent years, as exemplified by Industry 5.0. This paradigm focuses on the adaptability of workers that is expected to contribute to the flexibility of production systems to meet the diverse needs of consumers (Abubakar and Wang, 2019). Therefore, an important issue is how to model human performance and reflect them in the design of production systems.

Conventional simulation models of production systems have modeled operators similarly to machines performing tasks within a specific time. In Discrete-Event Simulation (DES), a typically used method for modeling production systems, operators are commonly represented as performing tasks with a specific processing time (Greasley and Owen, 2018). However, this method does not adequately represent the behavior of workers and overestimates the performance of production systems (Dode et al., 2016; Vilela et al., 2020). For this reason, incorporating aspects of human performance in simulation methods such as DES is considered the missing link and has been the subject of many studies (Baines et al., 2004; Taylor et al., 2015). For example, the effects of worker personality (Baines and Kay, 2002), circadian rhythm (Baines et al., 2004; Oliveira et al., 2017), fatigue (Dode et al., 2016; Perez et al., 2014), and motivation (Riedel et al., 2009) on work performance have been investigated. About worker competence, the learning curve has been used (Dode et al., 2016), and the competence of multi-skilled workers has been modeled using graph theory (Małachowski and Korytkowski, 2016). It has also been shown that DES models considering human factors contribute to better production line design (Neumann and Medbo, 2009). Nevertheless, these factors are often considered independently, and the impact of combined factors has yet to be thoroughly investigated. Therefore, this study focuses on human work in production systems and aims to investigate the impact of multiple factors on work performance.

2.2. Resilience in industry

In recent years, resilience has gained significant attention in the industrial sector. For instance, within the context of Industry 5.0, a concept aimed at transforming industries into human-centric and sustainable operations, resilience is highlighted as one of the three critical aspects (Ivanov, 2023). In this framework, resilience is defined as the ability of production systems to enhance their robustness against disturbances and to manage situations effectively (EC, 2021). With this context, numerous technologies have been developed to deploy sufficiently resilient and strategic value chains and enhance the adaptability of production systems (Johansen and Akay, 2022).

When discussing resilience in the industry, it is essential to consider the concept of resilience engineering. Resilience engineering is a paradigm in safety management that focuses on dealing with the complexity of systems and balancing productivity and safety (Patriarca et al., 2018). In this context, Hollnagel has defined resilience in human factors as the intrinsic capability of a system to adjust its functioning before, during, or after changes in conditions or disturbances to continue the operations required under both expected and unexpected conditions (Hollnagel, 2014). FRAM is one of the methods proposed in this context (Hollnagel, 2012). Initially introduced to address the challenges in traditional accident investigations (Hollnagel, 2004), FRAM is now employed for various purposes, including risk assessment and complexity management (Salehi et al., 2021). Its applications span diverse sectors such as aviation (Carvalho, 2011; Sawaragi et al., 2006), healthcare (Ross et al., 2018; O'Hara et al., 2020), and industry (Zheng et al., 2016; Gattola et al., 2018). Particularly in the industrial domain, studies focus on investigating the causes of manufacturing accidents (Amorim and Pereira, 2015), assessing risks by considering both technical and human factors (Gattola et al., 2018), and aiding in improving operational guidelines in manufacturing processes (Zheng et al., 2016). In addition, a recent application of FRAM lies in providing insights for managing complexity in intricate systems (Salehi et al., 2021). Examples include the study of human factors in offshore oil drilling plants (França et al., 2021; França and Hollnagel, 2023), the impact of automation introduced in air traffic control systems on human performance (Ferreira and Cañas, 2019), the relationship between vessel navigation support systems and safety (de Vries, 2017), and improvements in medical systems (McNab et al., 2018). The role of FRAM in complexity management is to understand the impacts of various factors in complex socio-technical systems on overall system performance, thus providing insights for their management.

Given the backdrop discussed above, this study has identified two research gaps. The first concerns the complex impacts of multiple factors on production systems. Since manufacturing settings are often subject to numerous disturbances, understanding these multifaceted influences can enhance the management of production systems. The second gap pertains to the interaction between workers' skills and other factors within the production system. The goal is to elucidate how skilled workers maintain their performance levels in environments fraught with multiple disturbances. This research aims to address these gaps through an approach using FRAM, seeking to provide new insights into the dynamic interplay of human performance aspects and the system in manufacturing contexts.

3. Methods

3.1. Functional resonance analysis method (FRAM)

This study applied FRAM to investigate how multiple disturbances affect human performance. FRAM models a system from the functional point of view (Hollnagel, 2012). Each function in a system is described with six aspects in Table 1, and the relationship between functions is shown by connecting them. Note that one end of the coupling is always

Table 1
Six aspects of FRAM.

Aspect	Description
Input	Something that triggers the function's execution.
Output	Outcomes provided from the function.
Precondition	Conditions to be satisfied before the function is executed.
Resource	Something consumed while the function is performed.
Control	Factors that control the performance of the function.
Time	Time constraints or other factors related to time.

connected to the output aspect, which means that the output of one function provides one of the input, precondition, resource, control, or time for another function. The function providing the output is called the upstream function, and the function receiving the output is called the downstream function. By making the dependencies between functions explicit in this way, a system can be modeled from a functional perspective.

3.2. FRAM model construction

This study used the Work Domain Analysis (WDA) as a supportive tool to build a FRAM model of the target work. WDA is a method that forms part of a framework called cognitive work analysis (Vicente and Rasmussen, 1990). This study uses the abstraction hierarchy of WDA to organize the system's functions, showing their means-ends links. FRAM and WDA are both methods for describing systems from a functional perspective, and some studies have combined these approaches (Patriarca et al., 2017a). This study used WDA to organize information on the target system as a preliminary step to formulate a FRAM model, as proposed in the previous paper (Zúñiga et al., 2023). Operational guidelines and interviews were used as sources of information at this step. The FRAM model was then constructed by extracting the functions corresponding to specific levels of abstraction in the hierarchy.

After building the FRAM model based on WDA, this study differentiated the FRAM models considering expert and novice workers. This is to examine the impact of the characteristics possessed by expert workers on their work performance. A similar approach was taken in the previous work to examine the impact of skilled workers' attention management strategies (Yasue and Sawaragi, 2022, 2024). The basic FRAM model created from WDA represented the work of novices who adhered closely to the operational guidelines, while expert workers were represented by extending that FRAM model. After differentiating these FRAM models, a simulation study was conducted to examine the impact of these differences on work performance.

3.3. Simulation method based on FRAM

A simulation method based on FRAM for envisioning the system's behavior (Hirose and Sawaragi, 2020) was utilized to examine the impact of multiple disturbances on work performance considering worker's skill levels. From the perspective of resilience engineering, considering variabilities in daily work, this simulation method quantitatively supports analyzing the impact of such variabilities on the system. Here, the variabilities are internal or external factors that can cause system performance variations. In this study, the external factors that affect the productivity of the production system are referred to as disturbances. This simulation method has been utilized in various domains, including semi-autonomous driving (Hirose et al., 2021) and manufacturing processes (Yasue et al., 2023). While there have been studies that combine FRAM with other methods to facilitate analytical procedures (Tian and Caponecchia, 2020), such as Monte Carlo simulation (Patriarca et al., 2017b) and Analytic Hierarchy Process (AHP) (Rosa et al., 2015), this study applied this simulation method to examine the effect of multiple variabilities in each simulation scenario on human performance.

This simulation method quantifies the FRAM model using two types of parameters: Probability of Action Failure (PAF) and Common Performance Condition (CPC) score (Hirose et al., 2021). PAF is a parameter in each function that represents its execution status. It is based on a four-level qualitative variable representing the function's status in CREAM—strategic, tactical, opportunistic, and scrambled (Hirose and Sawaragi, 2020; Hollnagel, 1998). An elevated PAF indicates an increased possibility that the function becomes dysfunctional. In contrast, the CPC score is a parameter that defines the context of the system. There are eleven types of CPCs, and the variation in these scores corresponds to the variabilities in the system: "1. Availability of resources", "2. Training and experience", "3. Quality of communication", "4. Human–Machine Interaction (HMI) and operational support", "5. Access to procedures", "6. Conditions of work", "7. Number of goals", "8. Available time", "9. Circadian rhythm", "10. Crew collaboration quality", and "11. Organization factor". CPC scores quantify linguistic variables defined in CREAM. This simulation model envisions the system's behavior when variability occurs by simulating the interactions between these PAF and CPC scores.

The details of the simulation method are outlined in Algorithm 1. The first to fifth lines concern the initial settings of the simulation, starting with importing the simulation scenario. The simulation scenarios encompass information regarding the skill level of workers and the types and timings of variabilities. As discussed in Section 3.2, the skill levels of workers are represented as different FRAM models, depending on whether the worker is an expert or a novice. The types of variabilities within the simulation scenarios are defined by eleven types of CPCs. The setting of multiple disturbances within a single simulation scenario is permitted to investigate the combined effects of disturbances, yet it is stipulated that only one disturbance occurs at any simulation time. This decision was reached after discussions with site managers in the case study, concluding that shifting multiple disturbances, rather than presenting them simultaneously, better aligns with the real-world situations of worksites experiencing successive disturbances.

From line seven onwards, the main loop of the simulation is presented. With each cycle of this loop, the simulation time t advances by one, continuing until the end time of the simulation is reached. Up to line ten, "Step 0: Intervention" corresponds to introducing the specified variability in the simulation scenario. For instance, if the scenario dictates a disturbance in CPC "1. Availability of resource" at time 0 and in CPC "2. Training and experience" at time 1, then at step 0 of each respective simulation time, the CPC score is changed to the value specified in the scenario. This portion of the algorithm was selectively updated in this research to investigate the combined effects of multiple variabilities. The subsequent parts of the algorithm adhere to the simulation method proposed by Hirose and Sawaragi (2020).

From line eleven, the process is referred to as "Step 1: CPC resonance". This step represents the propagation of the variability in one CPC to others based on the relationships between different CPCs, qualitatively defined by CREAM (Hollnagel, 1998). Eq. (1) illustrates this calculation.

$$\mathrm{CPC}_k^{t+1} = \mathrm{CPC}_k^t + \sum_l \{(\mathrm{CPC}_l^t - \mathrm{CPC}_k^t) w_l\} \tag{1}$$

CPC_k^t is the kth CPC score at simulation time t and w_l is the weight for the lth CPC (Hirose and Sawaragi, 2020). Based on this equation, variations in the lth CPC are propagated to the kth CPC.

The second step, Fuzzy CREAM, is described starting from line sixteen. This step involves calculating the PAF for each function based on the updated CPC scores. Fuzzy CREAM applies Fuzzy theory to CREAM, a method of the second generation of human reliability analysis (Hollnagel, 1998). While CREAM assesses the variability of eleven types of CPCs using linguistic indicators, Fuzzy CREAM evaluates these CPCs using membership functions, assigning a score from 0 to 100. Similarly, while CREAM qualitatively evaluates the system's condition

Algorithm 1 FRAM simulation

1: **Import** Simulation scenario and FRAM model
2: **Define** N_{func} as number of functions, function$[j]$ for $j = 1$ to N_{func} as each function
3: **Initialize** CPC$[i]$ for $i = 1$ to 11, PAF$[j]$ for $j = 1$ to N_{func}
4: **Define** $w[l]$ for $l = 1$ to 11 as weights for each CPC, $N_{\mathrm{upfunc}}[j]$ for $j = 1$ to N_{func} as number of upstream functions of function$[j]$
5: **Define Function** AspectToCPCMapping() as a function to define the relationship between the FRAM function's aspects and CPC
6:
7: **for** Simulation time $t = 0$ to (Simulation end time) -1 **do**
8:   **if** CPC$[i]$ is changed at t in the simulation scenario **then**
9:     Change CPC$[i]$(t) to the specified value ▷ (Step 0: Intervention)
10:   **end if**
11:   **for** $k = 1$ to 11 **do** ▷ (Step 1: CPC resonance)
12:     **for** $l = 1$ to 11 **do**
13:       $\mathrm{CPC}[k](t) += (\mathrm{CPC}[l](t) - \mathrm{CPC}[k](t)) \times w[l]\ (k \neq l)$
14:     **end for**
15:   **end for**
16:   **for** $j = 1$ to N_{func} **do** ▷ (Step 2: Fuzzy CREAM)
17:     $\mathrm{PAF}[j](t+1) = \mathrm{FuzzyCREAM}(\mathrm{CPC}(t))$
18:   **end for**
19:   **for** $j = 1$ to N_{func} **do** ▷ (Step 3: Function to function propagation)
20:     **for** each u in upstream functions of function$[j]$ **do**
21:       $\mathrm{PAF}[j](t+1) += (\mathrm{PAF}[u](t+1) - \mathrm{PAF}[u](t)) / N_{\mathrm{upfunc}}[j]$
22:     **end for**
23:   **end for**
24:   **for** $j = 1$ to N_{func} **do** ▷ (Step 4: Function to CPC propagation)
25:     **for** aspect in [Input, Precondition, Resource, Control, Time] **do**
26:       **if** function$[j]$ has connection to aspect **then**
27:         **for** m in AspectToCPCMapping(aspect) **do**
28:           $\mathrm{CPC}[m](t+1) = \mathrm{CPC}[m](t) \times \mathrm{PAF}[j](t) / \mathrm{PAF}[j](t+1)$
29:         **end for**
30:       **end if**
31:     **end for**
32:   **end for**
33: **end for**

in four stages as the control modes, Fuzzy CREAM quantitatively maps these indicators to PAFs using membership functions. Then, the PAF for each function in the FRAM model is calculated based on the scores of the eleven types of CPCs. Details about Fuzzy CREAM can be found in the study by Ung (2015).

Beyond line nineteen, the third step corresponds to the propagation of variability from one function to another. This step represents the process by which the PAF of one function affects the PAF of another, according to the couplings between functions in the imported FRAM model. Line twenty-one illustrates the influence that the jth function receives from the uth upstream function, as shown in Eq. (2).

$$\mathrm{PAF}_j^{t+1} = \mathrm{PAF}_j^t + \frac{\sum_u (\mathrm{PAF}_u^{t+1} - \mathrm{PAF}_u^t)}{N_{\mathrm{upfunc}}[j]} \tag{2}$$

PAF_j^t is the PAF of jth function at simulation time t. PAF_u^t is the PAF of uth upstream function of jth function at simulation time t. $N_{\mathrm{upfunc}}[j]$ is the number of upstream functions of jth function.

The final step is presented from line twenty-four onwards, demonstrating the propagation of variability from functions to CPCs. This step involves updating the CPC scores again based on the variations in the PAFs of each function. It determines which CPCs are influenced by variabilities, depending on which aspect of the function is coupled. The relationship between these aspects and the CPCs is defined in the function named AspectToCPCMapping on line twenty-seven, with more detailed information available in the literature (Hirose and Sawaragi, 2020). Based on this relationship, the calculation of CPCs on line twenty-eight is executed as in Eq. (3).

$$\mathrm{CPC}_m^{t+1} = \frac{\mathrm{PAF}_j^t}{\mathrm{PAF}_j^{t+1}} \times \mathrm{CPC}_m^t \tag{3}$$

Following this step, the simulation time is advanced by one, and the process returns to line seven, repeating until the simulation end time. The interaction between CPCs and PAFs of each function is formalized through these steps, allowing for examining the effects of disturbances on the system.

4. Implementation

The section below describes the implementation of the method in an industrial case study, followed by building the FRAM model. After that, the simulation results are presented in the next section.

4.1. Case study: Marine engine test and repair process

This study focused on the 'test and repair' process of a marine engine production line, in which operators have a critical role in handling the complexity of the production process. As depicted in Fig. 1, the production sequence begins with Assembly, followed by a Leakage Test. Failed engines are redirected to a Repair Area, while successful units are painted, undergo further Assembly, and are tested for performance (Hot Test). The production process of the studied marine engine manufacturer is detailed in the previous paper (Mahmoodi et al., 2024). The workforce's skills are central to managing these complex processes, particularly during testing and repair phases that require precise defect identification and remediation. This expertise directly influences product quality and production efficiency, highlighting the importance of human roles in a technologically advanced production environment. According to the significant probability of engine rejection at the Leakage Test and the limited capacity of the Repair Area, it is a regular event that the bottleneck of the production system shifts to the Test and Repair Area. Thus, the proficiency of the workforce is essential for quickly diagnosing and fixing engine defects, which mitigates the bottleneck and maintains throughput (Mahmoodi et al., 2022).

The repair process in this production line is a critical step that ensures any engines failing a Leakage Test are brought up to the required standards. As depicted in Fig. 2, when an engine fails the Leakage Test, technicians first review the test results to hypothesize potential causes of the leakage, including loose connections, quality defects in assembled components, and fractures in the engine body. Once a probable cause is identified, technicians perform the necessary repairs, followed by retesting for leakage. If the problem persists, technicians must reassess the situation and formulate a new hypothesis for the root cause, iterating the process until the engine passes the test.

4.2. Data collection

4.2.1. Data collection overview

Fig. 3 illustrates the process of data collection, analysis, and building and verification of the FRAM model. This study applies mixed qualitative methods, consistent with the existing literature on FRAM (Salehi et al., 2021; Tian and Caponecchia, 2020; Patriarca et al., 2020). The process starts with observations and document reviews to obtain fundamental information about the target process, followed by semi-structured interviews with multiple participants. The gathered information was organized through content analysis and WDA, which made the foundation for building the FRAM model. The built FRAM model was then verified in workshops and group discussions. Details of each step are described below.

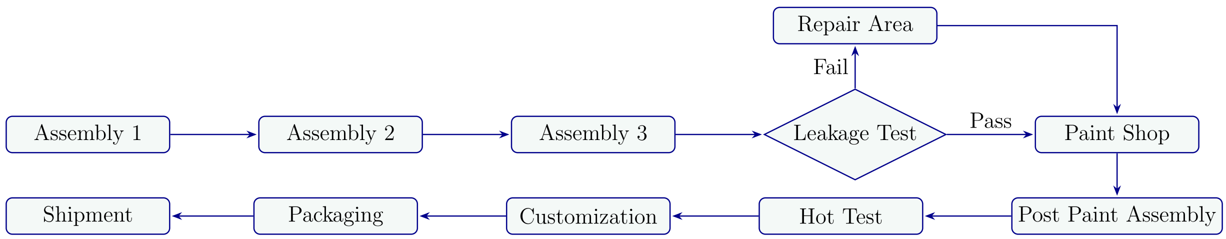


Fig. 1. General engine production flowchart.

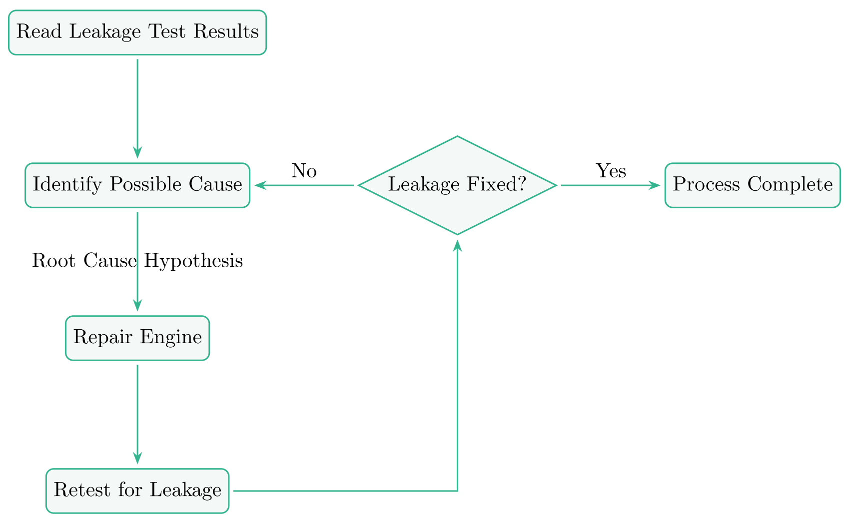


Fig. 2. Repair process flowchart performed by repair operator.

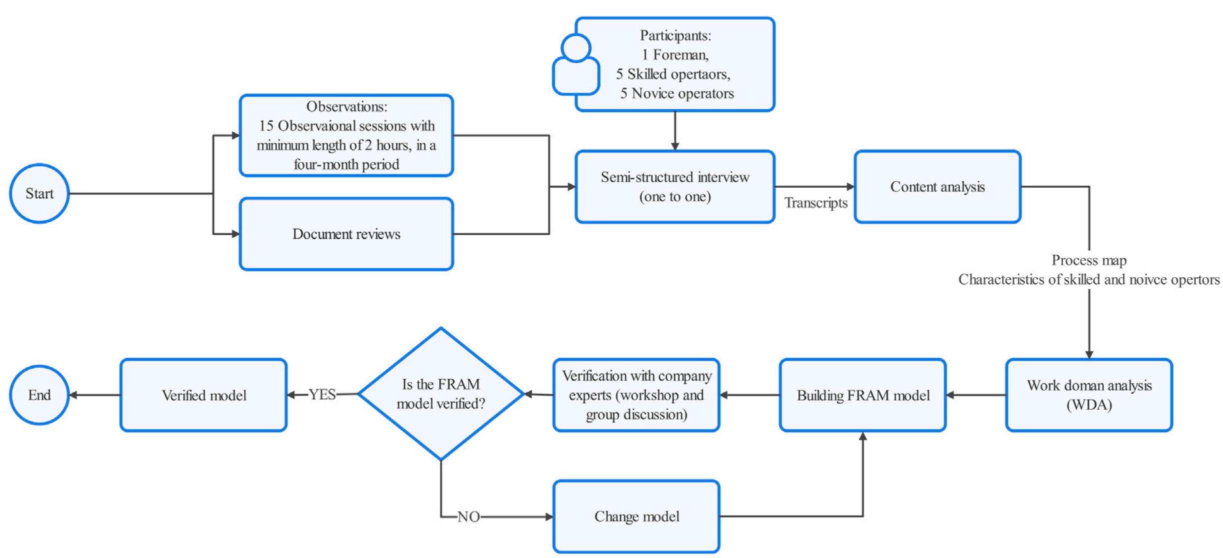


Fig. 3. The process of data collection and analysis, building, and verification of the FRAM model.

4.2.2. Observations and document reviews

This process begins with eight observational sessions, each lasting a minimum of two hours, conducted over a four-month period. Document reviews of the work procedures further complemented these sessions. The primary tasks comprising the test and repair process were extracted from the work procedures in these steps. The observational data and the document analysis results were a foundation for the subsequent interviews.

4.2.3. Semi-structured interviews with participants

The next step involves conducting semi-structured interviews with eleven participants—one foreman, five skilled operators, and five novice operators. The study focused on operators working in the company's repair area. Thus, a set of operators with varying levels of experience and expertise in the repair domain were selected through purposive sampling (Campbell et al., 2020), a non-probability sampling technique commonly used in qualitative research to ensure that

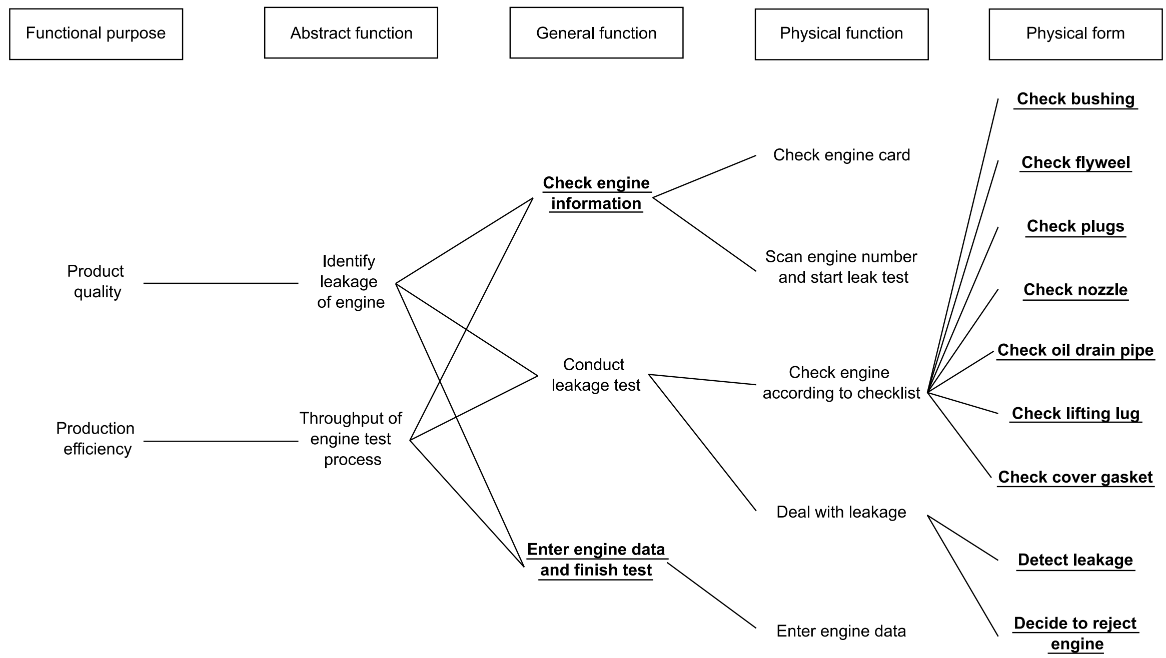


Fig. 4. Abstraction hierarchy of the target work. The underlined functions are included in the FRAM model.

relevant data is obtained from information-rich cases. The interviews were conducted using an open-ended format, which allowed for the collection of tacit knowledge regarding the various steps involved in the engine test and repair process.

4.2.4. Content analysis

The content analysis process employed in this study focused on using process coding to analyze the interview transcripts. Process coding utilizes gerunds (words ending in -ing) to code the data, with the aim of capturing activities described by the participants. In this research, the process coding was particularly relevant as the interviews centered around understanding the step-by-step processes, sequences of actions, and decision-making involved when operators were repairing problematic engines. By using process coding, the researchers could systematically identify and label the various activities that skilled and novice operators undertook during these complex repair tasks. Some of the process codes used include "interpreting test results", "prioritizing repair tasks", "troubleshooting issues", "replacing faulty components", "conducting diagnostic tests", "consulting repair manuals", and "coordinating with other technicians". These codes would provide insights into the chronological flow of activities, decision-making points, and strategies employed by operators when faced with challenging engine repair situations. The findings from interviews were triangulated with observations and document reviews and were checked with participants to verify interpretations. Based on the outputs of the content analysis, the FRAM model was built by the researchers, as described in Section 4.3.

4.2.5. FRAM model verification

As the final step, the FRAM model was verified through workshops and group discussions. These sessions involved company experts who possessed in-depth knowledge of the repair processes, as well as the participant group of operators (one foreman, five skilled operators, and five novice operators) who had participated in the semi-structured interviews. All the participants attended all the verification sessions.

During the workshops, the FRAM model was presented to the participants, explaining the functions, aspects, and relationships depicted in the model. The experts and operators then had the opportunity to review the model, provide feedback on its accuracy and completeness, and suggest modifications or additions based on their practical experiences while being allowed to communicate with each other. In the group discussions, greater emphasis was placed on participant interaction, allowing for a free-form exchange of opinions regarding the validity of the FRAM model. These sessions involved joint modeling activities, where participants collaboratively refined the model by adding, removing, or adjusting functions and their interconnections. The researchers facilitated structured discussions, using techniques like focus groups or guided questions, to capture diverse perspectives and ensure the model accurately represented the real-world repair processes. If discrepancies or inaccuracies were identified, the model would be updated and changed accordingly, iterating until it was verified as a valid representation by the participants. Readers are referred to the study by Nyumba et al. (2018) for detailed information on implementing qualitative research methods. Qualitative research methods involving multiple participants, such as workshops and group discussions, are commonly employed to verify the FRAM model (Salehi et al., 2021; Ross et al., 2018; Damen et al., 2021). Comparing and contrasting the diverse perspectives of multiple participants ensures that the FRAM model does not rely on the viewpoint of a single participant, thereby enhancing its credibility (Korstjens and Moser, 2018). Additionally, integrating diverse perspectives into the FRAM model achieves greater transferability (Korstjens and Moser, 2018), making it applicable to broader contexts.

4.3. FRAM model

Before building a FRAM model, this study conducted WDA to organize information on the target work. Fig. 4 shows the abstraction hierarchy of the target work in the case study. At the top layer, the functional purpose, the two main objectives of this work were described, i.e., product quality and production efficiency. These primary objectives were determined by the identification of leakages in engines and the throughput of the engine test process, as shown in the abstract function layer. The three main activities to accomplish the abstract functions were placed at the general function layer. The procedures described in the operational guideline were shown in the physical

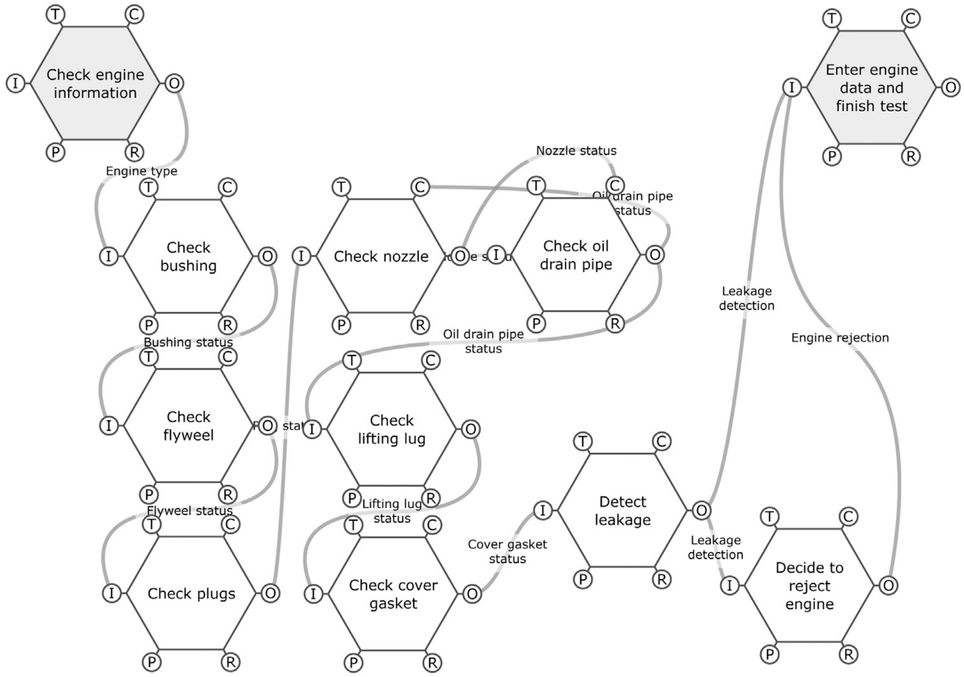


Fig. 5. FRAM model of the novice workers.

function layer. Five procedures relevant to the quality and efficiency of the engine test process were picked up and described. Finally, the checklist items for the leakage test were listed at the physical form layer, which relates to the "Check engine according to checklist" at the physical function layer. In addition, focusing on the function "Deal with leakage", two detailed activities were added at the physical form layer.

Based on the resultant abstraction hierarchy, the basic version of the FRAM model was constructed, as shown in Fig. 5. This FRAM model corresponds to the novice workers. The most critical functions for the quality of the test process, "Check engine according to checklist" and "Deal with leakage", were decomposed into physical form layers in the FRAM model to describe those in detail. In contrast, the functions not directly relevant to the work quality in the physical function layer were aggregated into "Check engine information" and "Enter engine data and finish test" in the general function layer. As a result, the underlined functions in Fig. 4 were included in the basic FRAM model, as shown in Fig. 5. This FRAM model has a relatively simple structure, which reflects the operational guideline as it is, such that almost all functions are connected sequentially at inputs and outputs.

This study extended the basic FRAM model to reflect the resilient characteristics of skilled workers. According to the concept of resilience engineering, the four abilities – monitoring, anticipating, responding, and learning – are critical for improving the system's resilience (Hollnagel et al., 2006). Based on this concept, the four functions representing these abilities were added to the FRAM model. The blue functions of the expert worker's FRAM model in Fig. 6 show these additional functions. The function "Anticipate leakage" represents the prediction of defects before the test, as indicated by receiving the function's output "Check engine information" at the upper left corner. In contrast, the function "Monitor leakage" corresponds to monitoring the leakage test results after conducting it. The function of "Learning" receives the outputs of these two functions and corresponds to updating the worker's knowledge based on the differences between predictions and observations. Finally, the function "Respond to leakage" on the far left updates the strategy of performing the test process by providing feedback connections to the "Checking" functions. These constructed FRAM models were verified as described in the data collection section.

5. Simulation results

5.1. Simulation settings

This study utilized the simulation method to investigate the composite effects of variability on work performance in the case study. This study also emphasizes how the unique characteristics inherent to expert operators play a crucial role in influencing the impact of composite variability, highlighting their importance in mitigating its effects. As detailed in the methods section, the execution of FRAM simulations involves generating simulation scenarios. The simulation scenarios in this study consist of two components: the operator's skill level and the types of variability occurring in the work environment. The operator's skill level was bifurcated into expert and novice, corresponding to importing the different FRAM models into the simulation execution program. Regarding the second component, information on when and which types of variability occur during simulation time was specified. This study considered two possibilities for each of the eleven CPCs: the presence or absence of the variability. By comprehensively considering all combinations of variabilities, $2^{11} = 2048$ simulation scenarios were generated. However, the scenario in which variability does not occur in any of the eleven CPCs was excluded, resulting in the consideration of 2047 unique simulation scenarios for a single operator. These combinations were examined separately for operators categorized as experts and novices, resulting in 4094 simulation scenarios in total.

The simulation scenario was implemented in the simulation algorithm as follows. Initially, the FRAM model corresponding to the worker's skill level was imported. Subsequently, the specified CPCs in the simulation scenario were varied at each time step. As demonstrated in Algorithm 1 of the methods section, the variation of the CPC was executed one by one as Step 0 every time the computation loop was run. When variability was introduced, the CPC score was reduced to one-tenth to examine the impact of each type uniformly. After all specified CPCs were varied, the algorithm continued the computation loop until the end of the simulation time. The end time of the simulation was set to 15 after exploring a duration that yielded sufficient results. Table 2 illustrates an example of the simulation scenario. After executing simulations across all scenarios, the results were categorized into three distinct groups, as follows.

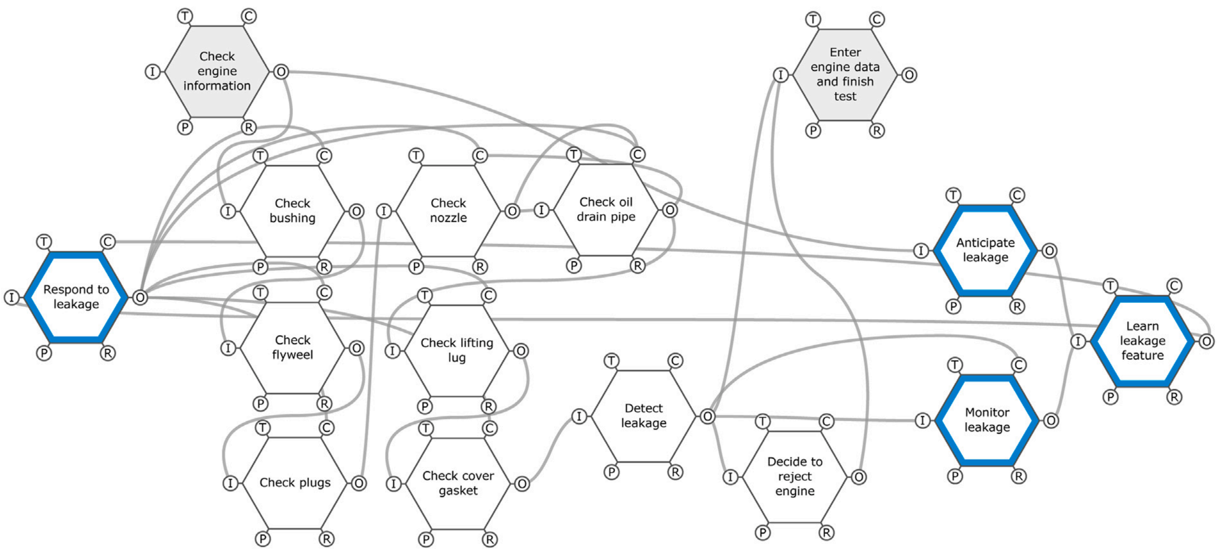


Fig. 6. The extended version of the FRAM model with the resilient characteristics of the expert workers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
An example of the simulation scenario (operator = expert, variability = CPC No. 1, 3, 6).

Operator's skill level: Expert						
Simulation time	0	1	2	3	…	15
Variability type (CPC No.)	1	3	6	–	–	–

5.2. Category I: Recovery from disturbances

The simulation results in category I indicate that the worker could recover from the disturbances and maintain work performance. As an example of this category, Fig. 7(a) shows the simulation result when an expert worker was assigned, and the variability related to resources occurred. The graph shows the logarithm of the PAF of each function. An increase in the graph indicates an increased possibility of becoming dysfunctional for each function. In this simulation scenario, the variability was set at the simulation time 0, and the graph shows that each function was affected temporarily. However, each function recovers to the normal status after the simulation time 6. This example illustrates that the expert worker could recover from the disturbance related to a lack of resources, although their work performance was temporarily affected.

5.3. Category II: No recovery from disturbances, oscillating state

The simulation results in category II indicate that the worker could not recover from the disturbances. In addition, the state of each function did not settle into a steady state and continued to oscillate. This result shows that although the state of each function temporarily recovers from variabilities, it is still difficult to carry out the work in a stable condition. For example, Fig. 7(b) shows the simulation result when an expert worker was assigned, and the two variabilities related to resources and human–machine interaction occurred. This example shows that when disturbances related to a lack of resources and interface malfunction occur, even expert workers cannot perform at a stable level.

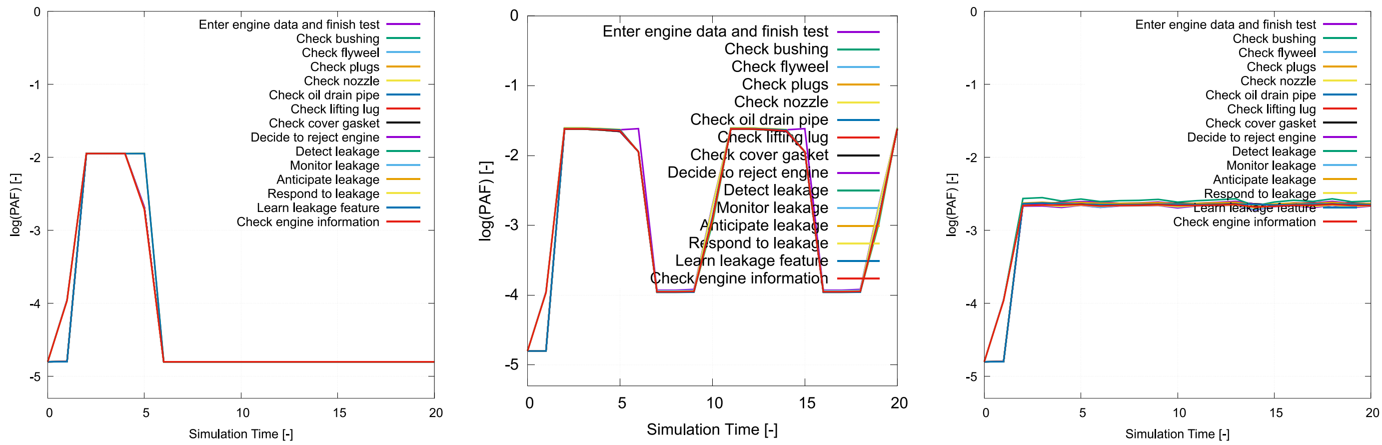
5.4. Category III: No recovery from disturbances, steady state

The simulation results in category III indicate that the worker could not recover from the disturbances. In addition, the state of each function settled into a steady state. As an example of this category, Fig. 7(c) shows the simulation result when a novice worker was assigned, and the variability related to resources occurred. This example illustrates the inability to recover work performance when the novice suffers the disturbance related to a lack of resources.

5.5. Summarizing key trends in simulation results

All simulation outcomes were classified into the three categories above. Fig. 8 illustrates the distribution of these categories across different simulation scenarios considering the number of variabilities and the operators' skill levels. The bar graphs in blue, yellow, and red represent the proportion of scenarios falling into Categories I, II, and III, respectively. The analysis shows that for both expert and novice operators, the proportion of Category III increases with the number of variabilities present in the scenarios. This trend suggests that as more variabilities compound, recovering from their impacts becomes increasingly challenging. This phenomenon would be due to the escalating potential for interactions between variabilities, which complicates the operational environment and overwhelms standard response strategies. Furthermore, the data indicates that expert operators have a higher proportion of Category I scenarios than novices. This difference underscores the structural advantages inherent in the FRAM model of expert operators, enabling them to maintain work performance across a broader range of scenarios.

This study also focused on the trends in the PAF values in the simulation results. Fig. 9 presents a box plot of the proportion of time during which the PAF values remained above the reference value ($\log \mathrm{PAF} = -3$) from the start to the end of the simulation. This threshold corresponds to the intersection of the "Opportunistic" and "Tactical" membership functions of the four linguistic variables—strategic, tactical, opportunistic, and scrambled—in the Fuzzy CREAM methodology (Ung, 2015). Consequently, values of $\log \mathrm{PAF}$ greater than -3 indicate a function's state that is closer to "Scrambled" or "Opportunistic", whereas values below -3 suggest proximity to "Tactical" or "Strategic" states. The analysis shows that as the number of variabilities increases, the duration with higher PAF values also extends, indicating a degradation in task performance. Moreover, the graph shows that the rise in PAF values is less prominent among expert operators than novices. This pattern suggests that higher variabilities lead to performance deterioration and that expert operators are less susceptible to their adverse effects.



(a) Simulation result example of category I. An expert worker was assigned, and the variability of CPC "1. Availability of resource" occurred in this simulation scenario.

(b) Simulation result example of category II. An expert worker was assigned, and the variabilities of CPC "1. Availability of resource" and "4. HMI and operational support" occurred.

(c) Simulation result example of category III. A novice worker was assigned, and the variability of CPC "1. Availability of resource" occurred in this simulation scenario.

Fig. 7. Simulation results examples of category I, II, and III.

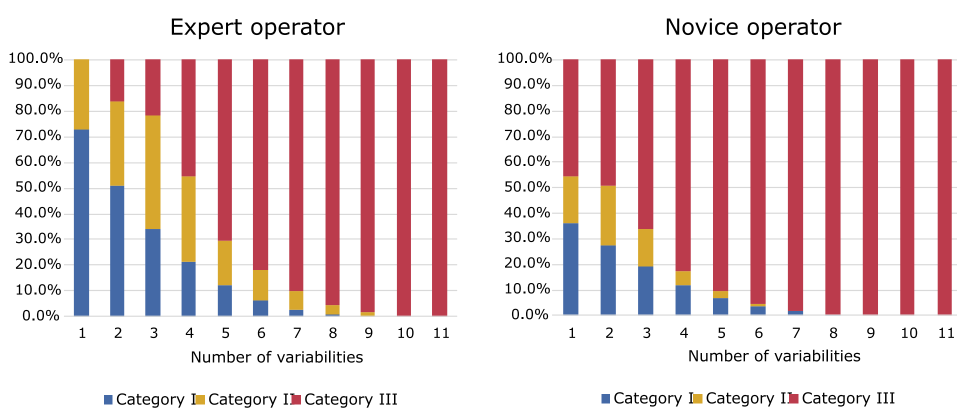


Fig. 8. Percentage of categories I, II, and III in the simulation results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

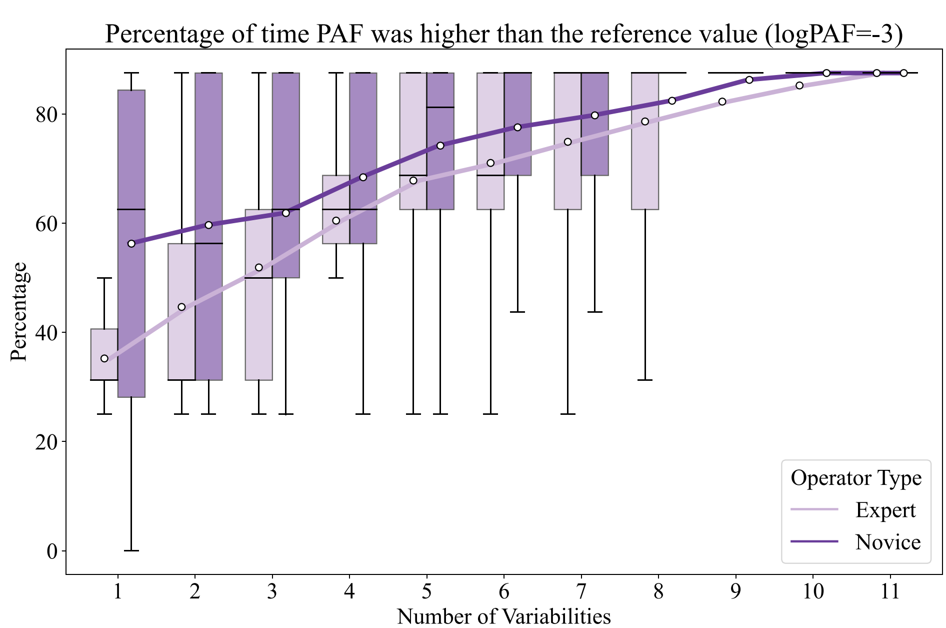
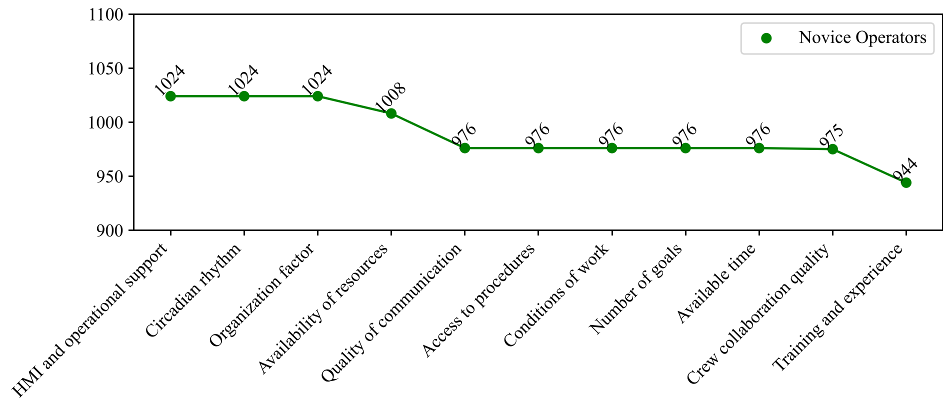
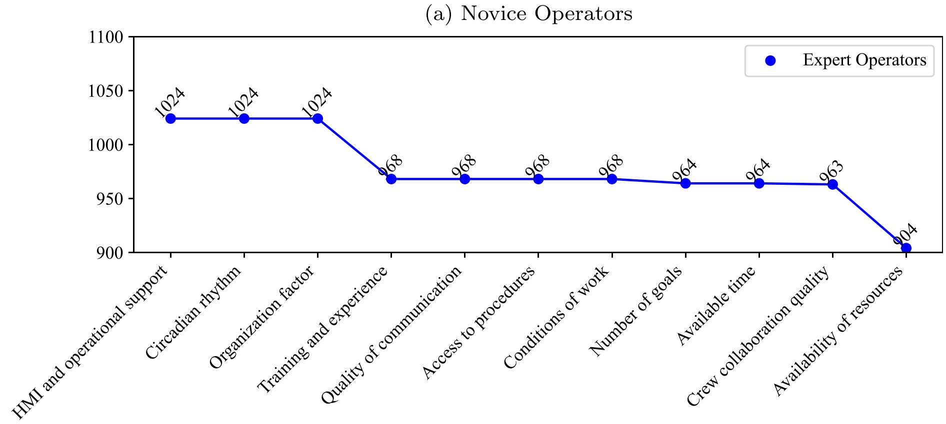


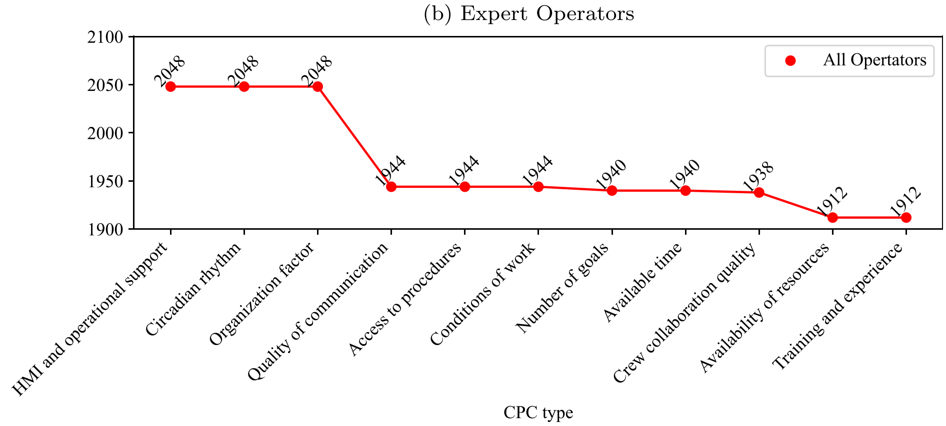
Fig. 9. Percentage of simulation time that $\log \mathrm{PAF}$ was higher than the reference value ($\log \mathrm{PAF} = -3$).



(a) Novice Operators



(b) Expert Operators



(c) Combined Data from Both Expert and Novice Operators

Fig. 10. Frequency of CPCs in scenarios where the percentage of having PAF higher than the reference value.

To gain deeper knowledge about the most influential CPCs on novice and expert operators, Fig. 10 presents the frequency of CPCs in scenarios where the percentage of having PAF was higher than the reference value. Fig. 10(a) reveals that the CPCs with the highest frequencies are "HMI and operational support", "Circadian rhythm", and "Organizational factors", indicating these are major contributors affecting novice operator performance in high PAF scenarios. Factors like "Training and experience" have relatively lower frequencies, suggesting they are less influential for novice operators in such scenarios. Fig. 10(b) interestingly reveals the top three highest frequency CPCs are the same for expert and novice operators. This implies that regardless of expertise level, these CPCs are critical factors impacting performance when PAF exceeds the reference value. The lowest frequency CPC, i.e., "Availability of resources", seems to play a lesser role for expert operators in high PAF conditions.

One of the key differences between novice and expert operators is the relative importance of "Availability of resources" and "Training and experience". For novice operators, "Availability of resources" is among the top four most influential CPCs, while "Training and experience" is one of the least influential ones. On the other hand, for expert operators, the situation is reversed. This difference in the relative importance of "Availability of resources" and "Training and experience" between novice and expert operators can be attributed to the varying levels of expertise and skill development. Novice operators, being less experienced, may rely more heavily on the availability of resources to compensate for their lack of training and experience when faced with challenging scenarios. In contrast, expert operators, having accumulated substantial training and experience over time, are better equipped to handle such scenarios, making the availability of resources a less prominent factor than their level of training and experience.

To get a more comprehensive view, Fig. 10(c) combines the data from both expert and novice operators, showing the overall CPC frequency trends across all operators in high PAF scenarios. Unsurprisingly, the top three highest frequency CPCs remain "HMI and operational support", "Circadian rhythm", and "Organizational factors", reinforcing their significance. Likewise, the two lowest frequency CPCs are "Training and experience" and "Availability of resources", consistent with the individual operator groups. This combined view highlights the universal importance of certain CPCs and the relatively lower impact of others.

6. Discussion

6.1. Methodological assumptions and specifics

This study employed a FRAM-based simulation approach to investigate the impact of compound variabilities and the resilience characteristics of expert workers. Works of novice and expert workers were modeled using FRAM, and comprehensive simulations were conducted under scenarios with multiple variabilities. This simulation method enabled the envisioning of the state of work in the simulation scenarios by calculating the interactions between the PAF inherent in each function and the CPCs that represent the work environment. During this process, the following important assumptions were made.

This study used the simulation method that utilizes eleven types of CPCs to represent the variability inherent in the system (Hirose and Sawaragi, 2020). CPCs were initially categorized into nine factors under CREAM, part of the second-generation human reliability analysis techniques (Hollnagel, 1998), later expanded to eleven with the introduction of FRAM (Hollnagel, 2004). As background, human reliability analysis evolved from the first generation, which focused primarily on quantifying the probability of human errors, to the second generation, which emphasizes analyzing how context influences the occurrence of human error. Consequently, CPCs, grounded in second-generation human reliability analysis, prioritize understanding the situational context of the system. Meanwhile, the representation of variability in FRAM has changed to express variability predominantly from the perspectives of timing and accuracy (Hollnagel, 2012), focusing more on the outputs of functions. This research deliberately used traditional CPCs to highlight the interaction between operators and their surrounding environment. By doing so, simulations could be run across all combinations of CPC scenarios, thereby assessing the complex impacts of variability.

The study differentiated the FRAM model into two types: expert and novice. Several studies have explored the impact of different operator skill levels on system performance, highlighting that the definition of expertise varies by country, company, and sector (Ghodrati and Kumar, 2005; Berlin and Söderström, 2019; Holm et al., 2017). In the manufacturing sector, expertise has often been assessed annually through a competence matrix for both blue and white-collar personnel, aiming to evaluate and update skills acquired through continuous improvement strategies (Ali et al., 2021). Salvendy has defined experts as individuals with extensive knowledge and experience capable of efficiently performing complex tasks, while novices lack experience and rely heavily on supervision and guidelines (Salvendy, 2012). Discussions with the factory stakeholders confirmed that considering the characteristics of the work process, this classification is also feasible for this case study.

This study's distinction between experts and novices corresponds to the differences between Work-as-Imagined (WAI) and Work-as-Done (WAD). In resilience engineering, the approach commonly involves comparing how a system was designed (WAI) versus how it is actually operated (WAD) to analyze discrepancies and improve system resilience (Gattola et al., 2018; Clay-Williams et al., 2015; van Dijk et al., 2022; Schutijser et al., 2019). In this research, the novice FRAM model emphasized adherence to work guidelines, reflecting the WAI perspective. Conversely, the expert FRAM model incorporated additional features that align with the four capabilities of resilience, effectively representing how skilled workers actually perform tasks (WAD). By comparing WAI—corresponding to the novice FRAM model—with WAD—corresponding to the expert FRAM model, this study contributes to identifying insights that maintain work performance resiliently.

6.2. Evaluating FRAM model's alignment with JCS principals

The joint cognitive system (JCS) approach recognizes that human performance and system performance are closely intertwined and that both the human and technological components need to be considered as a unified whole (Hollnagel and Woods, 2005). FRAM equipped with CPCs aligns well with this principle. The CPCs represent the key factors that influence the joint performance of the human and technological components within the system. For example, the three main CPCs identified through the simulation study could be described as follows. HMI and operational support address the design and usability of the human–machine interfaces, which directly impact the ability of the operators to interact with and leverage the technological components effectively. Circadian rhythm, a biological factor, can influence the performance of operators and, consequently, the overall functioning of the joint cognitive system. Lastly, organizational factors, such as organizational culture, policies, and structures, can shape the dynamics and interactions within the joint cognitive system, influencing its overall performance and resilience.

By considering these CPCs, the FRAM model acknowledges the complex interplay between human, technological, and organizational factors that characterize joint cognitive systems. This comprehensive approach aligns with the JCS principles, which emphasize treating the system as a whole rather than decomposing it into individual parts. While the provided FRAM model incorporates the CPCs and their potential impact on system performance, a limitation of the model is the lack of explicit consideration for the relationship between expert and novice operators. Options to overcome this issue include implementing a monitoring system for tasks and conducting in-depth interviews with expert and novice workers to collect additional data. However, data collection and observation processes face obstacles, such as handling video data and designing appropriate interviews, necessitating future work to integrate these perspectives into the JCS principle.

6.3. Effects of multiple disturbances and skill aspects on work performance

This study aimed to understand how production systems actually operate when workers are involved in key processes. For this purpose, the following two research questions were set. The first question was how multiple disturbances affect work performance. The second question was how worker's skills contribute to resilient work performance under multiple disturbances. In order to examine these two research questions, the simulation method based on FRAM was extended, and a case study in an engine test and repair process was conducted.

Regarding the first research question, the simulation results found that the more variabilities are compounded, the more difficult it becomes for the worker to maintain work performance. As more complex disturbances were expected to have a more substantial impact, the quantitative results showed that workers could recover their work performance in fewer scenarios when multiple disturbances were combined. This finding aligns with one of the principles underlying FRAM, i.e., the functional resonance (Hollnagel, 2012). This term refers to the fact that small variabilities in a number of interrelated functions reinforce each other, resulting in a considerable variability that puts the entire system at high risk. Similarly, when the daily variabilities are combined, they can degrade human performance in production systems. In addition, the simulation results showed that some critical variabilities correspond to the specific type of CPC. This result implies that these factors critically affect the engine test and repair process in the case study.

Regarding the second research question, the simulation results found that expert workers can recover from the effect of variabilities in more cases than novice workers. This indicates that the skills of expert workers contribute to the maintenance of work performance. This finding aligns with one of the principles underlying FRAM, i.e., the approximate adjustments (Hollnagel, 2012). According to this principle, workers in complex socio-technical systems must constantly cope with variabilities in their daily work. The results of this study showed that the four resilience capabilities included in the expert's FRAM model enabled them to cope with multiple variabilities in more cases. In addition, the finding of this study also supports the research that investigated workers' non-technical skills in socio-technical systems (França et al., 2021; França and Hollnagel, 2023). It has been found that non-technical skills such as situation awareness contribute to the safe operation of both usual and critical tasks. These findings can potentially enhance workers' skills to realize resilient work performance by supporting workers and managers in understanding how the process is operated.

The results could provide transformative insights for production line managers, emphasizing the importance of balancing investments in advanced technologies with attention to the human aspect. Managers are encouraged to understand operators' critical roles and interactions with system disturbances, which is essential for building resilient workflows that reduce risk and elevate performance. Key findings include the significant impact of increasing variabilities on the performance of both novice and expert operators. This finding underscores the need for proactive management and mitigating disturbances to maintain operator performance and system efficiency. Managers should prioritize monitoring and assessing these disturbances, implementing strategies to control and prevent their interaction. Additionally, certain CPCs, such as "HMI and operational support", "Circadian rhythm", and "Organizational factors", have a substantial impact on performance, particularly in scenarios where the PAF was high. Addressing these CPCs through targeted interventions, such as ensuring intuitive equipment design, improving organizational processes, and aligning work schedules with circadian rhythms, can enhance operational efficiency, reduce risks, and improve overall performance for operators.

This study compared two FRAM models representing expert and novice workers and analyzed the impact of FRAM model topology on system performance based on simulation results. As detailed in the methods section, the simulation methodology employed in this study involves executing five iterative steps, including an initial Step 0, to compute the PAF values for each function. During this process, the propagation of variability in Step 3 is directed from the outputs of upstream functions to the aspects of downstream functions. Thus, tracking which functions are connected to each output can broadly help understand how variability spreads through the system. The structural examination of the two FRAM models reveals that while the novice model exhibits unidirectional connections of functions from left to right, the expert model incorporates four additional functions, creating a feedback loop-like structure. Other studies have also suggested that feedback-like structures of the FRAM models contribute to system resilience (Yasue et al., 2023). Determining which FRAM model structures best contribute to resilient system performance necessitates further research.

7. Conclusion

This study focused on workers in production systems and how multiple disturbances affect work performance. Investigating how skilled workers contribute to resilient work performance under multiple disturbances was also the focus of this study. For this purpose, the simulation method based on FRAM was extended to consider multiple variabilities, and a case study in the test and repair process of the engine assembly line was conducted. The FRAM models reflecting the worker's skills were constructed based on document reviews, observations, and interviews. Then, a simulation study was conducted, setting the multiple variabilities with several types of CPCs. The results showed that multiple disturbances make it difficult to maintain work performance. In addition, some critical factors to resilient productivity were identified, such as human–machine interactions. With regard to the worker's skill aspects, the simulation study found that the four capabilities of resilience enable the workers to recover from the effect of variabilities in more cases.

7.1. Limitations and future research

As we look ahead, several future research directions emerge from our study, promising to extend the body of knowledge in human-centric production systems and address the limitations of this work. The main limitation of the proposed approach is that the model needs more explicit consideration for the relationship between expert and novice operators. The JCS principles emphasize the importance of treating the system as a unified whole, and decomposing it into individual components may contradict this approach. Future research should explore incorporating the dynamics and interactions between operators to address this limitation. Their collaboration, knowledge sharing, and potential differences in performance can significantly influence overall system resilience and adaptability. One potential approach could be to model the entire system with multiple workers, incorporating the CPCs and their potential variability. By addressing this limitation and incorporating the relationship between expert and novice operators, the FRAM model can provide more comprehensive insights into the system's resilient performance while remaining aligned with the JCS principles.

Another limitation of this study was its narrow focus solely on the test and repair area of the production system. This restriction potentially limited the variety of participants and the range of their skill levels involved in data collection. Consequently, this limitation may have led to the adoption of overly simplistic models that fail to capture the complexity inherent in production systems. Future work should consider expanding the analysis to encompass a broader range of production lines, including multiple workstations, to refine the FRAM model by incorporating potentially overlooked relationships. Additionally, there were inherent limitations in the complexity of the FRAM model itself. During the validation phase of the FRAM model, it was observed that several participants interpreted the FRAM as akin to a simple flowchart, which did not adequately incorporate the complexity of the tasks into the model. This observation highlights a limitation in our data collection and model validation methodologies. Future studies could explore more sophisticated data collection methods, such as video observation, to enhance the depth and accuracy of the analysis.

Moreover, further studies need to be carried out to integrate the impacts of a broader spectrum of human performance aspects, such as cognitive load, decision-making under stress, and team collaboration on production system resilience. Also, while this study examined the effect of incorporating the four resilience capabilities into the FRAM model, it is expected that investigations focusing on the relation between work performance and the topology of the FRAM model structure will yield more insights into the resilience of socio-technical systems as further research. These future research directions not only chart a course for scholarly inquiry but also resonate with the core objectives of Industry 5.0. As we continue to venture forward, it is vital to strike a harmonious balance between technological advancements and the enrichment of human labor, ensuring that future production systems are resilient and efficient.

CRediT authorship contribution statement

Naruki Yasue: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ehsan Mahmoodi:** Writing

– review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Enrique Ruiz Zúñiga:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Masood Fathi:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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