

Modeling Adaptive Expertise of Workers
for Resilient Performance in Production Systems
Using Functional Resonance Analysis Method

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Abstract

In recent years, the manufacturing industry has faced a critical issue of skill transfer due to the declining working-age population and the aging workforce. Regarding this background, abilities classified as routine expertise—enabling workers to perform defined tasks quickly and accurately—have seen progress in automation and systematic knowledge management. However, abilities classified as adaptive expertise, which allow workers to respond effectively to environmental fluctuations and uncertain situations, remain tacit knowledge ingrained individually in workers and require a long time to acquire. This study aims to model how workers adaptively respond to environmental changes using the Functional Resonance Analysis Method (FRAM) and related simulation techniques. FRAM, developed within the field of safety management, is designed for socio-technical systems with complex interactions among humans, machines, and organizations and is commonly applied in accident investigation, risk assessment, and complexity management. The resilience engineering background of this method focuses on human adaptive adjustment capacities that contribute to system resilience. This method aligns with the objective of this research, which is to clarify the adaptive expertise of workers. To this end, this study includes three main research items: (1) extracting the attention management characteristics of skilled workers in multitasking scenarios, (2) examining the effects of combined factors on task performance, and (3) establishing a systematic method for extracting workers’ knowledge. Each of these research items employs FRAM and related simulation methods, and they are discussed through the lens of metacognition, a critical factor in adaptive expertise. The findings of this study are anticipated to support skill transfer efforts within the industrial sector, contributing to a sustainable manufacturing industry.

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Chapter 1

Introduction

1.1 Adaptive Expertise in Industry

Recently, it has been reported that skill transfer from experienced workers to the next generation of novices has become increasingly challenging within the manufacturing industry. This challenge is primarily due to a decline in the working-age population and the aging of workers on production worksites [1]. As a result, there is a pressing need for immediate solutions to be implemented before a large number of skilled workers retire. There is a growing demand in the industry to analyze and systematize worker skills and to explore possibilities for supporting novice workers in acquiring those skills. In response to this issue, traditional approaches have included extracting characteristics specific to skilled workers and developing knowledge management systems.

Extracting workers' knowledge and transferring it to the next generation is one of the critical aspects of enhancing workers' skill levels in worksites. Workers' skills are often embedded through years of hands-on experience in the manufacturing industry and retained as tacit knowledge. To reduce dependence on individual workers possessing such implicit expertise, manufacturing companies commonly employ qualitative methods, such as interviews, to systematically document and organize these advanced experiences into manuals and databases [2]. Another common approach to extracting skill characteristics from expert workers involves measuring and analyzing eye movements [3]. Numerous studies have investigated how monitoring behaviors toward surrounding information differ between experts and novices by analyzing eye movements during tasks [4, 5, 6, 7]. Notably, efforts have focused on identifying workers' skill levels and workload using entropy metrics of gazing points obtained through eye-tracking measurements, offering valuable insights into skill assessment and workload estimation [8, 9, 10, 11]. In order to utilize the outcomes of these

works, research has been conducted on converting workers’ knowledge into explicit formats and modeling it using expert systems [12]. Furthermore, efforts to transfer skills extracted from experienced experts to the next generation are also essential. Approaches targeting complex manual tasks, such as assembly work, include providing appropriate guidance to novice workers using neural networks [13] and intuitively instructing tasks using augmented reality technologies [14].

However, skills that can be revealed through traditional approaches are primarily limited to explicit knowledge, which can be documented, leaving significant challenges in extracting aspects of skills acquired as tacit knowledge by workers. Recently, advancements in automation technology have increased the complexity and uncertainty of tasks, requiring workers to adaptively respond to various fluctuations and unpredictable conditions on manufacturing worksites. Thus, these adaptive skills, often embedded as tacit knowledge, are particularly challenging to extract using conventional approaches. Regarding this issue, Hatano and Inagaki [15] have proposed the concepts of “routine expertise” and “adaptive expertise.” While routine expertise stands for the ability to perform routine or repetitive tasks accurately and efficiently, adaptive expertise is the capacity to quickly recover a high level of performance when faced with unfamiliar and novel situations. Based on this concept, relevant factors contributing to the development of adaptive expertise have been studied, mainly in pedagogy. In particular, the effects of learner characteristics, personality factors, task and training characteristics, and the learning environment on adaptive expertise have been investigated [16]. The indicators have also been developed to assess and measure learners’ adaptive expertise [17]. While these efforts to understand adaptive expertise are underway, the processes through which adaptive expertise is manifested remain insufficiently understood. With the recent severe labor shortages affecting the manufacturing industry, there is a growing need to clarify how skilled workers demonstrate adaptive expertise in responding to various fluctuations and uncertain situations within the work environment. This knowledge is essential for supporting the transfer of skills to future generations.

1.2 Resilient Production in Industry 5.0

In considering adaptive expertise among workers in the manufacturing industry, the concept of Industry 5.0, which has recently garnered attention as the next generation of production systems, serves as an essential and relevant backdrop. While Industry 4.0 focuses on technological advancements, such as the Internet of Things (IoT)

and Cyber-Physical Systems (CPS), Industry 5.0 places emphasis on the cooperation between humans and machines [18, 19]. According to the European Commission, the paradigm of Industry 5.0 consists of three central policies, i.e., resilience, sustainability, and human-centricity [20]. In this framework, resilience is defined as the ability of production systems to adapt to various disturbances flexibly and to manage situations effectively. With this context, numerous technologies have been developed to deploy sufficiently resilient and strategic value chains and enhance the adaptability of production systems [21]. Also, human-centricity is an approach that prioritizes human needs and concerns at the heart of production systems [19]. As a similar concept, human-centered design, which leverages human factors and usability technologies to design user-friendly systems, has been traditionally advocated [22]. Human-centricity in Industry 5.0 covers more comprehensive research and practice fields by actively integrating humans to foster more resilient and sustainable industries [23]. It is increasingly recognized that rather than replacing workers with automation in production systems, it is essential to understand human characteristics and promote collaboration between humans and technology.

In line with this background, many studies have explored the human factors influencing production systems, aiming to maximize production performance considering workers' capabilities [24, 25]. Human characteristics significantly impact work performance, so production system models that ignore this can overestimate the system's productivity [26, 27]. For this reason, incorporating aspects of human performance in simulation methods such as Discrete-Event Simulation (DES) is considered the missing link and has been the subject of many studies [24, 28]. For example, the effects of worker personality [29], circadian rhythm [24, 30], fatigue [26, 31], and motivation [32] on work performance have been investigated. Regarding worker competence, the learning curve has been used [26], and the competence of multi-skilled workers has been modeled using graph theory [33]. These studies have demonstrated that it is possible to achieve improved productivity by considering human characteristics in the design and implementation of production systems [34, 35]. In particular, workers' experiences and skills have been deemed a significant factor affecting the entire productivity of production systems [36]. As with these approaches, it is crucial not only to make machines smarter but also to enhance workers' skill levels to improve the human-centricity of production systems [37].

Considering the development from these previous studies, this study aims to elucidate workers' adaptive expertise to contribute to resilient performance in production systems. Although modern production systems have advanced through increased

mechanization and automation, the ability to respond adaptively to various fluctuations in manufacturing environments remains heavily reliant on workers. By clarifying how workers’ adaptive expertise supports resilient performance in production systems and by facilitating skill transfer, this study seeks to contribute to realizing a sustainable industrial future.

1.3 Approach Based on Functional Resonance Analysis Method

This study adopts an approach based on the Functional Resonance Analysis Method (FRAM) [38] to investigate the adaptive expertise of workers. FRAM is a method proposed within the new paradigm of Safety-II, developed for managing safety in complex socio-technical systems. In the field of safety science, Hollnagel introduced the paradigm shift from Safety-I to Safety-II [39]. The traditional approach, Safety-I, focuses on identifying the causes of incidents after they occur and eliminating these causes to improve system reliability. However, as modern socio-technical systems become increasingly influenced by complex interactions among technical, human, and organizational factors, the limitations of Safety-I have become apparent, drawing attention to the Safety-II approach. Safety-II emphasizes not only adverse events like accidents but also routinely successful operations, aiming to enhance system resilience for safer operations. This resilience-enhancing approach, also known as resilience engineering, underpins the FRAM methodology, which has gained recognition across various fields, including aviation, healthcare, and manufacturing [40].

A key concept in Safety-II is the view that the safe operation of complex socio-technical systems is not solely due to the faithful execution of predefined procedures. Instead, it is attributed to the system’s capacity to adjust to variability. Variability encompasses a wide range of factors that can threaten the safety of socio-technical systems. Before everyday variability leads to emergent functional resonance that could result in catastrophic accidents, it is essential to enhance resilience proactively through adjustment capabilities. This adjustment capability is often fulfilled by humans, who adapt to variability and maintain resilient daily performance. FRAM, proposed within the Safety-II paradigm, has demonstrated significant utility in analyzing such adaptive human behavior. Since this background is critical for this research, more details will be presented in section 2.3.

In this study, we focus on the extensive use of FRAM within the Safety-II framework to analyze adaptive behavior, applying a FRAM-based approach to adaptive

expertise in manufacturing. FRAM models both human cognitive processes and machine operations as functions, allowing the depiction of skilled workers' adaptive responses to variability in interaction with their surrounding environment. Through this approach, this study aims to elucidate the adaptive expertise of workers, which has traditionally remained implicit as a "black box," and to support knowledge extraction and skill transfer among workers.

1.4 Overview of This Research

This research aims to model workers' adaptive expertise using FRAM, based on the Safety-II concept, to achieve resilient performance in production systems. The following three research items were conducted for this purpose.

- Modeling Resilient Attention Management of Expert Workers [41, 42]
- Modeling Resilient Performance of Workers Under Multiple Disturbances [43]
- Extracting Knowledge of Workers by Identifying Adaptive Behavior [44]

The first research objective focuses on the skilled workers' attention management, which contributes to resilient work performance. To adaptively handle changes in the work environment and unexpected situations, it is crucial for workers to monitor surrounding conditions and intervene appropriately. This feature is particularly crucial in highly automated production processes, where efficient attention allocation across multiple information sources, such as various monitors, is required. The ability to "Monitor" the work environment is one of the four essential capacities for resilience identified by Hollnagel, underscoring its fundamental importance in enhancing resilience. In this research objective, we targeted a steel plate processing operation to extract characteristics of workers' attention allocation when engaged in multitasking and to model the adaptive behaviors of skilled workers using FRAM. To achieve this study, we developed an approach based on the functional structure of tacit knowledge, integrating multiple analyses such as eye movement and interview analysis.

The second research objective examines how the adaptive abilities of skilled workers contribute to resilient performance when multiple factors that could reduce operational efficiency arise simultaneously. While the research field of human factors has seen advancements in incorporating worker performance into simulation models for production systems, the combined impact of multiple influencing factors has yet to be thoroughly investigated. To address this gap, we developed an FRAM-based

approach to analyze the influence of workers’ skills on such scenarios. This FRAM model incorporates not only the “Monitoring” capacity but also the four essential capacities for resilience proposed by Hollnagel: Monitoring, Estimating, Responding, and Learning [45]. By integrating these elements into the FRAM model, the model offers a comprehensive framework to analyze the workers’ adaptive behavior. This research objective suggests the potential for our study to contribute to the field of simulation model development for production systems.

The third research objective proposes a practical method for systematically extracting workers’ knowledge based on insights from this continuous work. This approach is grounded in comparing Work-as-Imagined and Work-as-Done, a key concept in Safety-II. By comparing Work-as-Imagined—tasks as envisioned in procedure manuals with Work-as-Done—the actual practices performed on-site—using FRAM, this approach identifies adaptive behaviors that align with workplace needs, enabling comprehensive knowledge extraction. This method was demonstrated in the etching process of semiconductor manufacturing. Additionally, this research item provides new insights into validating FRAM models. Traditionally, the validity of FRAM models could only be qualitatively assessed. In this study, we conducted FRAM-based simulations comprehensively and cross-referenced them with feedback from the field, contributing to a semi-quantitative validation of the FRAM model.

This study integrates the insights gained from the three research items through the lens of metacognition, a concept from psychology. Metacognition refers to cognitive activities related to one’s awareness of their mental processes, encompassing the ability of workers to comprehensively understand their situational context and the status of their tasks. Each chapter covering the research items discusses how the findings relate to metacognition. The remainder of this paper is organized as follows. Chapter 2 details the foundational concepts of this study, including tacit knowledge, metacognition, and resilience engineering. Chapter 3 introduces FRAM, the primary methodology employed in this research, along with its simulation techniques. Chapters 4, 5, and 6 provide an in-depth description of each of the three research items. Finally, Chapter 7 presents the conclusion, summarizing the insights from the three research items.

Chapter 2

Background

2.1 Tacit Knowledge

One of the reasons for the difficulty in extracting adaptive skills from expert operators is that they are acquired as tacit knowledge. This is because adapting to unfamiliar and novel situations is less reproducible and depends on individual situations, making it challenging to describe as unified knowledge. Polanyi [46] proposed the concept of tacit knowledge, stating that “we can know more than we can tell.” Here, tacit knowledge can be defined based on the relationship between proximal and distal terms. The proximal term is the immediate observable experience, while the distal term is the meaning or concept implied from that experience. This relationship is illustrated by the example of a psychological experiment called the latent cognitive process. In this experiment, the participants were shown a string of letters and given an electric shock only when the specific spelling appeared. With repeated trials, participants began anticipating or attempting to avoid the electric shock when the specific spelling linked to the shock appeared. However, post-trial interviews with participants showed they could not explain how they anticipated or attempted to avoid the electric shocks. Polanyi discussed that the relationship between the proximal term—specific spelling—and the distal term—electric shock—could explain this experimental result. Namely, the participants just detected the specific spelling as a result of paying attention to the electric shock. As in this example, people cannot explicitly describe the proximal term itself because they direct their attention to the distal term via the proximal term. This is called the functional structure of tacit knowledge. An integrated approach is needed to examine these proximal and distal terms and their relationships to identify adaptive skills that are tacit knowledge.

According to Mori [47], tacit knowledge can be classified into four types: diagnostic tacit knowledge, adjustment tacit knowledge, sensory tacit knowledge, and procedu-

ral tacit knowledge. Diagnostic tacit knowledge involves diagnosing the conditions of the work environment and predicting future situations based on the current context. Adjustment tacit knowledge pertains to quantitative adjustments of actions, where establishing criteria is critical. Sensory tacit knowledge relates to tasks relying on sensory inputs, such as visual or tactile information. Procedural tacit knowledge involves understanding and controlling the sequence of operations, requiring intellectual ability to analyze and infer from environmental information. The adaptive expertise targeted in this study primarily involves procedural and adjustment tacit knowledge related to the ability to adjust tasks according to the situation. Diagnostic tacit knowledge is also partially relevant due to the necessity of monitoring the surrounding environment. Although sensory tacit knowledge is also important, function-based representation inherent to FRAM limits the scope of analysis in this area. Similarly, the quantitative adjustment aspects of tacit knowledge have limitations for analyses because of an abstract functional representation of FRAM.

Mori [47] has further proposed that tacit knowledge can be understood across four hierarchical levels. The first level consists of knowledge that is externally observable and can be described. The second level includes knowledge that is difficult to observe directly but can be articulated through formal interviews. The third level encompasses knowledge that workers are not consciously aware of in their routine tasks yet can be elicited through deep, interactive interviews. The fourth level represents knowledge that workers execute unconsciously and is impossible to verbalize. Conventional efforts to convert tacit knowledge into explicit knowledge have primarily focused on the first and second levels, with the extraction of third-level knowledge being highly dependent on the interviewer’s skill. This study aims to contribute to the analysis of third-level tacit knowledge by modeling workers’ adaptive interactions with changing environments through FRAM, capturing the flexible responses of workers to environmental changes.

2.2 Metacognition

In focusing on workers’ adaptive expertise, this study positions metacognition as a critical conceptual foundation. Metacognition, a concept from educational psychology, refers to one’s knowledge and abilities of their own cognition and cognitive processes. Interest in metacognition began to grow in the 1970s when Flavell [48] emphasized the importance of monitoring one’s ability to store and retrieve memories

in the developmental process of memory, coining the term “metamemory.” Subsequently, the term “metacognition” emerged, referring to the processes and knowledge involved in monitoring and regulating their own cognitive processes, which has since become a prominent research topic in educational psychology [49].

Metacognition is broadly divided into metacognitive knowledge and metacognitive control processes [50]. Metacognitive knowledge, also known as knowledge of cognition, reflects how much an individual knows about their own cognition. Knowledge of cognition can be further categorized into three types: declarative knowledge, which involves awareness of factors that impact one’s performance; procedural knowledge, which helps execute skills automatically or effectively reordering procedures; and conditional knowledge, which pertains to understanding the conditions under which cognitive activities can be applied. On the other hand, metacognitive control processes, also called regulation of cognition, relate to how individuals adjust and control their cognitive activities [50]. Three critical skills are essential for this regulation: planning, monitoring, and evaluation. Planning involves effectively allocating resources and selecting appropriate strategies to accomplish a task. This feature includes selectively assigning time and attention before a task or determining the sequence to complete task components. Monitoring refers to the real-time awareness of task progress, such as periodically self-checking performance during a learning activity. The final skill, evaluation, involves assessing one’s outcomes and the adjustment processes. For example, an individual might reassess their goals and strategies after completing a task to gauge effectiveness. Based on these skills, regulatory competence enhances individual performance by facilitating the efficient use of cognitive resources. However, regulation processes such as planning, monitoring, and evaluation are often highly automated and executed unconsciously, making them challenging to articulate, as is widely observed in empirical studies.

Practical approaches for analyzing metacognition can be classified into several categories [50]. The first approach involves interviewing participants, which utilizes verbal report procedures to access individuals’ metacognitive frameworks and expertise. The second approach compares the performance of experts and novices on specific tasks. The third approach involves mathematical modeling and simulation, wherein models approximating metacognitive theory structures are built and used to perform theory-based simulations on a computer. Additionally, studies have measured metacognitive monitoring by evaluating participants’ performance scores and their confidence ratings in their responses [51, 52]. These approaches have developed methodologies for detecting individuals’ metacognitive theories.

This study focuses on the relationship between planning, monitoring, and evaluation skills—essential elements of the metacognitive control process—and adaptive expertise. It hypothesizes that implicit skills associated with the metacognitive control process, such as monitoring the environment, evaluating the current state, and planning strategies, play a critical role in developing expertise that enables adaptive responses to environmental changes. Additionally, the similarity of these three skills to the four core capacities of resilience—monitoring, estimating, responding, and learning—suggests the potential for analyzing these skills as FRAM functions. Based on these relationships, this study employs methodologies commonly used in metacognition research, including interviews, expert-novice comparisons, and mathematical modeling and simulation. Through this approach, we aim to clarify the characteristics of adaptive expertise in workers, providing deeper insights into their metacognitive processes.

2.3 Development of Resilience Engineering

Resilience engineering, which provides a critical foundation for the approach used in this study, is a concept developed in safety management. Traditional safety management approaches are based on reliability engineering. This approach involves quantifying the reliability of components within a mechanical system through statistical or physical models to calculate failure rates and availability rates. Standard methods associated with this approach include Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA). FMEA, introduced as a military standard by the U.S. military in 1949, systematically examines potential abnormalities in a product during manufacturing and usage stages [53]. Specifically, it involves creating a table that includes items such as component, failure mode, failure effect, severity, frequency, detectability, Risk Priority Number (RPN), and countermeasures. Among these, the three items—severity, frequency, and detectability—are rated semi-quantitatively, and these ratings yield the RPN. Typically, safety measures are prioritized for components with higher RPN values. In contrast to FMEA, which examines risks at the component level using a bottom-up approach, FTA is a top-down method for identifying the causes of incidents. As illustrated in Fig. 2.1, the fault tree represents the decomposition of an event (referred to as the top event) into underlying basic events through the use of AND and OR gates. In FTA, the probability of the top event can be calculated based on the quantified basic events. Thus, reliability engineering can

be described as an approach that determines the overall system reliability based on the reliability of individual components.

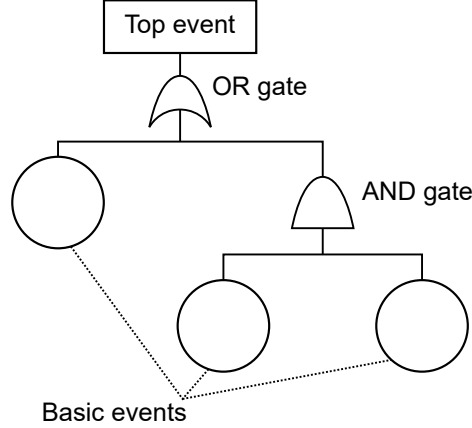


Figure 2.1: An example of a fault tree.

In the 1980s, the focus in the field of safety management shifted toward human factors, heavily influenced by the 1979 Nuclear Disaster at Three Mile Island, where human error played a significant role in exacerbating the crisis [54]. This shift led to Human Reliability Analysis (HRA), an approach designed to analyze human reliability. HRA is broadly divided into two generations: first-generation HRA and second-generation HRA. First-generation HRA was developed primarily for probabilistic risk assessment in nuclear power plants. It calculates the probability of human error occurring during abnormal situations within operational tasks, factoring in elements such as available time, sequence of operational steps, and the worker's experience level. Representative methods include THERP (Technique for Human Error Rate Prediction) [55] and Cognitive Environment Simulation (CES) [56]. However, these methods faced criticism due to the inherent difficulty in quantifying human error probabilities and treating humans as mechanical components, thus exposing the limitations of this approach. In response, second-generation HRA approaches emerged, positing that human error causes are not solely rooted in the individual but rather in the context in which they operate. One prominent example is the Cognitive Reliability and Error Analysis Method (CREAM) [57], which defines 11 Common Performance Conditions (CPCs) as contextual factors influencing human performance. By assessing dependencies among CPCs and their effects on worker performance, CREAM identifies control modes that reflect how individuals respond within specific contexts. Thus, the approach to human factors in safety management has evolved from viewing humans as mechanical elements to a more context-sensitive understanding of human reliability.

Accident models, which play a crucial role in the field of safety management, have evolved in line with these historical shifts. The progression of accident models can be explained through three main classifications: the sequential accident model, the epidemiological accident model, and the systemic accident model. The most traditional is the sequential accident model, exemplified by Heinrich’s domino model [58]. This model visualizes the causal chain of events leading to an accident as a series of falling dominoes, suggesting that preventing one of these intermediary events can stop the entire sequence and prevent the accident. FTA also aligns with this sequential approach. However, in the latter half of the 20th century, the limitations of this approach became apparent, especially in complex socio-technical systems where technological, human, and organizational factors interact intricately. The epidemiological accident model emerged in response to these limitations, accounting for situations where multiple factors co-exist across temporal and spatial dimensions. The Swiss cheese model is a prominent example, depicting layered barriers with holes, like slices of Swiss cheese, where a hazard can pass through these holes and ultimately lead to an accident. Despite its conceptual appeal, the practical application of this model proved challenging. The systemic accident model, which developed further from these earlier models, aims to represent emergent behaviors arising from interactions among system components. Representative methods include the Systems-Theoretic Accident Model and Process (STAMP) [59] and the Functional Resonance Accident Model (FRAM) [60]. These approaches focus less on evaluating the reliability of individual components and more on capturing the emergent properties that affect the entire system through the balance and interactions among elements. This characteristic distinguishes systemic models from their predecessors, offering a more holistic view of safety in complex systems.

These methodological developments are closely related to the historical transition of the safety management policy, i.e., Safety-I and Safety-II [39]. Though both concepts are oriented toward improving the safety of systems, they have adopted very different policies. Safety-I aims to enhance technical systems’ reliability by implementing those under the correct pre-defined procedures. For this purpose, failures of mechanical instruments and human errors, defined as deviations from the correct pre-defined procedures, are identified and eliminated. Some of the most well-known traditional methods based on Safety-I are Fault Tree Analysis (FTA) and Failure Mode and Effects Analysis (FMEA). These methods are based on reductionism and improve safety by disassembling the system and removing the causes of accidents and risk factors. However, in recent years, the limitations of this safety management

strategy have become apparent. One of the most critical limitations was caused by the prominence of organizational factors in accidents. It has been reported that some accidents in recent years cannot be simply attributed to technical or human factors. Complex socio-technical systems, such as aviation systems and large-scale plants, require a systemic methodology involving technical, human, and organizational aspects for safety management.

Safety-II, a new paradigm of safety management policy, was advocated to overcome this challenge. In contrast with Safety-I, Safety-II focuses on not only unfavorable incidents but also what works on everyday positive events and aims to improve the resilience of the target system. It has been emphasized that socio-technical systems have variability in the performance of those elements, such as human workers and automated machines, which fluctuate daily. In this context, accidents are regarded as an emergent outcome from interactions between system elements rather than along a linear causality triggered by potential hazards corresponding to the systemic accident model. In order to manage the safety of complex socio-technical systems according to the Safety-II concept, it is crucial to improve resilience, which is the adaptive capacity against functional performance fluctuations. Approaches that aim to enhance system resilience are also known as resilience engineering. The essential components of resilience are monitoring, estimating, responding, and learning, and the resilience analysis grid (RAG) is a method that evaluates resilience based on these four elements [61]. FRAM is also widely recognized as a resilience engineering approach aligned with these principles.

Chapter 3

Functional Resonance Analysis Method (FRAM)

3.1 Principles of FRAM

FRAM was proposed as an accident investigation method with a systemic perspective in the context described in section 2.3 [60] and extended as a general method for safety management and risk analysis [38]. There are four principles underlying FRAM [38]. When analyzing a system with FRAM, it is acknowledged that workers in dynamic socio-technical systems guide their tasks to success by approximately adjusting their performance to the situation at hand. This concept, known as “Approximate adjustment,” is one of the foundational principles of FRAM, emphasizing that workers always operate with some degree of performance variability. In addition, exogenous variability arising from changes in the system’s external environment is also assumed. In socio-technical systems where various elements interact, these variabilities combine and influence each other, leading to emergent outcomes. When representing a system from a functional perspective, these emergent phenomena correspond to the coupling effects of the variabilities inherent in multiple functions. This process is explained by the principles of “Functional resonance” and “Reality of emergence.” In addition, the principle of “Equivalence of success and failure” highlights that these outcomes either can trigger unsafe events in the system or are also essential for the daily safe operation of the system. FRAM is used following these four principles to analyze complex socio-technical systems and capture the effects of human performance variabilities [62].

3.2 Steps for Conducting FRAM

Four steps are defined to conduct the FRAM analysis [38]. Before these steps, it is also necessary to recognize the purpose of the FRAM analysis, which is positioned as step 0. The most basic purposes of using FRAM are event investigations of accidents that have already occurred and risk assessments of systems that are in operation. After the purpose of the analysis is determined, the following four steps are conducted.

3.2.1 Step 1: Identify and Describe System's Functions

First, the functions involved in the target system are identified to illustrate how everyday work is carried out successfully. FRAM describes systems from the functional perspective rather than the structure of parts and a whole. Usually, systems are defined as structures, how their interrelated components and objects are connected or put together as a whole. In contrast, in FRAM, systems are defined in terms of how they function. That is, it describes how multiple functions in a system are coupled and dependent on each other.

The following six aspects characterize each function in FRAM:

Inputs trigger the function or provide something processed or transformed by the function.

Outputs provide the result of the function.

Preconditions have to be satisfied before the function is conducted.

Resources have to be supplied to the function to be consumed during the process.

Controls are restrictions or control parameters that affect how the function is conducted.

Time is regarded as temporal constraints of the function, such as the starting time, ending time, and duration.

According to these definitions, a function in FRAM is illustrated as a hexagon with six aspects, as shown in Fig. 3.1. The connections between hexagons depict interrelated dependencies between functions. For example, in Fig. 3.1, the connection between the output of Function 1 and the input of Function 2 means that Function 1 triggers Function 2. Another example is that if it is connected to the resource instead of the input of Function 2, it indicates that Function 1 provides resources to Function 2.

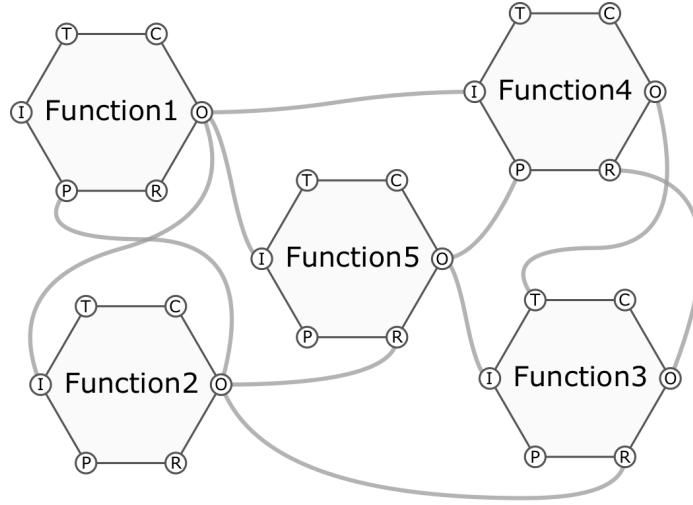


Figure 3.1: FRAM model example.

In these relationships between these two functions, Function 1 is called the upstream function, and Function 2 is called the downstream function. In this way, the socio-technical system focused on as a target of the analysis is modeled as a network of functions called a FRAM model.

Once the FRAM model of the target socio-technical system has been created, the following supplementary procedure, called instantiation, is required. The initial FRAM model is built to represent all potential functions and connections of the target system, which does not yet stand for any specific situation. Therefore, the initial FRAM model needs to be actualized by representing existing functions and connections in a given scenario or a set of conditions. For this purpose, specific functions and connections in the initial potential FRAM model are selected and actualized based on the focusing scenario. This phase is called the instantiation, and the realized FRAM model is called the instance.

3.2.2 Step 2: Identify Function Variability

Second, the performance variabilities of each function in the FRAM model are identified in this step. It is necessary to consider both the possible and actual variabilities of the function's performance. To determine the variabilities, analysts can start by distinguishing among the three categories: internal variability, external variability, and functional upstream-downstream coupling. The internal variability is attributed to the nature of the function itself, while the external variability is due to the working environment in which the function is carried out. On the other hand, variability propagation from an upstream function connected to the input, precondition, resource,

control, and time of a downstream function is called functional upstream–downstream couplings. This type is focused on the next step.

3.2.3 Step 3: Aggregate Performance Variability

The third step considers the functional resonance of the performance variabilities in the specific situation of the FRAM model. When a function has variability, it propagates through the output aspect of that function to the downstream function. However, the way variabilities travel depends on which aspect of the downstream function is coupled to and the type of the function: technical, human, or organizational. Hollnagel defines how the functional upstream–downstream couplings can be identified qualitatively [38]. As a result of this step, functional couplings that critically impact the potential risks or actual incidents can be identified.

3.2.4 Step 4: Manage Performance Variability

The last step is to propose countermeasures to improve the resilience of the target system. It can be achieved by managing the potential uncontrolled performance variabilities and critical functional couplings identified in the preceding steps. Because performance variability can result in both positive and negative outcomes according to the first principle, it is necessary to consider whether the countermeasure should enhance or dampen the effect of the identified variability. Countermeasures could include specific measures in conventional safety management, such as protection by introducing barriers or training to facilitate human-machine interaction. FRAM can provide another option that presents monitoring indicators to ensure that the target process usually proceeds.

3.3 Envisioning Scenarios Using FRAM

In recent years, FRAM has been utilized in many studies to envision the behavior of socio-technical systems. The most basic application of FRAM is accident investigation and safety management [63]. By modeling and analyzing the target system using this method, it is common to identify safety-critical functions and propose countermeasures to improve resilience based on the FRAM model [64, 65, 66]. Furthermore, FRAM has also been applied to the complexity management of systems where interactions between components play a critical role [67, 68, 69]. The domain of application

is also expanding, including healthcare [70, 68], aviation [71, 72], maritime [73], and industrial processes [74, 75, 76].

One of the trends in this research field is to combine or extend FRAM with other methods. Combinations with other methods are a common approach [69], as FRAM needs to be customized to the target and purpose due to its flexibility. Studies related to model building, the first step of FRAM, include organizing a hierarchical model with work domain analysis [77], developing the application to support model building [78], and combining it with formal model verification tools [79, 76]. On the other hand, the variability propagation, the third step of FRAM, is supported by Monte Carlo simulation [80, 81], analytic hierarchy process (AHP) [82, 83], and reinforcement learning [84]. However, a unified framework still needs to be created to make it applicable to various domains. In particular, since FRAM models systems at a high level of abstraction, mapping data to reality is a challenge.

Some studies have mentioned the skill aspect of human operators in socio-technical systems. According to the second principle of FRAM, “approximate adjustment,” human operators are constantly required to cope with the variabilities in their daily work to maintain the system’s performance. In this context, the effect of non-technical skills on the variability of daily work is investigated for offshore oil drilling [85, 86]. In these studies, the critical aspect related to non-technical skills was identified from the FRAM model, and the countermeasure to enhance the system resilience was proposed. However, previous studies have considered worker skills only as a factor that improves system resilience. In order to clarify the adaptive skills of operators, more attention must be paid to their adaptation process against environmental changes. Yasue and Sawaragi [41] focused on this aspect and conducted a pilot study of building the FRAM models of the specific work, which requires a high skill level. The current paper extends this pilot study to reveal how skilled workers adapt attention management to changes in the environment based on the functional structure of tacit knowledge.

3.4 Work-as-Imagined and Work-as-Done

In Safety-II, it is assumed that complex socio-technical systems are operated safely and efficiently through the continuous adaptation of actions by workers at the sharp-end [39]. This actual work performed on-site is referred to as Work-as-Done (WAD). The term “sharp-end” here denotes the hierarchical level within an organization, specifically referring to operators who are directly engaged in the processes subject to safety management. In contrast, “blunt-end” refers to those distant from direct

operations and involved in the management and decision-making processes, such as executives and managers. Unlike the sharp-end, the blunt-end views the work as an object of management focusing on how the work conditions should be, which is conceptualized as Work-as-Imagined (WAI). The sharp-end workers adjust their performance in response to the actual demands and conditions of the working environment. In other words, they can interpret and apply procedures according to the specific situation, allowing them to detect design flaws and functional failures and intervene before they escalate into serious issues. As a result, performance variability occurs, which should not be seen as a negative deviation from standard procedures. Instead, it is a positive adjustment that underpins safety and productivity, providing a reliable foundation for their operations [87]. Consequently, this adaptive behavior of workers leads to a gap between WAI and WAD.

Based on this conceptualization, recent studies have focused on approaches to comparing WAI and WAD within systems and reconciling the gaps between them. FRAM, which analyzes performance variability in socio-technical systems, aligns well with this approach and has been widely adopted. Particularly in the healthcare sector, Resilient Health Care has been practiced, as healthcare represents a prime example of a complex socio-technical system [87, 88]. The healthcare sector’s efforts to reduce medical errors have also contributed to the active adoption of this approach [89]. Specific studies include the revision of guidelines in intensive care units [70], analyzing the international differences in the implementation of measures to prevent blood coagulation before surgery [90], understanding the discrepancies between guidelines and routine activities in medication reconciliation at discharge [91], analysis of adaptive behaviors of medical staff in surgical simulations [92], and elucidation of the actual practice of double-checking during injectable drug administration [93]. Beyond the healthcare field, the approach has also been applied in other industries, such as improving guidelines for the aero-engine blade forging process in manufacturing [76] and the public health analysis of regulations versus actual incidents in tick eradication [94]. A common thread among these studies is using FRAM to compare WAI and WAD and analyze the impact of sharp-end performance adjustments that cause these gaps.

3.5 Data Collection and Validation

When modeling socio-technical systems using FRAM, it is common to employ a combination of multiple qualitative methods for data collection [63]. Specifically, methods

such as document reviews (e.g., guidelines and work procedures), observations, interviews, and focus groups are frequently used [40, 65, 90, 95]. Studies that compare WAI and WAD through FRAM tend to develop the WAI model based on document reviews, while interviews with individual workers or focus groups with multiple participants are used as information sources of WAD [96, 93]. Validating the constructed FRAM model is also essential. The validation process typically involves interviews with experts and group discussions or workshops focusing on the FRAM model [63]. In line with these prior studies, this research employed qualitative methods for data collection. A mixed-method approach was adopted to validate the FRAM model, combining the comparison between the FRAM-based simulation results and the actual behavior of workers with qualitative methods such as interviews. Incorporating simulation as a semi-quantitative method for validating the FRAM model represents a novel contribution, distinguishing this approach from previous studies.

3.6 Simulation Method Based on FRAM

A simulation method based on FRAM for envisioning the system’s behavior [97] 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 [98] and manufacturing processes [99]. While there have been studies that combine FRAM with other methods to facilitate analytical procedures [100], such as Monte Carlo simulation [80] and Analytic Hierarchy Process (AHP) [82], 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 [98]. 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 [97, 57]. 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. For instance, the CPC “Availability of resource” based on a three-level qualitative variable—adequate, adequate with limitations, and inadequate—is quantified to a numerical score [57, 97]. This simulation model envisions the system’s behavior when variability occurs by simulating the interactions between these PAF and CPC scores. Fig. 3.2 shows a conceptual diagram of this simulation method.

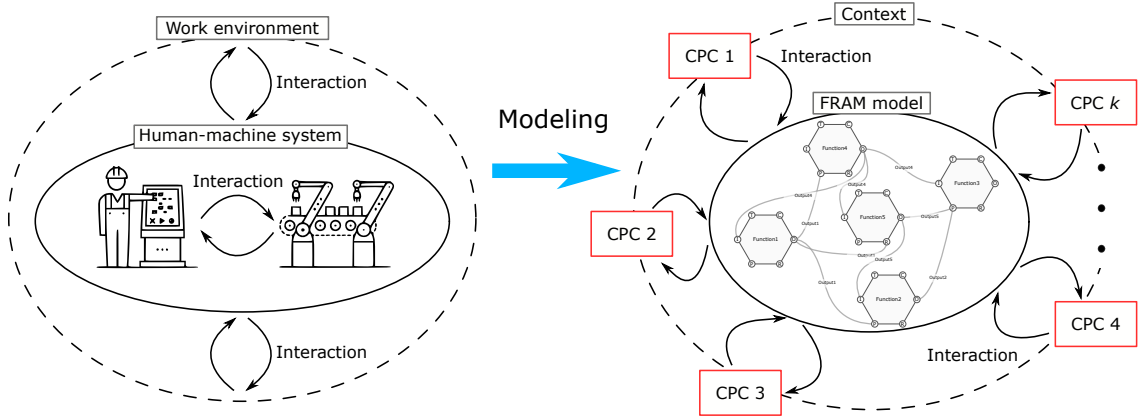


Figure 3.2: Concept of the simulation method based on FRAM.

The details of the simulation method are outlined in Algorithm 1. Also, Fig. 3.3 shows a conceptual diagram of the simulation method. 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. 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.

Algorithm 1 FRAM simulation

```
1: Import Simulation scenario and FRAM model
2: Define  $N_{\text{func}}$  as number of functions, function[ $j$ ] for  $j = 1$  to  $N_{\text{func}}$  as each function
3: Initialize CPC[ $i$ ] for  $i = 1$  to 11, PAF[ $j$ ] for  $j = 1$  to  $N_{\text{func}}$ 
4: Define  $w[l]$  for  $l = 1$  to 11 as weights for each CPC,  $N_{\text{upfunc}}[j]$  for  $j = 1$  to  $N_{\text{func}}$ 
   as number of upstream functions of function[ $j$ ]
5: Define Function AspectToCPCMapping() as a function to define the relation-
   ship 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:       CPC[ $k$ ]( $t$ ) $+$  = (CPC[ $l$ ]( $t$ ) - CPC[ $k$ ]( $t$ ))  $\times w[l]$  ( $k \neq l$ )
14:     end for
15:   end for
16:   for  $j = 1$  to  $N_{\text{func}}$  do ▷ (Step 2: Fuzzy CREAM)
17:     PAF[ $j$ ]( $t + 1$ ) = FuzzyCREAM(CPC( $t$ ))
18:   end for
19:   for  $j = 1$  to  $N_{\text{func}}$  do ▷ (Step 3: Function to function propagation)
20:     for each  $u$  in upstream functions of function[ $j$ ] do
21:       PAF[ $j$ ]( $t + 1$ ) $+$  = (PAF[ $u$ ]( $t + 1$ ) - PAF[ $u$ ]( $t$ ))/ $N_{\text{upfunc}}[j]$ 
22:     end for
23:   end for
24:   for  $j = 1$  to  $N_{\text{func}}$  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:           CPC[ $m$ ]( $t + 1$ ) = CPC[ $m$ ]( $t$ )  $\times$  PAF[ $j$ ]( $t$ )/PAF[ $j$ ]( $t + 1$ )
29:         end for
30:       end if
31:     end for
32:   end for
33: end for
```

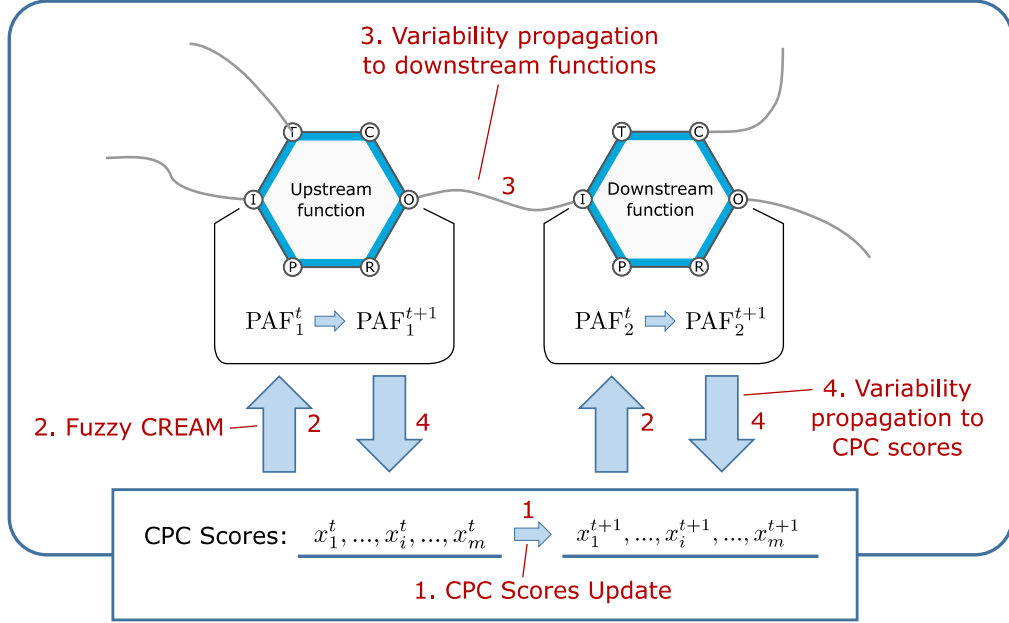


Figure 3.3: Overview of the simulation algorithm.

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 [97].

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 [57]. Equation 3.1 illustrates this calculation.

$$\text{CPC}_k^{t+1} = \text{CPC}_k^t + \sum_l \{(\text{CPC}_l^t - \text{CPC}_k^t)w_l\} \quad (3.1)$$

CPC_k^t is the k^{th} CPC score at simulation time t and w_l is the weight for the l^{th} CPC [97]. Based on this equation, variations in the l^{th} CPC are propagated to the k^{th} 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 [57]. 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 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 [101].

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. The coupling between functions is structured such that the output of one function connects to one of the following aspects of another function: Input, Precondition, Resource, Control, or Time. The function providing the output is termed the upstream function, while the function receiving the output is called the downstream function. Line twenty-one illustrates the influence that the j^{th} function receives from the u^{th} upstream function, as shown in Equation 3.2.

$$\text{PAF}_j^{t+1} = \text{PAF}_j^t + \frac{\sum_u (\text{PAF}_u^{t+1} - \text{PAF}_u^t)}{N_{\text{upfunc}}[j]} \quad (3.2)$$

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

The final step is presented from line twenty-four onward, 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 [97]. Based on this relationship, the calculation of CPCs on line twenty-eight is executed as in Equation 3.3.

$$\text{CPC}_m^{t+1} = \frac{\text{PAF}_j^t}{\text{PAF}_j^{t+1}} \times \text{CPC}_m^t \quad (3.3)$$

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.

Chapter 4

Modeling Resilient Attention Management of Expert Workers

4.1 Introduction

Expert skills have been analyzed for operators controlling complex systems such as industrial plants and aircraft, aiming at automation and supporting skill development. Extensive studies have attempted to extract cognitive properties specific to expert operators, such as eye movement and motion analysis. For example, eye movement research has shown that expert operators have systematic monitoring strategies even in cognitively demanding situations. However, these approaches have some limitations in investigating expert skills in human-machine systems. As advocated in Industry 4.0, operators are required to work in complex systems with information and communication technologies [102]. Due to these technological advancements, work systems have developed to have socio-technical aspects in which complex interactions with machinery and the surrounding environment play a critical role. It has been emphasized that in socio-technical systems, variabilities constantly occur in daily work as performance fluctuations of machines and human operators and external disturbances [38]. Socio-technical systems continuously force operators to adapt to and cope with such variabilities to maintain the system's resilience. Especially in the manufacturing domain, operators' adaptive aspects can contribute to resilient production against market volatilities and flexible production plans [21]. These adaptive skills of expert operators are challenging to investigate using conventional methods because they are acquired as tacit knowledge.

One of the essential aspects of the adaptive skills of operators to maintain resilient production is how they monitor the target system. According to Hollnagel [38], resilient performance requires four fundamental competencies—monitoring, anticipat-

ing, responding, and learning. Specifically, the monitoring function, linked to non-technical skills like situation awareness, plays a crucial role in enhancing resilience [85]. It is important for resilient performance to monitor the situation, identify the changes in the environment, and manage attention allocation even in cognitively demanding situations. With this background, many eye movement studies have shown that skilled operators can adapt their monitoring behavior and attention management strategy in difficult tasks [3, 8]. However, although much can be learned from eye movement analysis, the full picture of the expert operator’s attention management strategy has yet to be captured. This is because expert operators acquire these skills as tacit knowledge, which requires an integrated analysis from multiple aspects. This chapter pays particular attention to the operator’s attention management strategy in multitasking and takes a multi-perspective approach based on the concept of tacit knowledge. To this end, this study selected a case study that features multitasking, where characteristics of attention distribution are prominently displayed.

For this purpose, this study employed the integrated framework based on the functional structure of tacit knowledge. According to Polanyi [46], tacit knowledge can be defined as the relationship between proximal and distal terms. Here, the proximal term is the immediate observable experience, while the distal term is the meaning or concept implied from that experience. In order to ensure the proximal perspective, this study analyzed eye movements during multitasking. In order to determine what the operators were distally aware of, the operators were interviewed, and their responses were analyzed based on the work domain analysis (WDA). Finally, WDA and FRAM bridged these two perspectives. WDA describes the functional structure of the work and depicts the relationship between proximal and distal terms. In contrast, a simulation study based on FRAM envisioned workers’ behavior when variabilities occur in the actual work environment. Here, FRAM is a method that can provide a functional model and envision the behavior of complex socio-technical systems where interactions between components and the environment are crucial. This integrated approach attempted to reveal the attention management aspects of adaptive skills.

The remaining part of this chapter proceeds as follows. Section 4.2 describes the research background regarding tacit knowledge and the adaptive behavior of human operators. Section 4.3 introduces FRAM and its historical background. Section 4.4 explains the methodological framework utilized in this study. Section 4.5 describes the case study conducted by the authors. Section 4.6 reports the results. Sections 4.7 and 4.8 are discussion and conclusion, respectively.

4.2 Methods

4.2.1 Approach Overview

This study focuses on the attention management strategy as one important aspect of adaptive skills. In particular, this study focuses on multitasking, where attention management has a significant impact. This study took an integrated approach considering the functional structure of tacit knowledge—the relationship between proximal and distal terms—as shown in Fig. 4.1. In this study, the proximal term corresponds to the information the operator can directly sense, while the distal term refers to the abstract meaning behind the information. The eye movement analysis and the interview analysis take into account the proximal and distal aspects of attention management, respectively. This is because operators are assumed to focus on the abstract function of achieving the task purpose and consequently perceive the information in the environment. This abstract function related to the purpose of the work system is the distal term, and the information resources available to operators are the proximal terms. Thus, the eye movement analysis shows the superficial feature of the operator’s attention management as the proximal aspect. This study utilized an entropy metric derived from eye movement randomness for this purpose. On the other hand, the interview analysis reveals the abstract functions to what the operator’s attention is directed as the distal aspect during the work. For this purpose, the operator’s interview responses were mapped into the functional hierarchy using the work domain analysis (WDA).

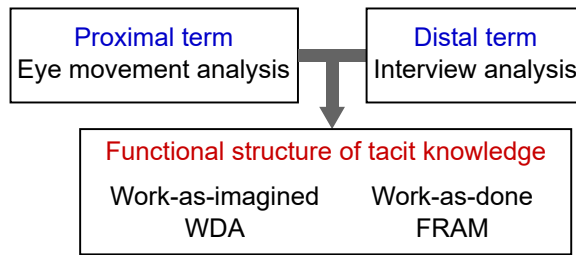


Figure 4.1: Approach overview of this study.

This study adopted a model-constructive approach using WDA and FRAM to integrate these two aspects of tacit knowledge. Both WDA and FRAM describe systems from functional perspectives, leading to combined applications in research. Patriarca et al. proposed a method to develop FRAM models hierarchically based on the Abstraction-Agency framework provided by WDA to address system complexity

[77]. Another study utilized WDA as a preliminary stage in constructing FRAM models for analyzing and improving production systems [103]. These studies demonstrate that combining WDA and FRAM allows for a comprehensive analysis of systems.

This study combined these two methods to compare Work-as-Imagined and Work-as-Done. Work-as-Imagined represents the behavior envisioned when the system was designed, whereas Work-as-Done corresponds to how the system operates in actual environments. Previous research has used FRAM to compare Work-as-Imagined and Work-as-Done, identifying discrepancies to enhance understanding of system operations [93, 91] and propose improvements in guidelines and management practices [70, 90, 104]. In this research, WDA was used to organize the fundamental procedures constituting work, and FRAM was utilized to represent characteristics of expert workers that do not appear in basic procedures. The former corresponds to the basic work procedures designed as Work-as-Imagined, and the latter corresponds to Work-as-Done as actually performed by workers on site. The rationale for using these two methods lies in their complementary strengths: WDA is suitable for capturing the overall picture of a system, while FRAM is apt for understanding how variability within the system actually impacts operations. This study aimed to identify the functional structure of tacit knowledge possessed by expert workers by comparing these two aspects.

4.2.2 Eye Movement Analysis

This study extracted expert operators' eye movement features in multitasking to investigate their proximal aspects of attention management. For this purpose, we compared the eye movements of expert and mid-level operators in single-tasking and multitasking. The relative entropy of Shannon's information theory based on AOI (Area Of Interest) was utilized to show the eye movement features in each condition. AOI is an arbitrary region within the operator's vision for the statistical analysis of eye movements within that screen [105]. In our approach, the objects to which the operators' attention is directed are set as the AOIs. During the work, the operator directs their gazing point to each AOI according to the attention target so that a series of gazing point AOI-to-AOI transitions could be obtained for each single measurement data. When there are n AOIs, the transition pattern between AOIs of a gazing point can be expressed as a probability distribution of $n(n - 1)$ ways. Relative entropy represents how far apart these probability distributions are. Therefore, the relative entropy between the respective gaze measurement data can indicate how similar the

gazing point shift patterns are. When the occurrence frequencies of the i -th inter-AOI transition pattern for the two eye movement data are $P(i)$ and $Q(i)$, the relative entropy D can be expressed by Eq. 4.1.

$$D(P||Q) = \sum_i P(i) \log_2 \frac{P(i)}{Q(i)} \quad (4.1)$$

This method analyzed expert and mid-level workers' attention management by comparing how much their eye movement features change in single-task and multitasking.

4.2.3 Work Domain Analysis and Interview Analysis

This study investigated the distal term of attention management by analyzing the interview responses of the workers. A semi-structured format was adopted for this purpose. Semi-structured interviews incorporate characteristics of structured interviews, where question items are predefined, and unstructured interviews, where questions emerge during the conversation, allowing for deeper exploration of topics [106]. These characteristics mean that while there is a set guide of open-ended questions, there is also flexibility to delve deeper into specific topics. Such features enable semi-structured interviews to balance consistency among interview participants with acquiring more in-depth responses. Due to these advantages, semi-structured interviews are one of the most commonly used methods for data collection in studies utilizing FRAM [63, 40, 65, 90]. In addition, according to Mori [47], to elicit deeper layers of tacit knowledge that workers might not be consciously aware of, it is necessary to go beyond basic questions and delve deeper into interviews based on hypothesis testing. Considering these characteristics of interview formats, this study chose semi-structured interviews to maintain consistency while comparing interviews between expert and mid-level workers, yet allowing for in-depth exploration. The basic questionnaire used in the interviews is listed in Appendix 7.

Skilled workers are considered to allocate their attention to multitasking by understanding abstract functions such as constraint relations between tasks and the purpose of the system. The relationships between these abstract functions and the observable information resources are described based on the functional structure of the system, e.g., by work domain analysis (WDA). WDA is part of a cognitive work analysis (CWA) framework, a methodology to analyze complex socio-technical systems focusing on human-machine interaction and human work activity [107]. CWA

contains six top-down steps: work domain analysis, control task analysis, strategies analysis, social organization and cooperation analysis, and worker competencies analysis. This framework is mainly used for the human-machine interface design in complex socio-technical systems, which allows human workers to intuitively operate the system by providing information based on the analysis results. The role of WDA as the first step of this framework is to provide a holistic view of the system as a foundation for human-machine interface design. WDA organizes the system’s functions in a multiple-layer form called the Abstraction Hierarchy (AH). AH has five layers: functional purpose, abstract function, generalized function, physical function, and physical form [107]. Each layer is more abstract as you go up and more concrete as you go down. Functions assigned in each layer are connected with means-end links. For example, when we focus on the two functions connected by a link, the upper function represents “why” the lower function is conducted, and the lower function represents “how” the upper function is conducted. The overall functional structure of the system can be organized in this way.

Another prominent method for decomposing work into elements is Hierarchical Task Analysis (HTA) [108]. HTA is a central approach in ergonomics, known for breaking down tasks into subgoals and organizing them hierarchically. However, while HTA excels in describing task structures, its relationships tend to be confined to whole-part relationships. In this study, we chose WDA because it focuses on the means-end relationships between functions and organizes these functions according to levels of abstraction, which is more suitable for mapping the functional structure of tacit knowledge.

This study visualizes the interview characteristics by mapping typical interview responses onto the functional hierarchy described by WDA. For example, when the worker mentions the system’s purpose, the utterance corresponds to the functional purpose layer. In contrast, when the worker mentions specific devices, they correspond to the physical function or physical form layer. In this way, utterances in a conversation can be mapped to functions at each level of abstraction.

In addition, WDA supports building an initial FRAM model by providing a comprehensive view of the target system. Among the functions identified in AH, those relevant to the target work are selected as candidates to constitute the initial FRAM model. The dependencies among those functions are then examined and shown as connections between hexagons. Based on observations and interviews, additional functions may be added to the FRAM model.

4.2.4 FRAM Simulation

Finally, a simulation study based on FRAM was conducted. As a result of the eye movement analysis and interview analysis, the attention management strategies in multitasking depending on the worker’s skill levels were clarified. Based on this result, a FRAM model including all potential functions and dependencies based on WDA was instantiated into two FRAM models of expert and mid-level workers. Because this study focuses on workers’ attention management, the difference between these two instances may appear in the functions related to monitoring the target system. After that, the FRAM simulation was utilized to envision the system’s behavior. It is a simulation method to simulate the functional resonance triggered by variabilities in complex socio-technical systems [109, 97]. This method was developed to provide quantitative support for FRAM, which was originally qualitative. The variabilities in the system are translated to numerical values based on Common Performance Conditions (CPC), which are the eleven items characterizing the environment surrounding the system [57]. These values are called CPC scores and range from 0 to 100. Also, performance fluctuations of each function in the FRAM model are expressed by the Probability of Action Failure (PAF), which represents how strategically the function is carried out. This method enables simulation of the effect of variability expressed with the specific CPC change on the entire system based on the function interrelations. This simulation method was utilized to investigate the effect of attention management strategies of expert and mid-level operators on work performance when multitasking.

In this simulation method, CPC indicates the system’s context and was introduced in the Cognitive Reliability and Error Analysis Method (CREAM), developed as part of second-generation human reliability analysis [57]. Human reliability analysis originated from investigating human factors in accidents within large-scale systems such as nuclear power plants. While the first-generation human reliability analysis focused primarily on quantifying the probability of human errors, the second-generation recognized the limitations of this approach in complex systems and shifted its emphasis towards analyzing the contexts in which errors occur. As one of the methods proposed under this second-generation framework, CREAM introduced CPC as an indicator of the system’s context. Later, when FRAM was proposed, it advocated representing variability in terms of timing and accuracy instead of using CPC, a practice still employed in many studies today. However, this approach to variability focuses on the fluctuations in function output to focus on functional resonance. In this study, we intentionally adopted CPC, derived from second-generation human reliability analysis,

to represent the context of the surrounding environment, which interacts with each function in the FRAM model represented as PAF values. This adoption allowed for the implementation of diverse scenarios corresponding to CPC in the simulation.

4.2.5 Hypotheses

This section summarizes the relationship between our approach and the functional structure of tacit knowledge, as shown in Fig. 4.1, and states the hypotheses of this study. In the operators' multitasking, the individual gazing objects are the proximal terms, and the system's abstract functions that govern their attention allocation, such as task constraint relations, are the distal terms. The entropy metric derived from the eye movement data sets characterizes the gaze point transition features from the proximal term aspect. On the other hand, mapping the interview conversation using WDA identifies what abstract functions the worker is managing attention based on as a distal term aspect. Based on these two terms, the first hypothesis is that the structured gaze point transition corresponds to the operator's better understanding of abstract functions in the higher layer in AH. This is because expert workers are assumed to be able to allocate attention systematically based on a good understanding of constraint relations in multitasking. The second hypothesis is that this attention management feature is the critical factor in maintaining work performance in multitasking. The model constructive approach based on FRAM tests this hypothesis by incorporating attention management strategies into the FRAM model and conducting a simulation study assuming multitasking.

4.3 Case Study

4.3.1 Case Study Description

This study used the data obtained from the previous case study by the authors [41]. The target was an operation in a steel plate processing line as a case study to investigate the features of expert operators. This process aims to produce flat steel plates from coiled steel strips. The steel plates must be uncoiled from the steel coil, flattened, and cut to predetermined sizes. Fig. 4.2 depicts the outline of this production line. The trimmer and the shear cut the steel plates after the leveler flattens them. The case study focused on a specific operation called the centering operation in this process. This operation aims to control the steel plate's position at the trimmer to accurately carry out the cutting process. The operator is positioned near the uncoiler

and must control the position of the steel plate at the trimmer, which is a dozen meters away. However, the operator can only operate the coil in a horizontal position in front of the uncoiler, which is more than ten meters away from the trimmer. Because the operator is arranged in front of the uncoiler and cannot directly see the trimmer, a monitor showing the trimmer is installed near the operator. In addition, each type of steel plate has a peculiar process flow between the plate's entrance site of the uncoiler and the trimming site, and the operator must have the knowledge and experience to deal with them. Due to these conditions, this operation requires a high level of skill.

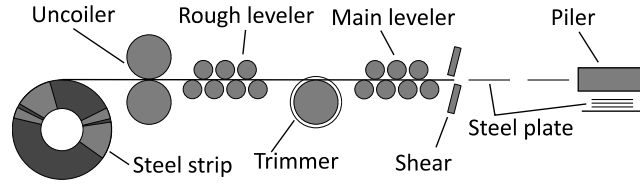


Figure 4.2: Overview of the target work.

We focused on multitasking in this operation to investigate the attention management strategy of expert operators in cognitively demanding situations. Even during the centering operation, another operator brings new coils to be processed by crane at any time. The operator in charge of the centering operation must handle the coil supply by controlling the coil car to catch the coil. This operation is called coil setting operation. *Single-tasking* is defined as performing only the centering operation, while *multitasking* is defined as performing the coil-setting operation in addition to in parallel.

4.3.2 Data Collection

This study conducted a comprehensive case study, harnessing the power of both qualitative data from interviews and quantitative data from eye-tracking measurements to provide a sufficient understanding of the research subject [41]. Fig. 4.3 illustrates this research's data collection and analysis flow. These steps were conducted with the cooperation of Token Machinery Works Co., Ltd. members. Initially, four observational sessions were conducted to understand the content of the target work and plan subsequent experiments. Each session lasted approximately one hour, spread over two months. Based on the outcomes of these observations, the experimental setup for eye-tracking experiments focusing on multitasking in daily work was determined. In

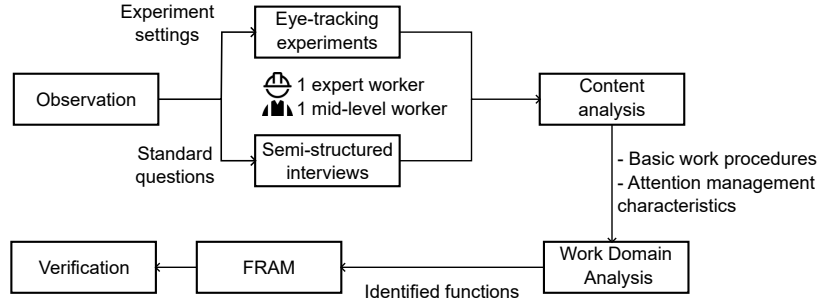


Figure 4.3: Data and analysis flow of the current case study.

addition, this step created a list of base questions for the semi-structured interviews.

As for the eye-tracking experiments, the participants included one expert worker and one mid-level worker, each of whom had worked in the target operation. Measurements were taken over periods that included both single-tasking and multitasking in the daily work. The measurement time was about 40 minutes per operator. The eye movements were measured using Tobii Pro Glasses 2 (Tobii Pro AB, Danderyd, Sweden) with a sampling rate of 50 Hz.

After the measurements during the operations, this study conducted interviews with the operators. The interview participants were the same two operators participating in eye-tracking experiments. Each interview was conducted one-on-one with each operator. In these interviews, the interviewer and the operator shared a movie. The movie included two synchronized videos: the recording of the operator’s gaze point movement and the video of the bird’s-eye view during the operation. Here, the results of the eye movement measurements were mapped into the operator’s view and converted to a video that recorded the operator’s gaze point movement. The interviewer and the operator shared the video while using a laptop computer. The interviewer posed the listed questions to the workers and delved deeper into the discussion of attention distribution, supported by the shared videos. The interview took about 40 minutes per operator. The experiments were approved by the Ethics Committee, Graduate School of Engineering, Kyoto University. Before the experiments, the participants were given instructions and signed the consent form.

The results of the eye-tracking measurements and interviews were subjected to content analysis that combined qualitative and quantitative data to extract the characteristics of workers’ attention distribution. As described in Section 4.2.2, the eye-tracking results utilized the relative entropy metric to extract features of gaze transitions among workers in each experimental scenario. Additionally, the interview results

aimed to differentiate the response characteristics of each worker based on common questions posed to both, as described in Section 4.2.3. These results identified the fundamental work elements and the workers’ attention distribution characteristics. To organize these findings, WDA was conducted to capture the overall picture of the work. This step also described the work-as-imagined model and identified the fundamental functions that constitute the FRAM model. Additionally, based on qualitative analyses of work observations and interview results, this step accepted to deliberately add functions to the FRAM model to represent the workers’ attention distribution characteristics. Finally, the constructed FRAM model and the analysis results were shared with corporate members to verify whether they constituted a valid work-as-done model of the target work. This mixed approach of constructing FRAM models based on multiple data sources, including qualitative data, is also commonly used in other studies [40, 100, 63].

4.4 Results

4.4.1 Eye Movement Analysis Results

The relative entropy based on eye movements was adopted to visualize the difference in monitoring behavior between single-tasking and multitasking of expert and mid-level workers. This measure indicates how different the probability distribution of transitions from one AOI to another is between the two eye movement data sets. The relative entropy between the four ways in the single-tasking and multitasking cases for expert and mid-level workers was calculated and mapped using multidimensional scaling [110]. As indicated by Eq. 4.1, calculating relative entropy requires the gaze transition patterns between AOIs from two measurement data sets, P and Q . This study computed the relative entropy for six combinations: from (Expert worker, Single-task) to (Expert worker, Multitask), from (Mid-level worker, Single-task) to (Mid-level worker, Multitask), from (Expert worker, Single-task) to (Mid-level worker, Single-task), from (Expert worker, Multitask) to (Mid-level worker, Multitask), from (Expert worker, Single-task) to (Mid-level worker, Multitask), and from (Expert worker, Multitask) to (Mid-level worker, Single-task). As a baseline, the relative entropy to a uniform probability distribution of AOI transitions was calculated for these four measurement data sets. Fig. 4.4 visualizes the relative entropy of each data pair as a pseudo-metric distance using multidimensional scaling. In this graph, the greater the distance between two data points, the more significantly their associated gaze movement characteristics differ. This graph was generated using mul-

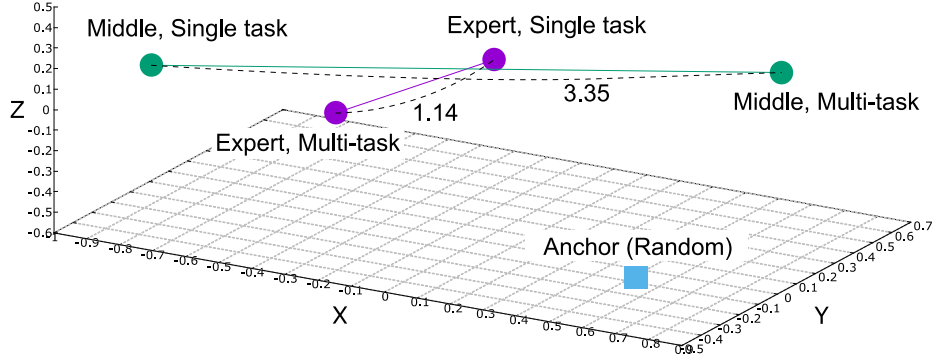


Figure 4.4: Visualization of the differences in the monitoring behavior using relative entropy and multi-dimension scaling.

tidimensional scaling, and thus, the X-Y-Z axes require interpretation based on the underlying data. The X-axis corresponds to the shift in gaze movement characteristics from single-tasking to multitasking among the mid-level worker. As values on the X-axis increase, the gaze movements approach a more random pattern, suggesting an increase in the complexity of eye movements. The Y-axis, on the other hand, corresponds to changes in the gaze movement characteristics of the expert worker, reflecting shifts in attention distribution strategies due to the introduction of new coils. The Z-axis implies that the gaze movement characteristics represented are consistent across all measurements, suggesting they are standard features of eye movements acquired by the workers, regardless of skill level or task scenario. The relative entropy from single-tasking to multitasking for the expert worker was about 1.14; for the mid-level worker, it was about 3.35. This means that the expert worker showed less change in the probability distribution of the inter-AOI transition pattern than the mid-level worker.

Table 4.1 shows the calculated relative entropy from the anchor to each eye movement data. This metric indicates that the smaller the value, the closer the gaze

Table 4.1: Relative entropy from the anchor (uniform distribution) to each eye-tracking data.

	Expert	Mid-level
Single-task	1.631	2.648
Multitask	1.318	1.031

transitions between AOIs in the measurement data were to be random. The random gaze point transitions imply that attention management becomes opportunistic, as attention is distracted by various events in front of them. In contrast, the structured

gaze point transitions correspond to systematic attention management in which the worker knows where to look next. For both of the workers, gaze point transitions approached randomness when multitasking. This fact suggests that multitasking made attention management opportunistic. In addition, the gaze point transitions of the mid-level worker significantly fluctuated when transitioning from single-tasking to multitasking, whereas the change was relatively small for the expert worker. These results show that the expert worker could maintain systematic attention management relatively well, as represented by the structured gaze point transitions.

4.4.2 Interview Analysis Results

Differences in the characteristics of the interview responses between the expert and the mid-level participants were analyzed. We focused on the part of the interview conversation that related to multitasking in centering and coil-setting operations. The results showed that answers replied with more abstract words are features of the expert participants. For example, when asked what they were conscious of during multitasking, the expert operator referred to the temporal relationship between centering and coil setting and the constraints of each other, whereas the mid-level operator focused only on the individual objects by mentioning the information resources they had to look at during each task. Similarly to the other questions, the expert operator was characterized by the answers relating to abstract relationships between elements and the purpose of the system as a whole, whereas the mid-level operator was characterized by the answers that focused only on individual concrete elements.

WDA was conducted to visualize these features of interview responses. This method builds an overall picture of the target operation as a series of chained functions based on the interviews. Fig. 4.5 shows the AH of the target operation, showing the functional structure of the system. The top hierarchy of the functional purpose places efficiency and product quality as objectives to be achieved in this work. The second layer of the abstract function describes the fundamental rules that cover the process, such as the flow balance and steel plate dynamics. Parts representing the general steps of the work process were placed at the level of the general function. In addition, substeps of the general functions were placed in the physical function layer. Finally, specific devices for conducting physical operations were placed in the physical form layer. Connections between functions represent the means–ends relationships between those components. The functional structure of this target work was obtained in this way.

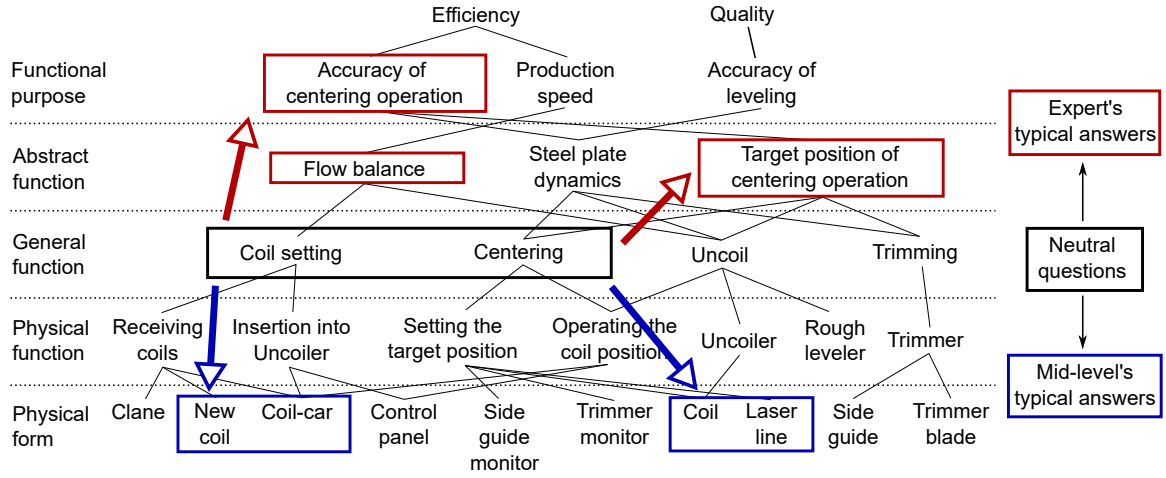


Figure 4.5: Characteristics of expert's and mid-level's answers mapped to AH.

Fig. 4.5 illustrates the results of mapping the differences in response characteristics between expert and mid-level workers in individual semi-structured interviews. Questions common to both interviews regarding multitasking strategies related to functions such as Coil setting and Centering within the general function layer are enclosed in squares. The typical response patterns seen in experts are visualized in red, while those typical for mid-level workers are shown in blue. The expert operator typically responded to the neutral question about multitasking by focusing on the abstract relationships between elements and the purpose of the whole system. This corresponds to the transition to higher levels of the abstraction hierarchy. Because the connections between functions represent means–ends links in AH, the upper transitions show that the expert workers know why the process is performed. In contrast, the mid-level typically responded to the neutral question by focusing only on individual concrete elements. This corresponds to exploring lower levels of the hierarchy of abstraction. The interview analysis showed that experts could carry out tasks with an awareness of the relationships between components and the purpose of the whole system, even when multitasking.

4.4.3 Brief Summary of Expert Attention Management Features

The following characteristics of expert operators were identified based on the eye movement and interview analysis results.

- The relative entropy from the anchor characterized how close to random the gaze point transition was in each condition. This index showed how consistently the

operators could allocate their attention within the constraints of multitasking. The results showed that expert operators could maintain their attention management strategy even when multitasking. In contrast, the mid-level operators' attention management strategy became opportunistic.

- The interview analysis showed that expert operators were aware of the abstract relationships between elements in the system. In contrast, mid-level operators focused only on individual elements.

These results support the first hypothesis of this study that structured gaze point transitions correspond to a better understanding of the system's abstract functions. The expert operator could associate the task constraints, distal terms, with each gazing object, proximal terms, so that gaze point transitions remained structured when multitasking. In contrast, the mid-level was not fully aware of the system's abstract functions, so their attention was diverted by multitasking, and the gaze point behaved randomly. Thus, the expert operator could maintain systematic attention management in multitasking because of a better understanding of the system's abstract functions.

4.4.4 FRAM Model Construction and Instantiation

For the FRAM model building, the functions of the target process were selected, referring to WDA. Fig. 4.6 shows the basic FRAM model focusing on the multitasking of centering and coil-setting operations. The operator mainly monitors the components corresponding to the physical form, such as the strip edge gap between the coil and the laser marker, the side-guide monitor, the trimmer monitor, and the new coil to be processed. Using this monitoring information, the operator sets the target position of the steel plate based on the estimation and controls the steel plate position by manipulating the lever. In parallel with this centering operation, the position of the coil car is controlled to receive the new coil brought in by another operator. In addition, the attention distribution function was added to the model. This additional function "Distribute the attention," was not identified in WDA but was added to the FRAM model to represent the attention distribution characteristics of expert workers based on work observations and insights from past research. It was explicitly identified through the observation that the most significant differences in performance between expert and mid-level workers occur during multitasking. This observation aligns with the conclusions of Section 6.1.3, which analyzed gaze movements during single-task and multitask scenarios. These findings are supported by previous insights



Figure 4.6: The basic FRAM model of the target work.

on adaptive expertise, which, as discussed in Section 2.2, corresponds to the ability to manage unforeseen situations flexibly. For adaptive expertise to be effective, it is known that metacognitive abilities to manage one’s cognitive processes are crucial [111, 112]. The function “Distribute the attention” in Fig. 4.7 integrates several monitoring functions and adjusts the focus of attention according to changes in multitasking situations, embodying the characteristics of metacognition. By adding this function related to metacognition, it is possible to represent the strategic attention distribution characteristics of experts in multitasking, as revealed through gaze movement analysis and interview analysis. Thus, this additional function was introduced based on work observations and past insights on adaptive expertise.

The functions are grouped into three categories: the monitoring group, shown in blue; the estimating group, shown in green; and the responding group, shown in red. These three groups correspond to the four capacities required for resilience: monitoring, estimating, responding, and learning [113]. Learning is omitted due to the different time scales. This functional grouping can be associated with the situation awareness theory. Situation awareness theory describes human decision-making as a process involving three stages: Perception, Comprehension, and Projection [114]. These are followed by the steps of Decision and Action, which are performed cyclically to make decisions in response to the surrounding environment. Our analytical approach involves mapping these stages to the three functional groups in Fig. 5 of the FRAM model. Specifically, the situation awareness steps correspond to the Monitor-

ing group, the subsequent Decision step to the Estimating group, and the final Action step to the Responding group. This study primarily focuses on the Monitoring group corresponding to the situation awareness steps, given its emphasis on worker attention distribution. However, as situation awareness involves the integrated execution of Decision and Action steps, the functions in the Estimating and Responding groups in this FRAM model are also represented as interacting with each other. Adopting this approach makes it possible to analyze work performance from a systemic perspective of the entire work process.

The grouping of these functions is also related to the Abstraction-Decomposition framework, a form of representation in WDA that describes the system along abstraction and decomposition axes. As introduced in Section 4.2.3, the axis of abstraction unfolds functions regarding means–end relationships, whereas the decomposition axis expands the system regarding part–whole relationships. It is common in WDA to grasp the system’s structure through these two axes. Patriarca et al. [77] proposed a method for representing the structure of complex systems systemically by combining an extended abstraction–agency framework with FRAM. This method organizes each agent’s functions according to levels of abstraction, thus enabling the visualization of the complex system’s overall structure. While the FRAM model in this current study groups functions not by the agent but by the cognitive processes of an individual worker, it similarly categorizes functions within the FRAM model, facilitating the analysis of which functions are crucial.

The basic FRAM model was instantiated according to the operators’ attention management strategy. Fig. 4.7 shows the two instances of the FRAM model of the expert and mid-level operators. All functions and connections were activated in the expert operator’s FRAM model instance. The connections from the output of the “Distribute the attention” to the other four monitoring functions colored in blue indicate that expert operators can distribute their attention based on the consistent attention management strategy even when multitasking. The feedback connections from the “Monitor...” functions to the “Distribute the attention” indicate that expert operators plan the attention allocation based on the relationships between components in the work domain. In contrast, the connections between functions shown in dotted lines were deleted in the FRAM model instance of the mid-level operator. The deactivated connections indicate that mid-level operators cannot maintain the attention management strategy and behave opportunistically in multitasking. These models represent differences in attention allocation features in multitasking, depending on the skill.

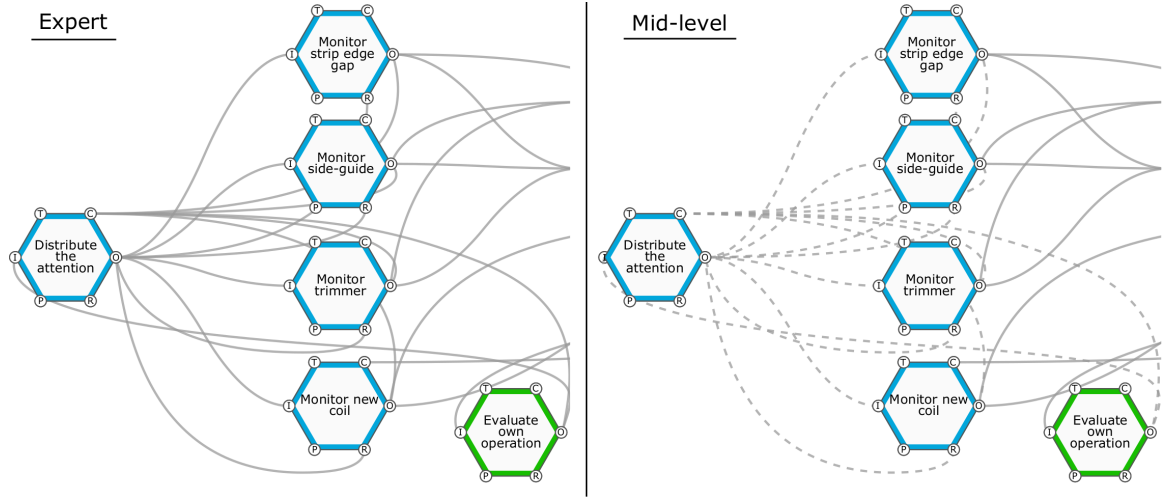


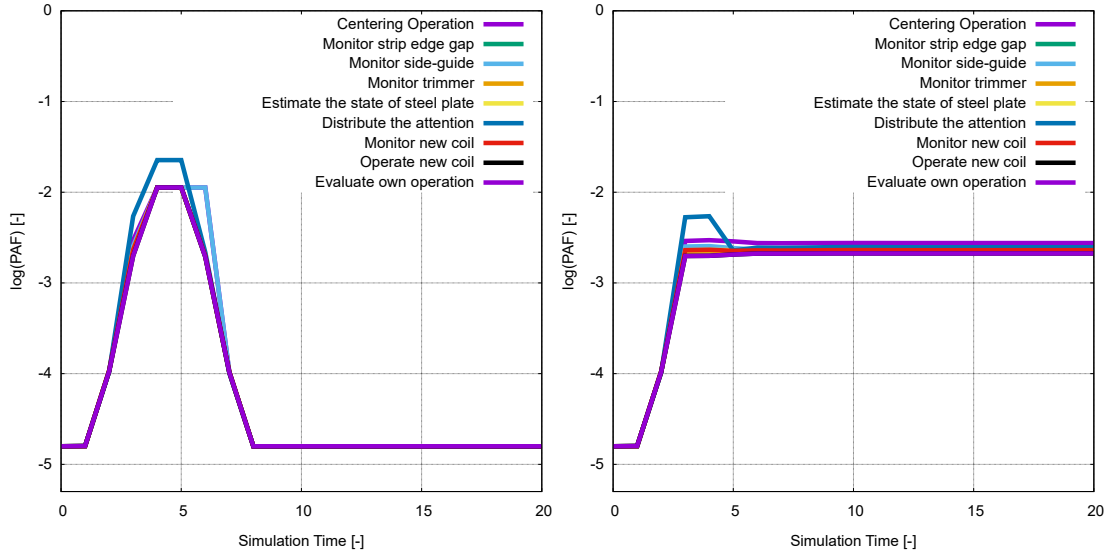
Figure 4.7: Instantiation of the FRAM model based on the monitoring behaviors of the operators.

4.4.5 Simulation Study

This study conducted a simulation study to investigate how attention management strategies affect work performance in multitasking. The attention management strategies are clarified through the eye movement and interview analysis and incorporated into the FRAM model structure, as shown in Fig. 4.7. The FRAM models show the difference between expert and mid-level operators in attention allocation features. This simulation study aims to show how this difference contributes to the operator's resilient performance in multitasking. The simulation scenario and the settings are as follows.

Scenario: The operator was conducting the centering operation as a single-tasking daily operation. Then, the other operator carried a new coil into the process to be processed next. The operator conducting the centering operation had to receive this new coil by controlling the coil car in parallel with the ongoing main task. Because the timing of the new coils being brought in cannot be controlled, multitasking was required at this moment. The operator faced multitasking in the centering and coil-setting operation.

The settings were established as follows to implement this scenario in the simulation. As described in the Methods section, the simulation method involves two variables: PAF corresponding to the state of each function and CPC representing the context surrounding the system, with defined interactions between them. Variability



(a) Simulation result of the expert operator in multitasking. (b) Simulation result of the mid-level operator in multitasking.

Figure 4.8: Simulation results based on FRAM.

specified in the scenario is introduced into the simulation as changes in CPC scores, allowing for investigating how variability propagates through the system based on the coupling relationships between functions. In the coupling between functions, one side always leads to output, with the function providing this output referred to as the upstream function and the function receiving this output called the downstream function. It is generally calculated that variability propagates from the upstream function to the downstream function. As a result, the PAF values of each function at each simulation time step are obtained.

Settings: The multitasking situation triggered by the new coil arrival corresponds to the “Number of goals,” which is one of the CPC scores defining the surrounding situation in this simulation method. Thus, the CPC score of the “Number of goals” was set from 100 to 0 at the simulation time 0 to implement this variability. How these fluctuations propagate to the functions comprising the work is simulated.

Fig. 4.8a and 4.8b show the simulation results. The horizontal axis shows the simulation time. The vertical axis shows the logarithm of PAF, which corresponds to how safe the functions in the FRAM model are conducted. For example, the function is conducted safely or strategically when the graph remains low. In contrast, an increase in the graph represents the high probability of dysfunction. Thus, this

simulation method allows us to investigate what state each function settles into after fluctuations are imposed on the FRAM model. In both cases of the expert and the mid-level operators, the $\log(\text{PAF})$ of the functions increased after the variability occurred at the simulation time 0. These increases represent that the shift to multitasking significantly affected the cognitive functions comprising the target operation. After this increase, the functions recovered to the normal status in the case of the expert operator, while they remained at the relatively dangerous status in the mid-level case. This trend of the mid-level operator indicates that the FRAM functions continued to have a high probability of malfunctioning. In contrast, in the case of the expert operator, the FRAM model can recover from the temporary hazardous conditions and perform multitasking stably.

These results support this study’s second hypothesis that the attention management strategies represented by the FRAM models had a critical role in maintaining work performance in multitasking. The difference between the FRAM model instances that produced this result was whether the attention management function was active. This difference corresponds to the first hypothesis, the relationship between proximal and distal terms for the operators. That is, the expert operator understood the abstract relationships in the system and was, therefore, able to allocate attention effectively even when multitasking. This feature was expressed by the active “Distribute the attention” function, which centrally managed the other monitoring functions in the FRAM model. Thus, the attention management strategies of the expert operator identified based on the structure of proximal and distal terms were critical for the work performance in multitasking.

4.5 Discussion

4.5.1 Attention Management in Multitasking

This study investigated attention management strategies considering the functional structure of tacit knowledge. Attention management strategies are an important aspect of clarifying the adaptive expertise of skilled workers. In particular, we focused on multitasking, a typical situation in manufacturing worksites where attention management is crucial. Because operators acquire attention management as tacit knowledge, the approach considering its structure—the relationship between proximal and distal terms—was needed. This study applied eye movement and interview analysis for the proximal and distal aspects. By combining these two perspectives, we investigated

which abstract function the operators were aware of and, consequently, what their attention management strategies were.

The eye movement analysis examined how the operators allocated their attention to the surrounding information resources as the proximal term. The relative entropy showed how the attention management features changed in single-tasking and multitasking for expert and mid-level operators. In addition, the relative entropy from a uniform probability distribution of inter-AOI gaze point transitions showed how structured or random the eye movements are under each condition. As a result, the mid-level operator's gaze point transitions were significantly approached to random when multitasking. In contrast, the expert operator's gaze point transitions remained relatively structured in the same situation. These results showed that the expert operator could maintain attention management in multitasking while the mid-level operator's monitoring behavior became opportunistic.

The interview analysis investigated what abstract functions the operators are aware of during work as the distal term. For this purpose, the typical responses of the expert and the mid-level operators were mapped onto the functional hierarchy of WDA. As a result, the expert operator focused on the task constraint relations and the system's objective, which correspond to the upper layer of the abstraction hierarchy. In contrast, the mid-level operator only focused on the individual components, corresponding to the abstraction hierarchy's lower layer. These results showed that the expert operator was aware of abstract functions in multitasking while the mid-level operator was occupied with focusing on individual elements.

These two analyses indicated that the attention management strategy can be described under the functional structure of tacit knowledge—the relationship between the proximal and distal terms. The gazing objects to which attention was allocated was the proximal term, and the abstract relations between components were the distal term. The expert operator could associate task constraint relations with individual gazing objects, allowing them to maintain systematic attention allocation even when multitasking. In contrast, the mid-level operator's attention was more opportunistic, just reacting to changes in individual objects in multitasking without fully understanding the system's abstract functions. These results confirmed the first hypothesis that structured gaze point transitions correspond to a better understanding of the system's abstract function. This finding is consistent with the previous studies. Chanijani et al. [115] indicated that experts have low gaze entropy with a systematic attention management strategy because they understand where to look during the task, while novices hunt information by aimlessly browsing the display. Horiguchi

et al. [6] reported that experienced train operators could better maintain gaze point movement patterns than novices when the situation changed. Similar to these studies, the present study shows expert workers' attention management characteristics in cognitively demanding situations.

4.5.2 Integrated analysis with WDA and FRAM

In order to integrate proximal and distal aspects, this study employed a model constructive approach using WDA and FRAM. While WDA organized the overall picture of work from the Work-as-Imagined perspective using an abstraction hierarchy, FRAM incorporated attention distribution features into the model and provided a Work-as-Done perspective, examining the impacts when multitasking occurs.

WDA showed that the two tasks in multitasking—centering and coil-setting operation—shared the system's objective of quality and efficiency. Also, these two tasks have several connections to specific devices in the lower layer, so the operator must allocate attention to these components. Thus, the abstraction hierarchy of WDA can be interpreted as the relationships between observable proximal terms at the lower layer and distal terms, which are important for task management, at the upper layer. However, this only shows the static relationship between the two. In order to clarify how this relationship is demonstrated in actual work, we need a method to examine the system's behavior dynamically.

We conducted a simulation study with a multitasking scenario based on the FRAM model instances reflecting the operators' attention management strategies. In this study, the simulation output assessed the impact of variability on the FRAM models of expert and mid-level workers using PAF. The PAF value quantifies the control modes defined in CREAM—strategic, tactical, optimistic, scrambled—using membership functions and is an indicator for evaluating functional safety. In our research, this metric corresponded to how successfully each function within the FRAM model was performed, and it was used to evaluate work performance when variability was introduced. The FRAM models constructed in this study mostly correspond to the cognitive processes of the workers; therefore, an increase in the PAF of these functions is considered to correlate with an increase in the mental workload of the workers. It is well-known that a high mental workload can impede working memory, decision-making, and situation awareness, negatively affecting safety behavior and performance and increasing the risk of accidents [116, 117]. Thus, the analysis in this study is also considered to contribute to safety management.

This simulation study was based on the second hypothesis that the expert’s attention management strategy is critical to resilient work performance in multitasking. The expert operator’s attention management strategy was expressed by the “Distribute the attention” function. This function centrally manages the attention among the other monitoring functions, which are proximal terms, based on their abstract relationships, which are distal terms. The simulation results showed that the FRAM model with the expert’s attention management strategy recovered the performance after the variability of multitasking. In contrast, the mid-level’s FRAM model remained likely to be dysfunctional. These results indicate that the attention management strategy of the expert operator contributes to resilient work performance. In addition, the expert’s FRAM model had a perceptual action cycle that involved monitoring, estimating, responding, and then monitoring again. This structure in the FRAM model may correspond to the resilience of the expert operator to adapt to changes in the environment and maintain their performance.

Our approach investigated the attention management strategy in multitasking, considering the functional structure of tacit knowledge. Since these skills are related to the adaptive behavior of workers and are tacit knowledge, a multifaceted approach not limited to gaze analysis is necessary. Following this idea, this study considered proximal and distal aspects using eye movement and interview analysis. Furthermore, the model constructive approach described this relationship using FRAM and enabled us to clarify how this feature contributes to work performance.

4.5.3 Analyzing Skills Using FRAM

These results of FRAM can relate to the theory of situation awareness. Endsley [114] has proposed a theoretical model of situation awareness with three levels to describe human decision-making. The first level is the perception of individual elements in the current situation. The second level is comprehending the current situation by integrating relevant individual components. The third level is the projection of future status based on the current system status and future goals. This study confirms that the target work can be described by following these levels. At the first level, the operator perceives the individual information, such as the display of the trimming process and the reference laser line. The operator integrates that information at the second level to build an overall comprehension of the current process, including the steel plate status. Finally, the operator projects the future steel plate condition as it moves through the process and operates adequately. These levels possibly correspond to the FRAM model of the target work, as shown in Fig. 4.6. The four monitoring

functions allocated at the center of the FRAM model represent the first “perception” level; the “Distribute the attention” function corresponds to the second “comprehension” level; and finally, the “projection” results are passed on to the estimating group of the FRAM model. Because the critical factor of the expert’s FRAM model was the active “Distribute the attention” function, the performance difference of the operators may be characterized by the second “comprehension” level.

The attention allocation characteristics identified as skilled workers’ aspect in this study can be discussed with metacognition. As described in Section 2.2, three skills—planning, monitoring, and evaluation—are essential to the metacognitive control process, which involves managing one’s cognitive activities. Planning includes efficiently allocating cognitive resources, such as attention, during a task. Within the FRAM model constructed in this study, the function responsible for attention allocation directly relates to this planning capability. Moreover, the interconnections between functions—those planning attention allocation based on peripheral information and task outcomes—correspond to the monitoring and evaluation skills, respectively. Thus, the FRAM model functions identified as distinguishing features between skilled and mid-level workers linked to the abilities within the metacognitive control process. This finding suggests that aspects of skilled workers’ adaptive abilities may be explained through metacognition.

This study utilized FRAM to investigate the adaptive aspect of expert operators who work in socio-technical systems. This application partly differs from the typical use of FRAM in previous studies. Much of the FRAM research has focused on identifying safety-critical functions of large-scale complex systems and proposing countermeasures to improve resilience [71, 63]. In contrast, our approach dares to focus on the specific operators in the system and to model their adaptive behavior using FRAM. However, this study confirms that our approach matches the research objectives. In the resilience engineering approach, workers in socio-technical systems must continuously adapt to the variabilities in their daily work. This feature is the second principle of resilience engineering, “approximate adjustments.” This aspect is precisely the skill required of expert manufacturing workers. FRAM based on resilience engineering has been shown to be a suitable method for investigating this in the present study. The results further suggested that our approach has contributed to elucidating the adaptive skill mechanics through modeling and simulation, which were previously difficult to verbalize as tacit knowledge. In addition, the proposed framework can be applied to other work in socio-technical systems. Note that the

methods for extracting features of expert operators are not limited to eye movement and interview analysis but must be selected appropriately.

The case study conducted in this research to reveal the attention distribution characteristics of workers was limited to one expert and one mid-level worker as participants. This study adopted a deductive learning approach to overcome this limitation. Generally, an approach that extracts common features from quantitative data and statistical analyses corresponds to inductive learning, which identifies patterns from a large amount of training data. In contrast, deductive learning is an approach that extracts targeted concepts from a small number of cases based on established rules and logical reasoning. Notably, the method of developing abstract knowledge representations based on actual specific cases is called Explanation-Based Learning (EBL) [118]. In EBL, the initial step involves constructing a causal model that extracts only the parts relevant to learning from the training instances. In this step, domain-specific knowledge, pre-established in the system as domain theory, is used to integrate fragmentary information manifested in the descriptions of the training instances. The output of this step is a causal model equipped with a structure that explains the training instances, generally represented in a tree structure. At this stage, information from the training instances that do not align with the target concept is discarded and not included in the explanation structure. In the next step, the causal model extracted from the training instances is generalized into an explanation structure encompassing other instances where the same interpretation applies. Here, constants at each node of the tree structure are replaced with variables to represent generally applicable concepts. Through these steps, it is possible to identify the explanatory structure from a few instances. Recently, research based on EBL has expanded to analyses of the learning processes in infants, demonstrating its growing scope [119]. For more detailed information, please refer to the relevant literature [120].

The approach based on FRAM in this study can be interpreted in line with EBL. Initially, the EBL step of discarding non-relevant features from the training instances to create a model corresponds to the phase in which the FRAM model is constructed from the case study of worker performance. In this step, based on the results of the Work Domain Analysis, which includes domain-specific knowledge, we extracted only the functions related to attention distribution in multitasking, which is the focus of this study, to construct the FRAM model. The construction of the FRAM model in this study aligns with the first step of EBL, which involves creating a causal model by extracting only the information relevant to the target concept from various

information in the training instances. Furthermore, the simulation study step in this research is analogous to generalizing the causal model derived from a single instance. In this step, our study differentiated the models of expert and mid-level workers in the FRAM model construction phase above and compared the simulation results to identify crucial functional structures in tacit knowledge. Thus, the simulation study in this research corresponds to identifying generalizable variables and constants from the constructed causal model. As outlined above, the methodology used in this study, which focuses on the overall structure of tacit knowledge, is consistent with EBL based on a limited number of instances. This study believes it has gained substantial insights even with few participants by adopting such a deductive learning approach.

4.5.4 Limitations and Future Work

The current research has some limitations. First, since FRAM models the target work at an abstract level, it is challenging to correspond to simulation results and actual data. It is necessary to overcome this point to validate the FRAM model further. Second, the present research had a limited number of experiment participants. Assembling a large number of skilled personnel for a particular task is often fraught with difficulties. In the case study of this research, there were inherently few workers engaged in the task under analysis, and it was impossible to recruit additional participants for the same work. The issue of skill transfer is pronounced in smaller enterprises where resources are relatively limited, making it difficult to avoid this problem. This study adopted a deductive learning approach that extracts explanatory structures from a limited number of cases, responding to this aspect. However, it is anticipated that further insights can be gained by combining this with an inductive learning approach based on a larger sample size. Future work will also examine the features of expert workers in other subjects and determine whether there are common attributes. Third, WDA and FRAM currently need more objectivity when building a model. An objective and systematic method of carrying out these procedures must be developed. Finally, the present study employed a static FRAM model for analyzing adaptive behavior. The FRAM model should dynamically change over time as workers transform their practices in response to environmental changes. FRAM needs to be further extended to investigate this feature.

4.6 Brief Summary

This study aimed to investigate the attention management strategies of expert operators in multitasking. This expert's feature is crucial to adaptively cope with daily work variabilities and maintain a resilient work performance. For this purpose, this study utilized the framework based on the functional structure of tacit knowledge. The data from a case study focusing on the steel plate processing operator was applied. First, the eye movement and interview analysis were conducted to clarify the proximal and distal aspects of the target work. The results showed that the expert operator could maintain attention management systematically in multitasking by understanding the abstract relations in the system. Then, the model constructive approach based on WDA and FRAM was taken. The identified attention management strategies were incorporated into the FRAM model structure. The simulation study showed that the expert's attention management strategy contributed to the resilient work performance in multitasking. In the data collection process conducted in this study, there was a limitation due to the small number of participants; however, this study took a deductive learning approach, and it was possible to test hypotheses based on the relationship between the proximal and distal terms of tacit knowledge through a multifaceted approach centered on FRAM. It was shown that the integrated approach based on the concept of tacit knowledge is valuable and applicable to manufacturing works.

Chapter 5

Modeling Resilient Performance of Workers Under Multiple Disturbances

5.1 Introduction

As discussed in Section 1.2, extensive research has been conducted in the field of human factors focused on estimating worker performance within production systems. For example, studies have investigated how factors such as fatigue, age, and experience impact task performance. However, 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 [36]. Regarding this point, 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?
- 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 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 [38]. This study

applied the 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 chapter is organized as follows. Section 5.2 describes methods, including FRAM and the simulation method. Section 5.3 shows the implementation of the methods in a case study. Section 5.4 shows the simulation results examining the effects of multiple disturbances. Sections 5.5 and 5.6 present the discussion and conclusions of the paper, respectively.

5.2 Methods

5.2.1 FRAM Model Construction

This study used the Work Domain Analysis (WDA) as a supportive tool to build the FRAM model for the target work. WDA is a method that forms part of a framework called cognitive work analysis [121]. 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 [77]. 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 [122]. 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 [41, 42]. 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.

5.3 Case Study

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.

5.3.1 Case Study Description

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. 5.1, 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 [123]. 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 [124].

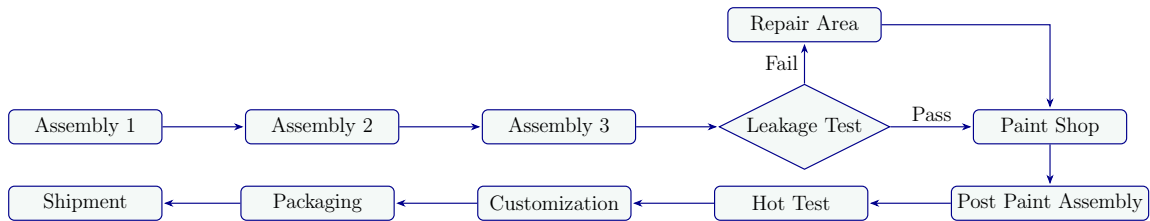


Figure 5.1: General engine production flowchart.

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. 5.2, 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.

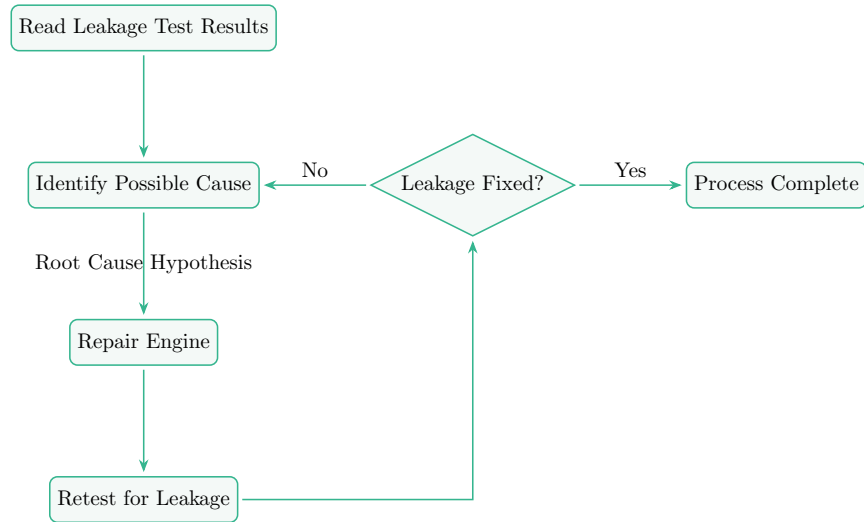


Figure 5.2: Repair process flowchart performed by repair operator.

5.3.2 Data Collection Overview

Fig. 5.3 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 [63, 100, 40]. 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.

5.3.3 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.

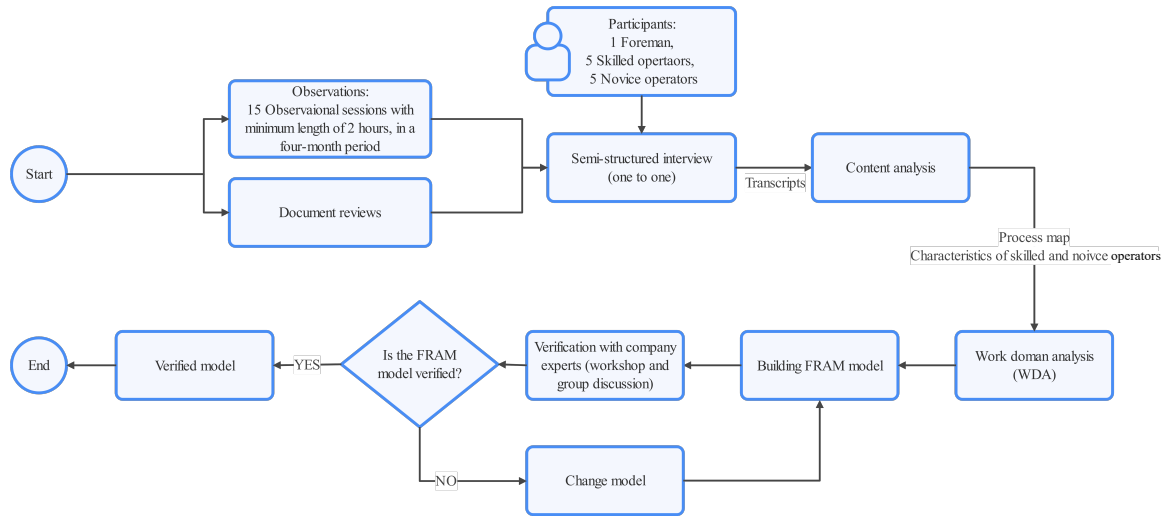


Figure 5.3: The process of data collection and analysis, building, and verification of the FRAM model.

5.3.4 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 [125], a non-probability sampling technique commonly used in qualitative research to ensure that 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.

5.3.5 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 5.4.1.

5.3.6 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. [126] 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 [63, 66, 90]. 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 [127]. Additionally, integrating diverse

perspectives into the FRAM model achieves greater transferability [127], making it applicable to broader contexts.

5.4 Results

5.4.1 FRAM Model

Before building a FRAM model, this study conducted WDA to organize information on the target work. Fig. 5.4 shows the abstraction hierarchy of the target work in the case study. At the top layer, the functional purpose, the two main objectives

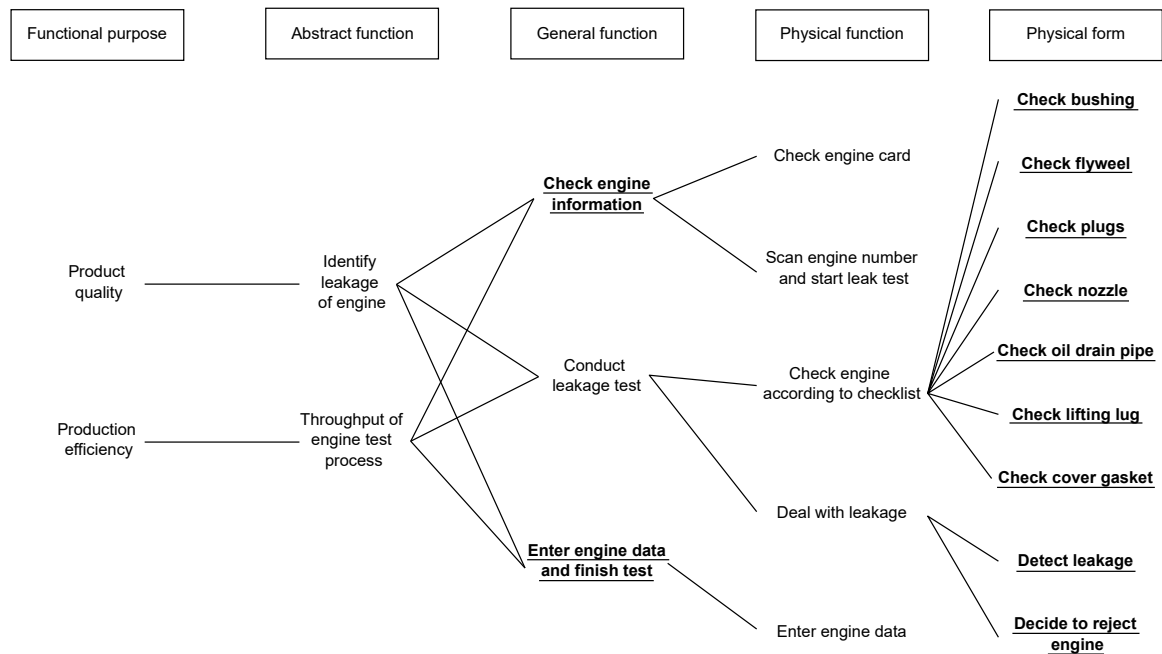


Figure 5.4: Abstraction hierarchy of the target work. The underlined functions are included in the FRAM model.

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 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. 5.5. This FRAM model corresponds to the novice workers. The most critical functions for the quality of the test process,

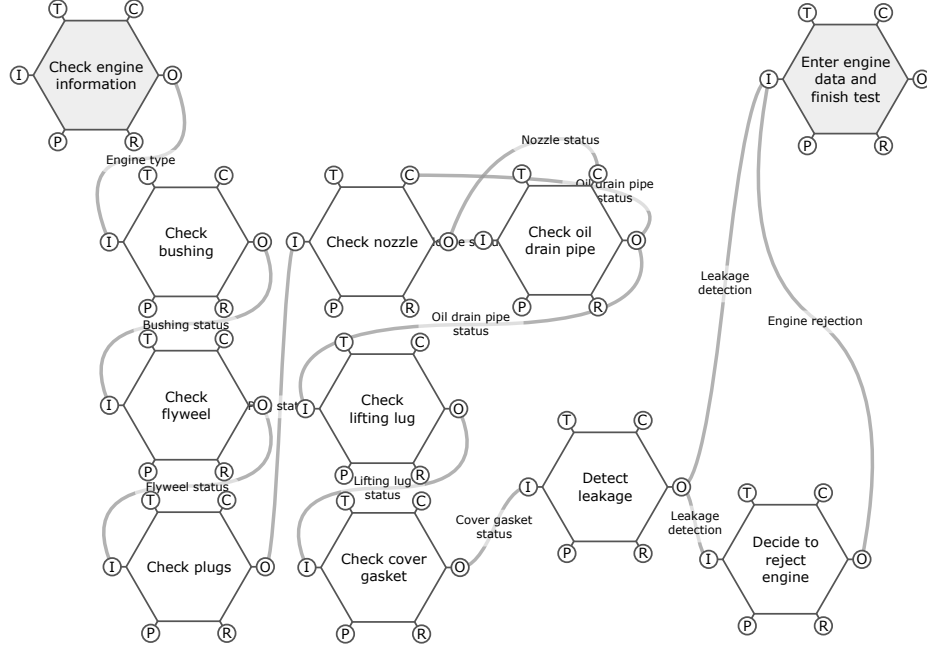


Figure 5.5: FRAM model of the novice workers.

“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. 5.4 were included in the basic FRAM model, as shown in Fig. 5.5. 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 [45]. The four functions representing these abilities were added to the FRAM model based on this concept. The blue functions of the expert worker’s FRAM model in Fig. 5.6 show these additional functions. The function “Anticipate leakage” represents the prediction of defects before the test, as indicated by

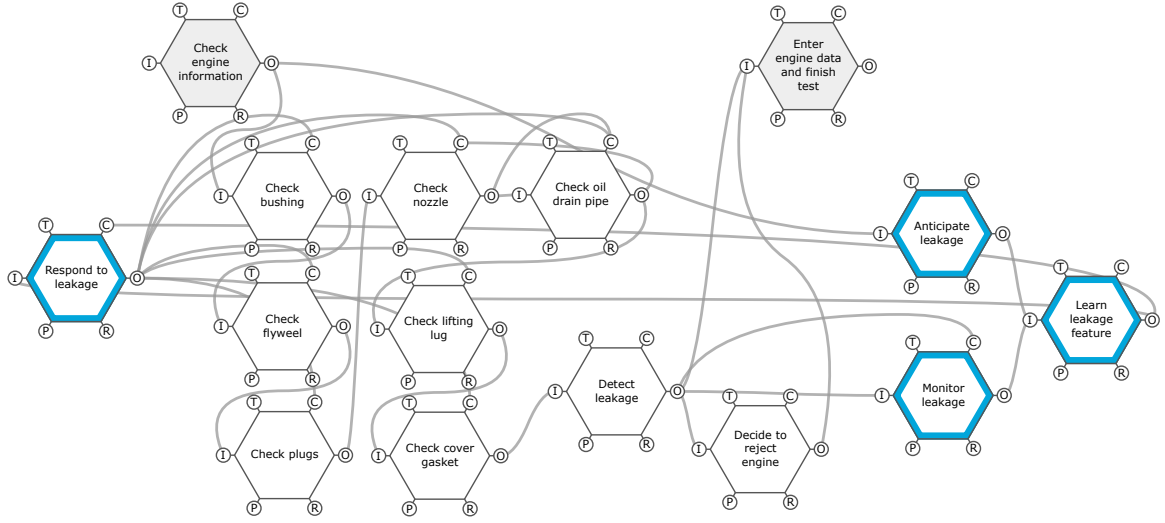


Figure 5.6: The extended version of the FRAM model with the resilient characteristics of the expert workers.

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.

5.4.2 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 5.1 illustrates an example of the simulation scenario. After executing

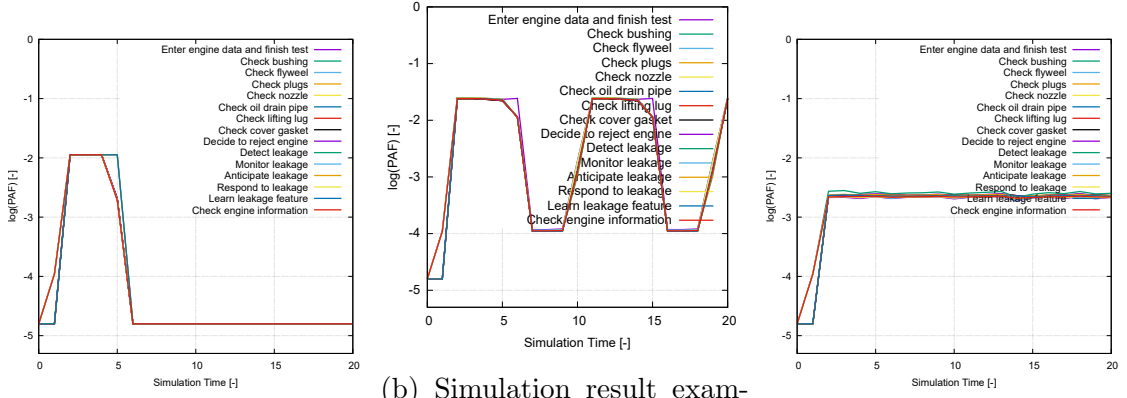
Table 5.1: An example of the simulation scenario (operator = expert, variability = CPC No. 1, 3, 6).

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

simulations across all scenarios, the results were categorized into three distinct groups, as follows.

5.4.3 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. 5.7a 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



(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 in this simulation scenario. (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.

Figure 5.7: Simulation results examples of category I, II, and III.

the disturbance related to a lack of resources, although their work performance was temporarily affected.

5.4.4 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. 5.7b 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.

5.4.5 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. 5.7c 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.

5.4.6 Summarizing Key Trends in Simulation Results

All simulation outcomes were classified into the three categories above. Fig. 5.8 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.

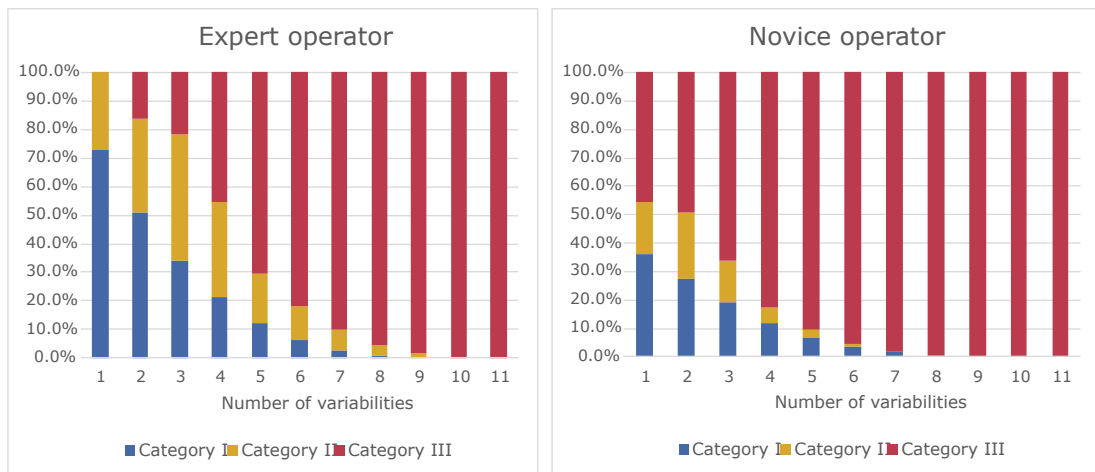


Figure 5.8: Percentage of categories I, II, and III in the simulation results.

This study also focused on the trends in the PAF values in the simulation results. Fig. 5.9 presents a box plot of the proportion of time during which the PAF values remained above the reference value ($\log \text{PAF} = -3$) 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 [101]. Consequently, values of log 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.

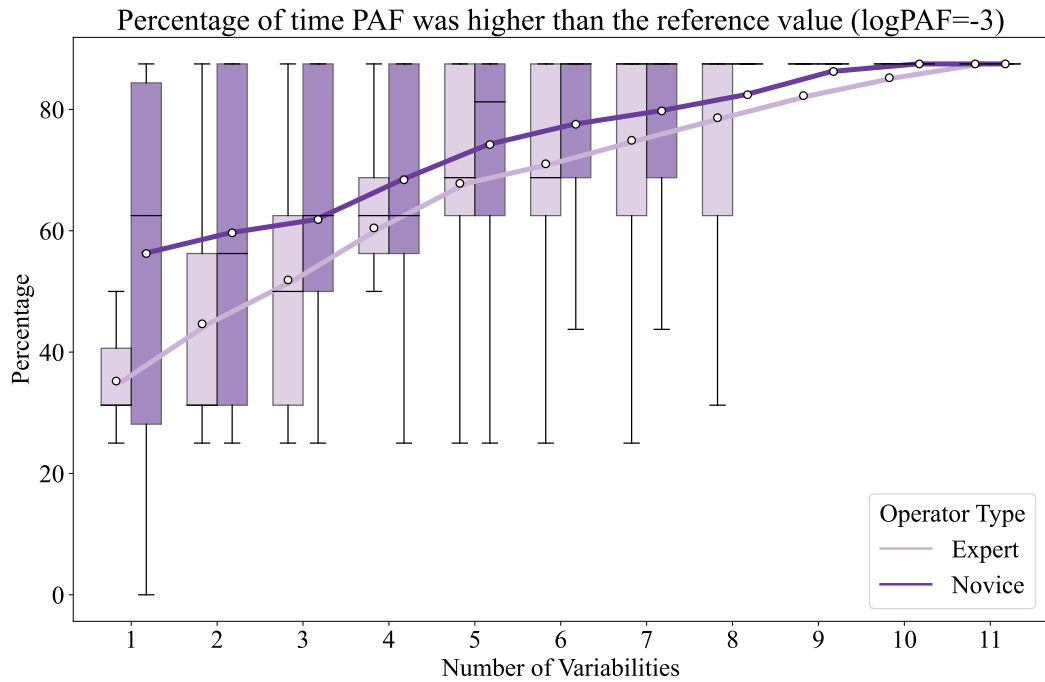
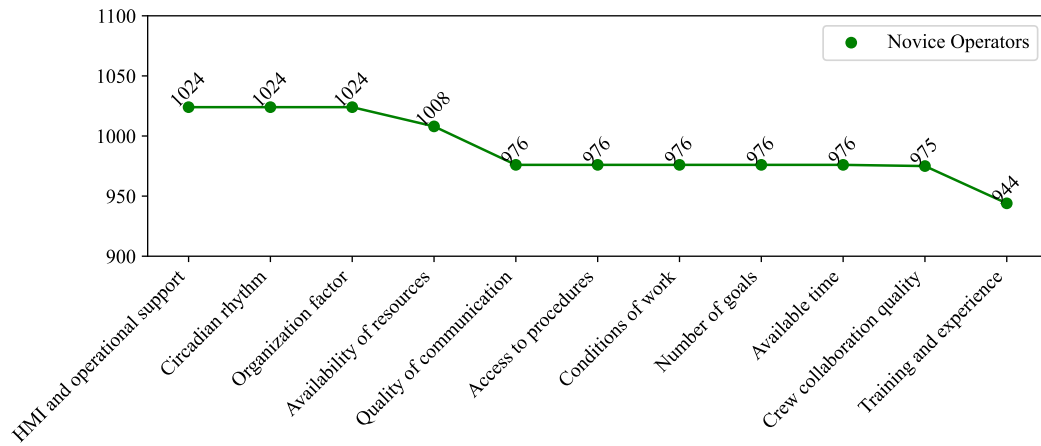
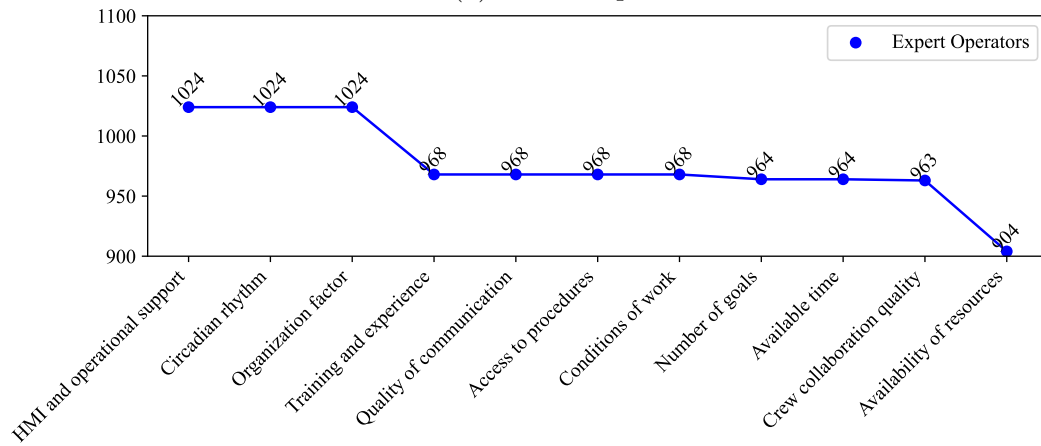


Figure 5.9: Percentage of simulation time that log PAF was higher than the reference value ($\log \text{PAF} = -3$).

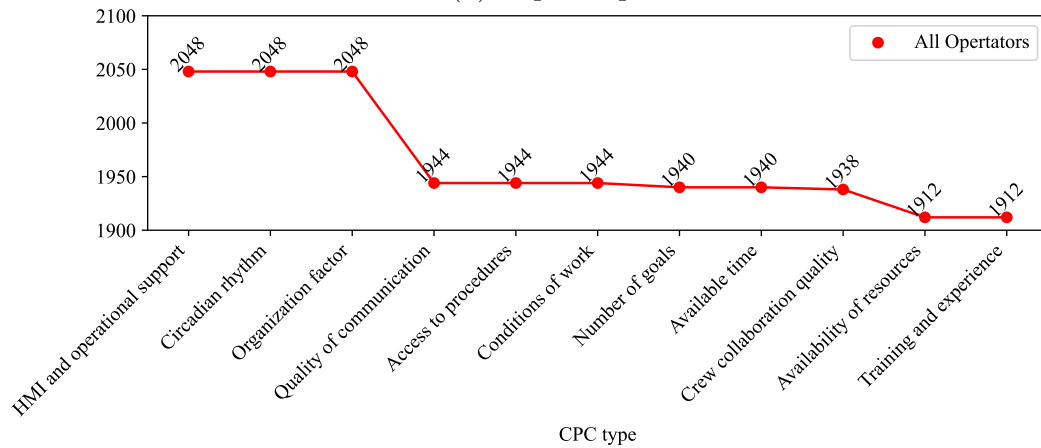
To gain deeper knowledge about the most influential CPCs on novice and expert operators, Fig. 5.10 presents the frequency of CPCs in scenarios where the percentage of having PAF was higher than the reference value. Fig. 5.10a reveals that the CPCs with the highest frequencies are “HMI and operational 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. 5.10b interestingly reveals the top



(a) Novice Operators



(b) Expert Operators



(c) Combined Data from Both Expert and Novice Operators

Figure 5.10: Frequency of CPCs in scenarios where the percentage of having PAF is higher than the reference value.

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. 5.10c 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.

5.5 Discussion

5.5.1 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 state of work in the simulation scenarios to be envisioned 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 [97]. CPCs were initially categorized into nine factors under CREAM, part of the second-generation human reliability analysis techniques [57], later expanded to eleven with the introduction of FRAM [60]. 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 [38], 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 [128, 129, 130]. 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 [131]. Salvendy and Karwowski (2021) have 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 [132]. 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 [75, 70, 91, 93]. 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.

5.5.2 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 [133]. 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.

5.5.3 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 [38]. 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. For example, the simulation results showed a high possibility of malfunction when the variability of "HMI and operational support," "Organizational factors," and "Availability of resources" are compounded with other variabilities. This result implies that these factors critically affect the engine test and repair process in the case study. These findings could contribute to designing production lines to maintain work performance resiliently even when disturbances occur.

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 [38]. 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 [85, 86]. 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 FRAM model developed in this study can be discussed with the concept of metacognition. Section 2.2 describes three critical skills essential to the metacognitive control process for managing cognitive activities: planning, monitoring, and evaluation. Specifically, planning involves allocating cognitive resources and selecting strategies, monitoring refers to overseeing the execution of one's cognitive activities, and evaluation entails assessing these cognitive efforts. These skills are closely linked to the four resilience capacities integrated into the FRAM model for skilled workers. In the FRAM model, tasks are performed by monitoring the execution status, evaluating ongoing activities, and reallocating resources through responding functions based on these assessments. Rather than the functions simply representing the basic steps of a task, additional resilience-related functions within the FRAM model illustrate the processes of metacognition, supporting resilient performance through continuous adjustment. These findings suggest that functions aligned with metacognitive processes enable workers to manage variability adaptively, contributing to their resilience to respond to fluctuating work conditions.

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 [99]. Determining which FRAM model structures best contribute to resilient system performance necessitates further research.

5.5.4 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. It is also recommended that cross-industrial comparative studies be conducted to test the generalizability of the current study’s findings or to discover industry-specific characteristics of human-centric production systems. 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. With other technologies, investigating the potential of augmented reality (AR) and virtual reality (VR) to bolster operators’ capabilities in managing disturbances within production environments is suggested as a further study. Further progress is also possible in addressing the policy and ethical implications of integrating human-centric approaches into production systems, with a focus on labor policies, workforce diversity, and ethical standards. These future research directions not only chart a course for scholarly inquiry but also resonate with Industry 5.0’s core objectives. 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.

5.6 Brief Summary

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. Concerning 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.

Chapter 6

Extracting Knowledge of Workers by Identifying Adaptive Behavior

6.1 Introduction

This study proposes a novel approach for extracting workers' knowledge based on the concepts of Work-as-Imagined (WAI) and Work-as-Done (WAD), commonly used in safety management. In the new paradigm of safety management, known as Safety-II, WAD refers to the work actually performed at the operational sites where systems are implemented. In contrast, WAI refers to the work envisioned by system designers and managers [39]. For example, individuals working in complex socio-technical systems, such as aviation, healthcare, or industrial plants, consistently achieve high reliability by adapting their actions to the specific context. Consequently, there is often a discrepancy between WAI, which corresponds to work guidelines, and WAD, the actual work performed. Safety-II emphasizes that the performance adjustments made by human operators, which create this discrepancy, are crucial not only as potential sources of failure but also as critical factors in ensuring success. A review of the relevant literature reveals numerous studies that compare WAI and WAD in complex socio-technical systems and propose improvements to system safety management and work guidelines [70, 134]. This study hypothesizes that workers' know-how, tailored to the needs of the specific manufacturing situations, can be extracted by comparing WAI with WAD. This hypothesis is derived from the idea that WAI corresponds to the work procedures that provide instructions to workers in a manufacturing setting, while the expertise that skilled workers develop in response to specific situations that are not included in the work procedure is encapsulated in WAD.

For this purpose, this study developed an approach based on the Functional Resonance Analysis Method (FRAM), which has been frequently utilized for modeling

socio-technical systems and comparing WAI and WAD. This method, FRAM, is proposed within the Safety-II paradigm and analyzes the dynamic processes through which performance variability, brought about by individuals working in complex socio-technical systems, contributes either to the system's safe operation or to the induction of unsafe events [38]. In addition, the approach proposed in this study utilizes a semi-quantitative simulation method based on FRAM. Once the difference between WAI and WAD are visualized through FRAM, a simulation study explores which added or deleted functions in WAD play a critical role in resilient work performance within a specific exogenous variability to identify the essential know-how of the worker. This approach aims to overcome the limitations of traditional methods about capturing the adaptive capabilities necessary for responding to environmental changes and uncertain situations.

The following sections of this chapter are organized as follows. Section 6.2 explains the method used in this study. Section 6.3 shows the results obtained from the conducted case study. Sections 6.4 and 6.5 are the discussion and conclusion, respectively.

6.2 Methods

6.2.1 Study Design

This study followed the approach of previous research in Safety-II that compared WAI and WAD, as shown in Fig 6.1. First, a FRAM model of WAI was constructed based on document reviews of the work procedures and observations of the target work. In this step, the basic functions constituting the target work were identified and converted into a FRAM model. The WAI model was then validated in focus groups with the managers who formed the work procedures. The focus groups in this study adopted an approach based on facilitation techniques commonly used in qualitative research [126], encouraging multiple participants to engage in interactive discussions on specific topics. Second, a FRAM model of WAD was constructed based on the workers' experiences. This study conducted interviews with the workers and identified discrepancies between the work procedure and the actual work. The identified discrepancies were included in the WAD model by adding or deleting functions and couplings from the WAI model. Third, a simulation method based on FRAM was employed to examine how the difference in the FRAM models between WAI and WAD affects the safety and productivity of the overall work. A sensitivity analysis-based approach was adopted to identify which functions play a critical role

in workers' knowledge, among the differences between WAI and WAD. The investigation process involved sequentially removing differential functions from the WAD model and repeatedly running simulations to evaluate their impact. Finally, another focus group was conducted with the participation of on-site stakeholders. The purpose of this second focus group was not only to validate the WAD-based FRAM model qualitatively but also to assess the validity of the extracted practical knowledge of workers. This validation was achieved by comparing findings gained from the simulation results with the observed actual behavior of the workers. This qualitative data collection approach, such as document reviews, interviews, and focus groups, is consistent with the previous studies [100]. More details about data collection are described in section 6.3.2.

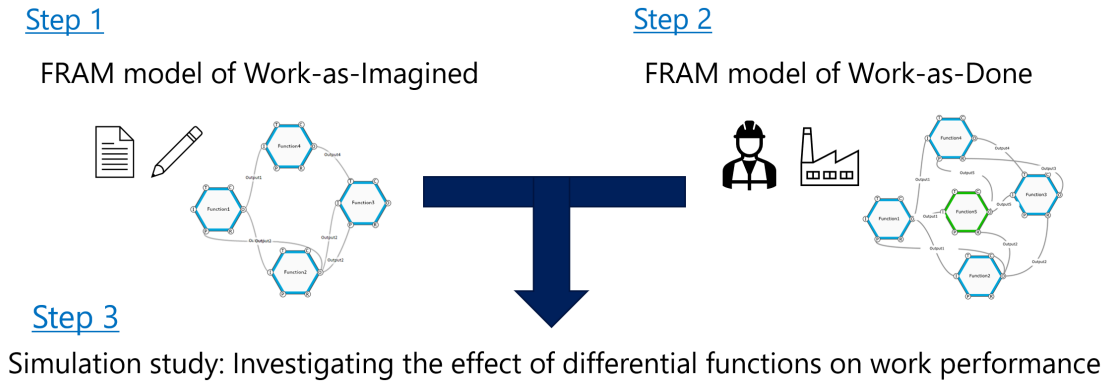


Figure 6.1: Overview of the framework comparing WAI and WAD.

6.2.2 Simulation Method Based on FRAM

This study employed a semi-quantitative approach to examine the effects of differences between WAI and WAD in FRAM models. FRAM is originally a qualitative approach; however, recent efforts have developed semi-quantitative approaches that combine FRAM with techniques such as Monte Carlo simulations [80, 135] and the Analytic Hierarchy Process (AHP) [82] for use in a wide range of applications. The simulation method used in this study is one such approach, which combines FRAM with Fuzzy CREAM [97], a second-generation human reliability analysis method [57, 101].

In this simulation method, two main parameters were defined: Probability of Action Failure (PAF), representing the execution status of each function, and Common Performance Conditions (CPC) score, representing the status of the system's surrounding environment. PAF is a quantification of the linguistic evaluation of the

system’s execution state, as defined by CREAM, using fuzzy theory. An increase in the PAF value indicates a higher probability of dysfunction. The CPC score represents the state of eleven factors that affect system safety, each expressed as a value ranging from 0 to 100. This simulation method envisions the impact of performance variability on the system by considering the interaction between each function’s PAF and the surrounding conditions represented by the CPC. The simulation is performed in four steps: 1) Interaction between CPCs, 2) Variability propagation from CPC to function using Fuzzy CREAM, 3) Variability propagation from function to function, and 4) Variability propagation from function to CPC. Details about this simulation method can be found in the study by Hirose and Sawaragi [97]. The current study employed this simulation to examine the effect of the difference between WAI and WAD on the entire work performance.

6.3 Case Study

6.3.1 Semiconductor Etching Work

A case study on manual etching work in the compound semiconductor manufacturing process was conducted to demonstrate the proposed approach. Semiconductor manufacturing involves several highly precise and complex steps to create integrated circuits (ICs) on wafers. It begins with wafer manufacturing, where material is formed into ingots, sliced into wafers, and polished to create a smooth substrate. The front-end of line processing then builds circuits on these wafers through a series of steps, including epitaxy, photolithography, doping, etching, and deposition, which are repeated multiple times to form intricate, multi-layered circuits. In the back-end of line processing, the wafers are tested, diced into individual chips, and packaged. The chips undergo final testing to ensure quality before being assembled into electronic devices. For more details about the general semiconductor manufacturing process, readers are referred to Geng [136].

In the semiconductor manufacturing process, etching involves removing layers from the wafer substrate according to the shape of the mask formed on the wafer surface through photolithography, thereby obtaining the desired circuit pattern on the wafer. There are two types of etching: wet etching, which involves immersing the wafer in a chemical solution to induce a chemical reaction, and dry etching, which consists of exposing the wafer to plasma. This study focuses on wet etching, characterized by isotropic etching due to the chemical reaction between the solution and the wafer surface. This isotropy can cause undercutting, where the area beneath the mask

is etched away, making it necessary to carefully consider the conditions of the chemical solution and other factors. While etching for silicon wafers is often performed automatically by equipment, the manufacturing process examined in this study involves a specialized wafer made from compound semiconductors, requiring manual etching by workers. The worker places the wafer on a specialized jig, immerses it in a chemical solution, and agitates it vertically to promote the chemical reaction necessary for etching. To ensure uniform etching across the wafer surface, it is essential to precisely control the jig's movement and the immersion time in the solution. Additionally, the post-etching cleaning process must also be performed manually. Therefore, achieving the specified dimensions for the depth and width of the etched areas on the wafer requires high skill and experience.

6.3.2 Data Collection

Following the study design described in Section 6.2.1, this case study conducted the following qualitative data collection. Document reviews and observations were conducted to build the WAI FRAM model. The researchers reviewed work procedure documents to extract the essential steps of the target work. Additionally, since the target work involved a specialized task within the semiconductor manufacturing process, observations were conducted to gain a fundamental understanding of the work. These observations were conducted using recorded sessions totaling two and a half hours. Based on this information, a WAI-based FRAM model was constructed. Subsequently, a focus group was conducted to validate the WAI model, with two managers responsible for creating the work procedure documents participating in the discussion. In this focus group, the researcher briefly introduced the concept of FRAM and the draft WAI FRAM model to the managers first. Then, the researcher and the two managers verified and updated the WAI FRAM model by discussing each functional coupling. During the focus group, the WAI FRAM model was displayed using the FRAM Model Visualizer (FMV) software, enabling the collaborative modification of the FRAM model in real-time. Also, the parameters required to run the simulation were determined based on a questionnaire administered to the two managers in this focus group. This focus group took approximately one and a half hours.

For building the WAD FRAM model, eight workers in the target work were selected as participant candidates, and five of them participated in the data collection due to the time restriction of the work schedule. The operators were classified as follows: two experts (A, B) with over ten years of experience, two mid-level workers (C, D) with more than three years of experience, and one novice (E) with less

than three years of experience. Workers A, C, and E belong to the same work team, while workers B and D belong to another. First, the etching work of each worker was recorded using a video camera. Next, interviews were conducted with each worker individually. During the interviews, the video recordings were displayed to the worker and the interviewer to support the facilitation of the interviews. The main focus of the interviews was identifying the discrepancies between the standard work procedure and the actual work performed. The interviews lasted about one hour each. Before the workers participated in the data collection, they were provided with a detailed explanation of the experiment and the data processing, and written informed consent was obtained. The identified discrepancies were then incorporated into the FRAM model as WAD, and a simulation study examining those effects on work performance was conducted.

After the simulation study, a second focus group was conducted with the two managers who participated in the first focus group. Notably, one of the managers frequently visits the work site, providing both the perspectives of a worker and a manager. The purpose of the second focus group was to validate the WAD-based FRAM model qualitatively and to examine whether the findings related to workers' knowledge, derived from the simulation results, aligned with the actual behavior of workers. The researchers presented key insights into workers' expertise identified through the FRAM-based simulations, and the discussion focused on whether these insights corresponded with the real-world practices observed on-site. The focus group was conducted in two separate sessions at this step, each lasting about one hour.

6.4 Results

6.4.1 FRAM Model of Work-as-Imagined

The FRAM model of WAI was built as shown in Fig. 6.2. This FRAM model was constructed based on the work procedures, resulting in a structure where the functions' input (I) and output (O) were sequentially connected, corresponding to the step-by-step execution of work elements. The function "Preparation for etching" in the upper left corner corresponds to the preparation for the etching process, including tasks such as preparing the chemical solution, and indicates the initiation of the etching process from this function. The function "Perform etching" represents immersing the wafer in the chemical solution to perform etching. During the etching process, to enhance the chemical reaction on the wafer surface, the jig holding the wafer is oscillated; thus, "Shake the wafer for etching" is connected to the control

aspect (C) of “Perform etching.” After the wafer has been immersed in the solution for a specified period, it undergoes cleaning in multiple stages using substances such as methanol and water, indicated by the consecutive “Wash...” functions that follow. The final function, “Cleanup work,” refers to the post-etching cleanup tasks.

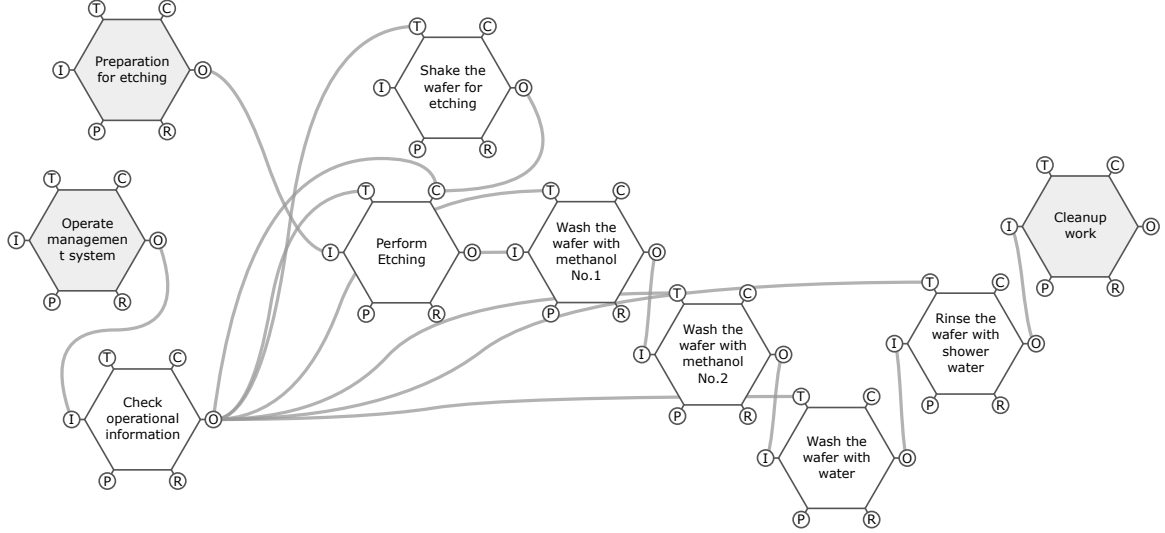


Figure 6.2: FRAM model of Work-as-Imagined.

6.4.2 FRAM Model of Work-as-Done

The FRAM model of WAD is shown in Fig. 6.3. As a result of interviews with the workers, five characteristics were identified that were common among multiple workers but are not included in the work procedure manual. Since these five characteristics involved actions not documented in the work procedure manual, each corresponding function was integrated into the WAD FRAM model. The functions numbered 1 to 5, highlighted in blue in the figure, represent the additional features incorporated as WAD, while the white-colored functions are common with WAI. The five additional functions in WAD are described as follows.

Orientation for placing the wafer on the jig

The additional function “1. Place the wafer on the jig” in the FRAM model corresponds to this feature. Workers A, B, C, and E consistently aligned the orientation of the wafer each time they placed it on the jig. This task was performed by aligning the notch, known as the orientation flat, with the jig handle to determine the wafer’s orientation. Worker C stated that they deliberately aligned the orientation flat because they believed its position could affect the uniformity of the etching. In

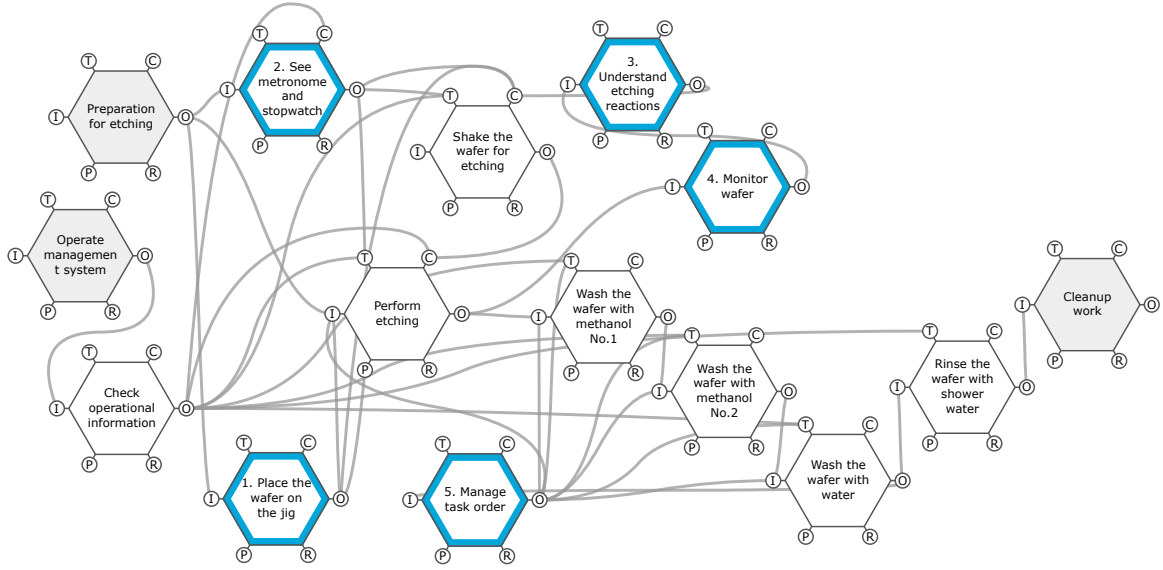


Figure 6.3: FRAM model of Work-as-Done.

the FRAM model, since aligning the wafer's orientation is necessary for etching, this function was connected as a precondition (P).

Managing the etching time

The additional function “2. See metronome and stopwatch” in the FRAM model corresponds to this feature. Several workers devised methods to manage the etching time despite the absence of such practices in the work procedures. They used a metronome to maintain a rhythm while moving the wafer up and down to stir the chemical solution and a stopwatch to control the duration of the wafer's immersion in the solution. For example, workers A, B, and D adjusted the starting position of the wafer's movement based on whether the designated etching time was an even or odd number of seconds. Additionally, worker A reported that they slightly adjusted the timing of removing the wafer from the solution using a stopwatch, as repeated etching would cause slight changes in the solution's concentration, thereby diminishing its etching capability. These observations underscore the workers' understanding that immersion time directly impacts etching performance, leading them to adapt their actions according to on-site demands. In the FRAM model, these characteristics were represented by connecting them to the time (T) and control (C) of the “Shake the wafer for etching” function, as well as to the time (T) of the “Perform etching” function.

Attention to shaking the jig

The additional function “3. Understanding etching reactions” in the FRAM model corresponds to the conscious movement of the jig to influence the flow of the chemical solution over the wafer’s surface during agitation. In interviews, multiple workers commonly reported that they achieved uniform etching by understanding the chemical reaction of the wafer and being aware of the solution’s flow over the wafer surface. Workers B and C demonstrated their adaptability by maintaining the wafer in the center of the container to prevent hand movement deviations. In contrast, worker D showed a different approach by moving the wafer along the side of the container. In the FRAM model, a function related to understanding the reaction between the wafer and the solution was added, with its output (O) connected to the control (C) of the “Shake the wafer” function.

Observing the wafer surface

The additional function “4. Monitor wafer” in the FRAM model corresponds to observing the wafer surface and evaluating the performance of the etching work. Since the etched patterns on the wafer surface are on the nanometer scale, it is challenging for inexperienced individuals to extract information from the wafer’s surface. However, in interviews, workers B and C stated that they could determine whether the etching was successful by observing the wafer surface after the process. Evaluating the performance of the etching process can enhance their understanding of how their actions influence the chemical reactions on the wafer surface. In the FRAM model, a function for monitoring the wafer surface was added, and this was connected to the function related to understanding the chemical reactions on the wafer.

Cleaning order management

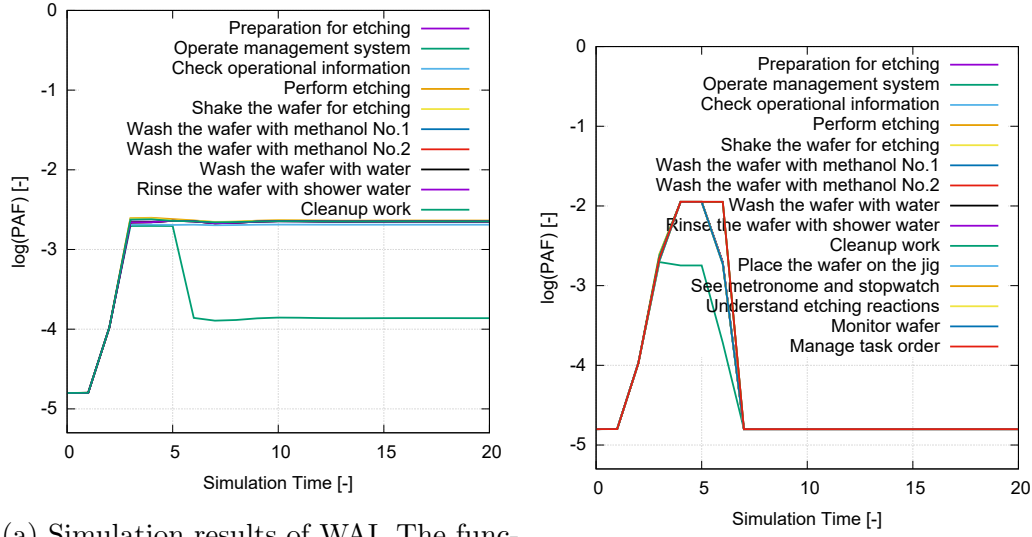
The additional function of “5. Manage task order” in the FRAM model corresponds to enhancing efficiency by performing the etching and cleaning steps in parallel when processing multiple wafers. For instance, it was observed that when processing two wafers, the operator would clean the first wafer while etching the second one to reduce overall processing time. Additionally, the workers understood the importance of each cleaning process and adjusted the cleaning times flexibly. These characteristics were identified from interviews with all five participants. In the FRAM model, a function for managing the order of tasks was added, and this was connected to the input (I) and time (T) of the etching and cleaning functions.

6.4.3 Simulation Results

The present study conducted simulations to examine the effect of additional functions in the FRAM model, characterized as the discrepancy between WAI and WAD. The simulation method adopted in this study envisions the system’s behavior when variability occurs [97]. For the simulation execution, it was necessary to set the type of variability occurring as a simulation scenario, which is defined according to eleven types of CPCs. In this study, a simulation was performed by setting a scenario where the same variability occurs in both the WAI and WAD FRAM models, and the results were compared to investigate the effect of the additional functions in WAD. Regarding selecting the CPCs for the simulation scenarios, “Available time” was chosen based on the results of focus group discussions with work managers and interviews with workers. In these sessions, participants were asked about the factors that significantly impact the target work.

As the simulation scenario, this study assumed a situation where the time constraints for routine etching operations become stricter, requiring tasks to be completed in a shorter time frame. This situation is related not only to the on-site demands concerning product delivery deadlines but also to the fact that the work takes place in a clean room. For instance, if workers leave the clean room for breaks, the work may be interrupted for a prolonged period. Thus, there may be situations where time constraints become tighter to avoid such interruptions. Based on this scenario, the simulation was implemented by reducing the CPC score for “Available Time” from 100 to 10 at time zero of the simulation. The effects of this change in CPC score on each function were simulated based on the interactions defined by the simulation method.

Fig. 6.4 shows the simulation results. The horizontal axis represents the simulation time, while the vertical axis represents the common logarithm of the PAF for each function included in the FRAM model. After the variability related to available time is introduced at time zero, the graph illustrates how its effects propagate across the functions. In the case of the WAI FRAM model, the PAFs of each function increase, and the state of heightened probability of failure persists (Category I). In contrast, although the PAFs temporarily rise in the WAD FRAM model, they eventually return to their initial values, indicating recovery (Category II). The difference between these simulation results reflects the effect of the five additional functions incorporated into the WAD FRAM model. This result demonstrates that the on-site practices of workers, which are not documented in the official work procedures, contribute to more resilient productivity.



(a) Simulation results of WAI. The functions' status could not recover after the variability was implemented (Category I). (b) Simulation results of WAD. The functions' status recovered after the variability was implemented (Category II).

Figure 6.4: Simulation results under the scenario of limited available time.

6.4.4 Identifying Critical Activities

In Section 6.4.3, the simulation was conducted with the WAD FRAM model, which includes all five additional functions identified as part of WAD. As a further analysis, an investigation was conducted to determine which of the five additional functions constituting WAD contribute to work performance. As the investigation methodology, a sensitivity analysis-based approach was employed, wherein the five additional functions from the FRAM model in WAD were sequentially removed, and simulations were conducted under the same simulation scenario. The results of this further analysis are presented in Table 6.1. This extended analysis also presents selective results on the variability related to time constraints, represented by the CPC “Available time,” based on insights from the interviews and focus group discussions. Thus, the simulation scenario is the same as in Section 6.4.3. The table’s left column shows the IDs of the remaining functions after removing specific functions. For example, when the “Remained functions” is “1-2-3-4,” it indicates the function “5. Manage task order” was deleted, and the other four functions, ID 1 to 4, were still activated. “None” refers to the WAI model shown in Fig. 6.2, where no additional functions were activated, and “1-2-3-4-5” corresponds to the WAD model shown in Fig. 6.3, where all additional functions were activated. The right column of the table indicates the simulation result’s category (I or II), as shown in Fig. 6.4. The definitions of

Category I and II are consistent with those in Section 6.4.3. Specifically, suppose the PAF values of each function at the end of the simulation are higher than those at the start, indicating a persistent tendency toward dysfunction; the scenario is classified as Category I. Conversely, when the PAF values of each function decrease to the same value as at the beginning of the simulation, indicating a recovery to a stable operation, the scenario is classified as Category II.

Table 6.1: Summary of the simulation results investigating the critical additional functions.

Remained functions	Category	Remained functions	Category
1-2-3-4-5 (WAD)	II	1-2	II
1-2-3-4	II	1-3	I
1-2-3-5	II	1-4	II
1-2-4-5	II	1-5	II
1-3-4-5	II	2-3	I
2-3-4-5	II	2-4	II
1-2-3	II	2-5	II
1-2-4	II	3-4	I
1-2-5	II	3-5	I
1-3-4	II	4-5	I
1-3-5	II	1	I
1-4-5	II	2	I
2-3-4	II	3	I
2-3-5	II	4	I
2-4-5	II	5	I
3-4-5	II	None (WAI)	I

According to Table 6.1, the simulation results are classified as Category II even when one or two additional functions (ID 1 to 5) were deleted. These results suggest that the ability to recover work performance from the impact of variability related to time constraints is not achieved by any one of the five additional functions individually. When three of the five additional functions are removed, leaving only two, the system becomes unable to withstand the effects of variability in some cases, causing the simulation results to shift to Category I. Table 6.1 shows that when two or more additional functions with IDs 1, 2, 4, and 5 were activated, the simulation results were Category II. An exception occurs with the combination of functions 4 and 5, which still results in Category I. In this case, the simulation result shifts to Category II when function ID 3 is additionally activated. These results suggest that while functions ID 1, 2, 4, and 5 do not individually contribute to operational resilience, combining two or more functions proves effective in maintaining performance under variability.

6.4.5 Assessing Findings from the FRAM Analysis

The correspondence between the analysis results using FRAM and the knowledge from the worksite was discussed to assess the research findings in the focus group. The discussion was primarily based on the relationships shown in Table 6.2, which indicate which workers possess the characteristics corresponding to the additional functions identified in WAD. In the table, check marks are placed on the items for which workers indicated in interviews that they practice those behaviors in their daily work.

Table 6.2: Correspondence between worker and WAD additional functions.

Function	Expert A	Expert B	Mid-level C	Mid-level D	Novice E
1	✓	✓	✓		✓
2	✓	✓		✓	
3		✓	✓	✓	
4		✓	✓		
5	✓	✓	✓	✓	✓

The first insight gained from the discussion is that the combination of additional functions contributing to operational resilience, “1. Place the wafer on the jig” and “2. See metronome and stopwatch,” are characteristics possessed only by the two experienced workers, A and B. “1. Place the wafer on the jig” refers to aligning the orientation of the wafer with the jig, while “2. See metronome and stopwatch” involves managing the time the wafer is submerged in the chemical solution using a metronome and stopwatch. Both functions are related to ensuring the quality of uniform etching on the wafer surface. During the focus group, the managers suggested that the skilled workers achieve high-quality etching by implementing these two techniques. The wafer measurement results conducted previously have shown that experienced workers tend to have less variance in the depth and width of etching across the wafer surface, which aligns with the results of the FRAM analysis in this study.

The second insight gained from the discussion is that all workers possessed either the combination of additional functions (1, 5) or (2, 5). This feature is also related to the work teams: members of the first team, consisting of workers A, C, and E, had the combination of “1. Place the wafer on the jig” and “5. Manage task order” while members of the second team, consisting of workers B and D, had the combination of “2. See metronome and stopwatch” and “5. Manage task order.” While additional functions ID 1 and 2 relate to improving etching quality, the function “5. Manage task order” improves etching efficiency by reducing the time required to process multiple

wafers. In the focus group, it was suggested that workers complete etching even under tight time constraints by applying techniques that address both quality and efficiency in their work. Thus, the findings from the FRAM analysis, which indicated that specific combinations of additional functions within the WAD FRAM model contribute to resilient performance under time-constrained conditions, were validated through focus group discussions with on-site staff, confirming their correspondence with practical know-how.

6.5 Discussion

The present study proposed an approach to extract workers' knowledge by comparing WAI and WAD. This approach is grounded in the Safety-II concept, which suggests workers in socio-technical systems adjust their work to meet on-site demands and deal with uncertain situations, leading to performance variability [39]. As a result, discrepancies arise between WAI, as typically described by work guidelines, and WAD, as performed in the field. While safety management approaches based on Safety-II aim to reconcile the gap between WAI and WAD to improve system safety, this study focused on extracting the skills and knowledge that workers have developed on-site. For this purpose, this study adopted FRAM, a framework proposed under the Safety-II paradigm. Unlike conventional knowledge management approaches, which primarily focus on modeling and storing the extracted knowledge, this study used FRAM-based simulations to analyze workers' adaptive skills to cope with variabilities. Taking this approach made it possible to model and analyze the adaptive skills of workers dealing with disturbances, which have been beyond the scope of the previous approach.

This study applied the proposed approach to the etching process in semiconductor manufacturing to demonstrate its practical application. As a result, several techniques commonly practiced by multiple workers but are not described in the work guidelines were identified. This finding aligns with the "Approximate adjustment" principle in FRAM, which suggests that workers adjust their work in response to on-site demands, leading to discrepancies between WAI and WAD. These discrepancies are not considered negative deviations from standard procedures but rather positive adjustments made to perform the tasks more efficiently and safely [87]. Additionally, as shown in Table 6.2, deviations from the work guidelines were more frequently observed in experienced workers than in novices. This trend can be attributed to

workers becoming more adept at flexibly adapting to on-site needs as they gain more experience.

A notable finding from the FRAM analysis is that the additional functions identified as part of WAD do not individually contribute to operational resilience. Instead, when multiple functions are activated together, they significantly enhance the system’s capacity to cope with time-strict conditions. Table 6.1 demonstrates that when two or more of the functions ID 1, 2, 4, and 5 are activated in combination, the simulation results shift toward Category II (recovery from variability). This outcome aligns with the principle of “Functional resonance” in FRAM, illustrating how the combined capabilities of multiple functions contribute to the safe execution of tasks. This emergent property is challenging to capture through traditional knowledge management or systematic methodologies based on Safety-I. In particular, the combination of additional functions ID 1, 2, and 5 was related to the Efficiency-Thoroughness Trade-Off (ETTO) principle proposed by Hollnagel [60]. This principle suggests that human performance is always governed by a trade-off between efficiency, which prioritizes throughput, and thoroughness, which emphasizes safety and quality. In this case study’s FRAM model, the functions “1. Place the wafer on the jig” and “2. See metronome and stopwatch” were associated with the thoroughness of the task focusing on quality, while “5. Manage task order” was related to efficiency, emphasizing the management of task sequence. In this case, the workers have combined functions related to efficiency and thoroughness to execute tasks even when resources such as time are limited. A novel contribution of this study is the ability to reveal workers’ behavior corresponding to the ETTO principle within a socio-technical system by utilizing a semi-quantitative simulation method. These aspects were revealed through FRAM, which focuses on the emergent effects of functional couplings.

The FRAM model developed in this study can be discussed in relation to metacognition. As outlined in Section 2.2, the metacognitive control process—crucial for managing one’s cognitive activities—relies on three core skills: planning, monitoring, and evaluation. Specifically, planning involves allocating cognitive resources and selecting strategies, monitoring refers to overseeing the execution status of one’s cognitive activities, and evaluation includes assessing one’s cognitive activities. The functions identified in the FRAM model as WAD are connected to these skills. For example, the additional functions “4 Monitor wafer” and “3 Understand etching reaction” correspond to monitoring the status of one’s work and adjusting performance based on evaluation. Also, the additional function “5 Manage task order” aligns with allocating temporal resources to execute tasks efficiently. These adaptive actions, emergent in

response to real-world demands, indicate that the metacognitive control process can somewhat explain the WAD behavior. This finding demonstrates how metacognitive strategies contribute to the adaptive expertise necessary for addressing variability in dynamic work environments.

This study adopted a semi-quantitative approach using simulations in addition to the traditional qualitative methods for validating the FRAM model. While it is common to validate FRAM models qualitatively through expert interviews and focus groups, these approaches require significant time and resources [63]. Recently, the development of semi-quantitative methods that integrate FRAM with other approaches has gained traction [80, 135], offering the potential to make research more manageable. This study employed an approach in which the WAD-based FRAM model was incrementally modified and comprehensively simulated to explore functions critical to workers' knowledge. Following this exploration, focus group discussions with work managers were conducted to validate whether the identified functions aligned with the practical know-how of the workers. This approach identified the importance of functional resonance involving multiple functions. These results demonstrate that FRAM models exhibit strong non-linearity due to functional resonance and emergent properties, necessitating an exploratory approach using comprehensive simulations to validate the model effectively. These findings present a new option for validating FRAM models.

The proposed approach is applicable to a wide range of tasks involving workers in socio-technical systems. Thus, it is expected to contribute to revising work procedures, enhancing safety management, and improving worker training in various domains. Although the performance variability corresponding to discrepancies between WAI and WAD is vital for the safe operation of systems in the Safety-II concept, it also poses a risk of safety hazards and quality degradation due to variations in working conditions among workers [70, 76]. The proposed approach can contribute to revising work procedure documents for task standardization by assessing the impact of discrepancies between WAI and WAD on system safety. This perspective is also relevant to system safety management, as understanding how front-line workers adapt their behavior regarding discrepancies between WAI and WAD is crucial for safety management within the Safety-II framework [89, 104]. Furthermore, the proposed approach is valuable for training support, as it helps identify which adaptive behaviors of workers contribute to task performance, thereby suggesting priority items to be taught during worker training. These adaptive behaviors have conventionally relied on tacit knowledge gained through long experience. However, by treating these

adaptive actions as additional functions in the FRAM model, this approach can also contribute to the elucidation of tacit knowledge. Also, when combined with efforts to improve workers' non-technical skills, it is expected to enhance worker training methods effectively [85].

A limitation of this study is that WAD for multiple workers is represented in a single FRAM model, leading to an abstract representation of the additional functions in WAD. An analysis focused on each worker would also be necessary to apply the proposed approach to individual worker training. Additionally, the number of participants in the case study was limited. Recruiting more participants and conducting validation in other domains will be necessary to demonstrate the proposed approach's effectiveness. Moreover, in the FRAM simulation phase, the types of analyzed CPCs were limited, indicating the need for further analysis covering the diverse variability in the work environment.

6.6 Brief Summary

This study proposed a FRAM-based approach to extract workers' tacit knowledge by comparing WAI and WAD in manufacturing tasks. A case study was conducted on the etching process in semiconductor manufacturing to demonstrate the practicality of the proposed approach. A FRAM model of WAI was constructed based on a review of work procedure documents and focus group discussions with managers. In contrast, a FRAM model of WAD was developed through worker interviews. Five differences between the two FRAM models were identified, and the impact of each difference on work performance was evaluated through comprehensive simulations. The results revealed that specific combinations of additional functions in WAD contributed to the resilience of the work. Some of these combinations were interpreted through the FRAM principles. The proposed approach holds significant potential to contribute to revising work procedures, enhancing worker education, and improving safety management.

Chapter 7

Conclusion

This study aimed to elucidate the adaptive expertise of workers to enhance resilient performance in production systems. Adaptive expertise refers to the ability to respond flexibly to various fluctuations and unexpected situations in the work environment, contrasting with routine expertise, characterized by executing tasks quickly and accurately according to prescribed procedures. This adaptive capability is typically acquired as tacit knowledge through years of experience, making it challenging to identify using conventional methods. This study adopted a novel approach based on FRAM to address this issue. FRAM has been developed within the resilience engineering framework, a new paradigm in safety management. Unlike Safety-I, which focuses on identifying accident causes by breaking down a system into individual components, resilience engineering is grounded in Safety-II. Safety-II emphasizes factors that contribute to the successful everyday operation of a system, with a focus on enhancing resilience. This approach centers on human adaptive adjustment capabilities as critical factors that enable systems to operate safely under everyday conditions. Recognizing that FRAM has been widely used to analyze adaptive human behavior in this context, the present study applied FRAM to shed light on the adaptive expertise of workers within production systems.

This paper comprises three chapters to achieve this objective. Chapter 4 focuses on attention allocation in multitasking scenarios—a critical aspect of adaptive expertise—and demonstrates this in the context of steel plate processing tasks. In order to extract the attention management characteristics of skilled workers, this research adopted an approach based on a functional structure that represents the relationship between distal and proximal terms in tacit knowledge. This approach integrates eye-tracking analysis and interview data through FRAM, allowing analysts to capture distinctions between skilled and mid-level workers. In the FRAM model, these

differences were represented by a function that centrally manages attention allocation. Chapter 5 expands the analysis to scenarios where multiple factors concurrently impact worker performance, using quality inspection work on an engine assembly line as a case study. Through qualitative data collection and semi-quantitative simulation based on FRAM, this study identified critical factors that significantly affect task performance. Furthermore, the findings demonstrate that the resilience capabilities of skilled workers contribute to stable performance across a broader range of scenarios. Chapter 6 proposes a systematic method for extracting adaptive skills from workers, validated in the context of etching tasks within semiconductor manufacturing. This approach is based on comparing Work-as-Imagined and Work-as-Done, a key concept in Safety-II. This study presents a method for systematically capturing workers' knowledge by iteratively modifying the FRAM model identified as Work-as-Done and conducting comprehensive simulations.

A key theme common to these research findings is the connection to metacognition. Metacognition, a concept originating in educational psychology, refers to knowledge about one's own cognitive processes. Specifically, the ability to regulate one's cognitive activities, known as the metacognitive control process, involves three core skills: planning, monitoring, and evaluation. Across the three chapters of this paper, it has been demonstrated that the distinguishing features of skilled workers' FRAM models are not related to the basic procedural functions of tasks but rather to functions associated with metacognitive processes. These functions align with the ability to monitor environmental changes, evaluate one's own performance, plan strategies, and efficiently allocate resources such as attention and time. It is suggested that skilled workers have developed these metacognitive abilities through extensive experience, enabling them to adapt to changes in their work environments. This metacognitive framework thus underpins the adaptive expertise that characterizes skilled performance in complex, dynamic production settings.

As a future work, this study is expected to support skill transfer in the manufacturing industry. By modeling adaptive expertise and dynamically simulating responses to environmental changes, the study aimed to provide a deeper understanding of essential aspects of workers' adaptive behavior. In particular, the work presented in Chapter 6 successfully extracts practical know-how for actual manufacturing tasks and allows for envisioning the impact of this expertise through simulation. This capability could help prioritize training items or select critical points for inclusion in task manuals, enhancing the effectiveness of worker training. At the same time, these contributions to worker training are positioned as a direction for future research

work. In order to enable broader applications of FRAM, it will also be essential to develop standardized methods for constructing and analyzing FRAM models. Such advancements could make the process more accessible and consistent across different contexts, further enhancing FRAM's utility in complex production environments.

Appendix 1: Semi-structured interview questions

- What information do you base your decisions on when centering?
- Which of the information do you consider the most important? Please list them in order of importance.
- How much attention do you pay to the cleanliness of the coil winding?
- When inserting, do you only focus on aligning the laser line with the edge of the plate?
- What is the typical relationship between the laser line and the right edge of the plate?
- How do you maintain the target position when centering the plate?
- During centering, does the target position ever change? If so, how do you make that decision?
- Does the operation change depending on the type of plate?
- Are there any types of plates that are difficult to handle? How did you learn to manage them?
- Do you have any failure stories from past centering attempts? What was wrong with those failures?
- From the information in question 1, are there any choices that you feel are deeply related and interact with each other?
- Do you ever predict the movement of the plate?
- Are you only looking at the current state of the plate, or do you also consider the conditions it has been through?
- For example, during the trimming process, are there things you visualize in your mind that you can't directly see, like the position of the steel plate?
- Do you ever watch others work? If so, do you ever think there are better ways they could be doing their tasks?
- Does having a clear view of the trimming on the monitor help with centering?

- Does the width or thickness of the plate make centering more difficult?- Is the centering quality judged by how well the edges of the steel plate are cut?
- What does an ideal edge of a steel plate look like?

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その他の講演

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受賞

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- [27] 第 22 回計測自動制御学会システムインテグレーション部門講演会 (SICE SI2021) 優秀講演賞 (2021 年 12 月)
- [28] ヒューマンインタフェース学会 第 22 回学術奨励賞 (2022 年 3 月)
- [29] 2021 年度 日本機械学会三浦賞 (2022 年 3 月)
- [30] 第 66 回システム制御情報学会研究発表講演会 (SCI'22) SCI 学生発表賞 (2022 年 5 月)
- [31] 令和 4 年度 馬詰研究奨励賞 京都大学大学院工学研究科 (2022 年 7 月)

- [32] 令和 4 年度 工学研究科長賞 京都大学大学院工学研究科（博士フォーラムへの貢献）
（2023 年 3 月）
- [33] 2023 年度 システム制御情報学会 学会賞奨励賞（2023 年 5 月）
- [34] ヒューマンインタフェース・ステップアップキャンプ 2024 優秀発表賞（2024 年 3 月）
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- [36] 一般財団法人森記念製造技術研究財団 後期博士課程支援 給与奨学金および研究諸掛
- [37] 京都大学教育研究振興財団 令和 5 年度 国際研究集会発表助成