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FRAM-PSO: A semi-quantitative framework integrating multi-dimensional sustainability criteria

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ABSTRACT

The increasing complexity of modern industrial systems, particularly those integrating smart wearables, makes it harder for traditional risk analysis methods to keep up. Systemic approaches such as the Functional Resonance Analysis Method (FRAM) help to understand how systems behave; however, there is an opportunity to develop more reliable quantification methods and integrate sustainability criteria, which current methods often do not emphasize. To address these gaps, this paper introduces a novel semi-quantitative framework that integrates FRAM with the Particle Swarm Optimization (PSO). This hybrid approach provides a structured methodology to systematically identify system functions, quantify performance variability, and model risk propagation. A key contribution is the explicit integration of multi-dimensional sustainability criteria (environmental, economic, and social) into the risk management process. This allows for the selection of optimized mitigation strategies. Three case studies involving smart wearables in assembly and disassembly systems were used to demonstrate the effectiveness of the proposed methodology. The results showcase the model's ability to identify high-risk pathways and prioritize mitigation efforts. This confirms its potential as a decision-support tool. This study contributes a novel methodological structure for embedding sustainability and optimization into systemic risk management.

1. Introduction

The increasing complexity of Industry 4.0 systems challenges (Aniceski et al., 2024; Zheng & Liu, 2025) the efficacy of traditional risk assessment methods (Berx et al., 2022), driving the adoption of systemic approaches that analyze how entire systems function rather than focusing solely on component failures (Karevan & Nadeau, 2024b; Read et al., 2021). Among prominent systemic methods like STAMP (System Theoretic Accident Model and Process) and AcciMap (Accident Causation, Consequence, and Investigation Mapping Process), FRAM has gained significant popularity for its ability to model non-linear interactions and performance variability in complex sociotechnical systems (Bellini et al., 2019; Hollnagel, 2012; Karevan & Nadeau, 2024c; Patriarca et al., 2020). In systemic models, STAMP, FRAM, and AcciMap are some of the most commonly referenced (Moslem et al., 2025; Yousefi et al., 2019).

FRAM is widely applied in aviation, healthcare, and industrial processes and accounts for over half of the published studies on the method (Patriarca et al., 2020). Beyond these fields, FRAM has also been popular and used in maritime operations (Salihoglu & Beşikçi, 2021), offshore drilling (França et al., 2021), coal mine accidents (Qiao et al., 2019), and software engineering (de Carvalho et al., 2021). While FRAM is typically used in high-risk industries, it has also been found to be relevant in manufacturing (Melanson & Nadeau, 2019). It provides valuable qualitative insights into system resilience and potential hazards.

However, FRAM's inherently qualitative nature presents limitations when precise risk quantification is needed. Recognizing this, researchers have explored various quantitative extensions (Patriarca et al., 2020). Monte Carlo Simulation (MCS) is the most common, particularly in oil and gas (Yu et al., 2025), healthcare (Kaya & Hocaoglu, 2020; Zhou et al., 2023), transportation (Kaya et al., 2021), aviation (Patriarca, Di Gravio, & Costantino, 2017), manufacturing (Costantino et al., 2018), offshore wind farms (Köpke et al., 2020), marine industry (Peng et al., 2022), due to its ability to model uncertainty. As demonstrated by Patriarca, Di Gravio, and Costantino (2017), the primary strength of the FRAM-MCS approach is diagnostic risk analysis. It uses simulation to generate a probability distribution of risk (the VPN) to identify which parts of a system are most likely to become critical.

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Beyond simulation, other prominent quantitative extensions have focused on probabilistic modeling and structured decision-making. Bayesian Networks (BN) and Dynamic Bayesian Networks (DBN) are also widely applied in the construction (Wang et al., 2023), marine (Guo et al., 2023), gas pipeline industry (Zhang et al., 2022), oil and gas industry (Bahoo Toroody et al., 2017), and chemical industries (Zinetullina et al., 2021) for predictive risk assessment. Their strength lies in dynamic resilience assessment and tracking system performance over time. The Analytic Hierarchy Process (AHP) is frequently used in construction (Haddad & Rosa, 2015; Rosa et al., 2017, 2020), the oil and gas industry (França et al., 2020), and socio-technical systems (de Carvalho et al., 2016) for structured decision-making. Additionally, newer approaches like fuzzy logic rough sets (Slim & Nadeau, 2019), reinforcement learning (Salehi et al., 2022), and genetic algorithms (Patriarca et al., 2025) are emerging, signaling a shift toward AI-driven risk analysis in complex systems from diverse industries.

While these methods provide powerful tools for risk analysis, they are primarily diagnostic. Techniques like MCS and DBN allow the identification of the parts of a system that are most at risk, but they do not inherently guide the selection of optimal interventions. This challenge is particularly relevant in modern industrial environments where processes like assembly and disassembly involve intricate interactions between humans, machines, advanced robotic systems (Torres et al., 2022), and smart wearable technologies (Karevan & Nadeau, 2024a). While wearables, such as smart gloves and glasses, have benefits for maximizing efficiency and safety, a systematic understanding and quantification of the risks associated with their deployment is lacking in the literature (Karevan & Nadeau, 2023). Prior work has initiated qualitative analysis using FRAM/STPA (Mofidi Naeini & Nadeau, 2023) and quantitative assessment via STPA-PSO for specific wearables (Karevan & Nadeau, 2024a, 2025), highlighting the need for more integrated and comprehensive systemic approaches.

This paper addresses this gap by proposing a hybrid methodology that moves beyond risk analysis to prescriptive risk optimization. Our contribution is a novel framework that integrates three distinct elements:

- Systemic Modeling (FRAM): Capturing the non-linear interactions and functional resonance of complex systems.
- Automated Optimization (PSO): Moving beyond simulation to actively search for and identify the most effective mitigation strategies from a predefined set of options.
- Integrated Sustainability Criteria: Explicitly embedding environmental, economic, and social factors as core objectives within the optimization process, a dimension largely absent from prior quantitative FRAM literature.

The FRAM-PSO method is designed to systematically identify, quantify, and guide the mitigation of risks within complex industrial processes that incorporate smart wearables. To clarify its unique contribution, a comparative analysis of this method against other quantitative FRAM methodologies is summarized in Table 1. This work therefore contributes a novel framework specifically designed for sustainability-driven, multi-objective risk optimization, filling a gap between purely diagnostic risk analysis models and single-objective optimization approaches. By applying this integrated framework, we anticipate the establishment of a feedback loop that continuously enhances sustainability and reduces system risk over time. We believe this work establishes a foundation for future research aimed at promoting more sustainable and resilient industrial practices.

The remainder of this paper is organized as follows: Section 2 details the FRAM-PSO methodology. Section 3 presents the case studies. Section 4 outlines the results. Section 5 discusses the findings and limitations. Section 6 provides conclusions and future studies.

2. Methodology

This study uses FRAM to identify and analyze the system's risks, and PSO is added to effectively quantify, mitigate, and improve the identified risks. The FRAM analysis process typically includes four key steps: defining the functions within the system, analyzing the variations in how each function performs, exploring the relationships and interactions among functions, and developing methods to observe and regulate these variations (Sujan et al., 2025).

However, before proceeding, it is essential to define the primary objective of the study, whether it is an accident investigation or a system risk assessment, commonly referred to as Step 0 (Patriarca, Di Gravio, & Costantino, 2017). In this case, the analysis focuses on assessing the system's risk.

The next steps are outlined below and illustrated in Fig. 1. The figure presents the FRAM-PSO framework, illustrating the sequence of steps involved. It distinguishes between steps requiring human input from the decision-making team and steps processed by the intelligent algorithm (PSO). The diagram also highlights which elements build upon previous studies and pinpoints the specific contributions introduced in this paper. The entire framework is encompassed by a green border, visually emphasizing the ultimate objective: to improve system performance and sustainability.

2.1. Identification and description of the system's functions

Each function can be described through six key attributes: Input (function trigger), Output (function results), Precondition (actions to be considered or prepared), Resource (consumable resources), Control (any instruction that control the function), and Time (time requirements) (Kaya & Hocaoglu, 2020; Qiao et al., 2022). Also, these functions can be categorized into foreground functions and background functions. Foreground functions are central to the analysis and require a definition of all six aspects whenever feasible. In contrast, background functions are outside the scope of the analysis and only require a definition of either

Table 1
Comparative analysis of quantitative FRAM methodologies.

Feature	FRAM-MCS (Patriarca, Di Gravio, Costantino, et al., 2017)	FRAM-GA (Patriarca et al., 2025)	FRAM-DBN (Zhang et al., 2022)	FRAM-PSO (This study)
Primary goal	Risk analysis (diagnostic)	Cost optimization (single-objective)	Resilience modeling (dynamic)	Risk optimization & decision support (multi-objective)
Core engine	Monte Carlo Simulation	Genetic Algorithm	Dynamic Bayesian Network	Particle Swarm Optimization
Primary output	Probability distribution of risk (VPN)	Cost-effective maintenance plan	System performance profile over time	An optimal sequence of mitigation strategies balancing risk and sustainability
Handling of mitigations	Manual, post-analysis task	Optimized based on cost	Modeled as events in a timeline	Automatically selected and sequenced based on both risk reduction and sustainability scores
Sustainability integration	Not included	Not included	Not included	Explicitly integrated as a core, multi-dimensional component of the optimization objective.
Key question answered	Which parts of my system are most at risk?	What is the cheapest way to schedule maintenance?	How will my system's performance evolve during an incident?	What is the best sequence of actions to reduce overall risk in a sustainable way?

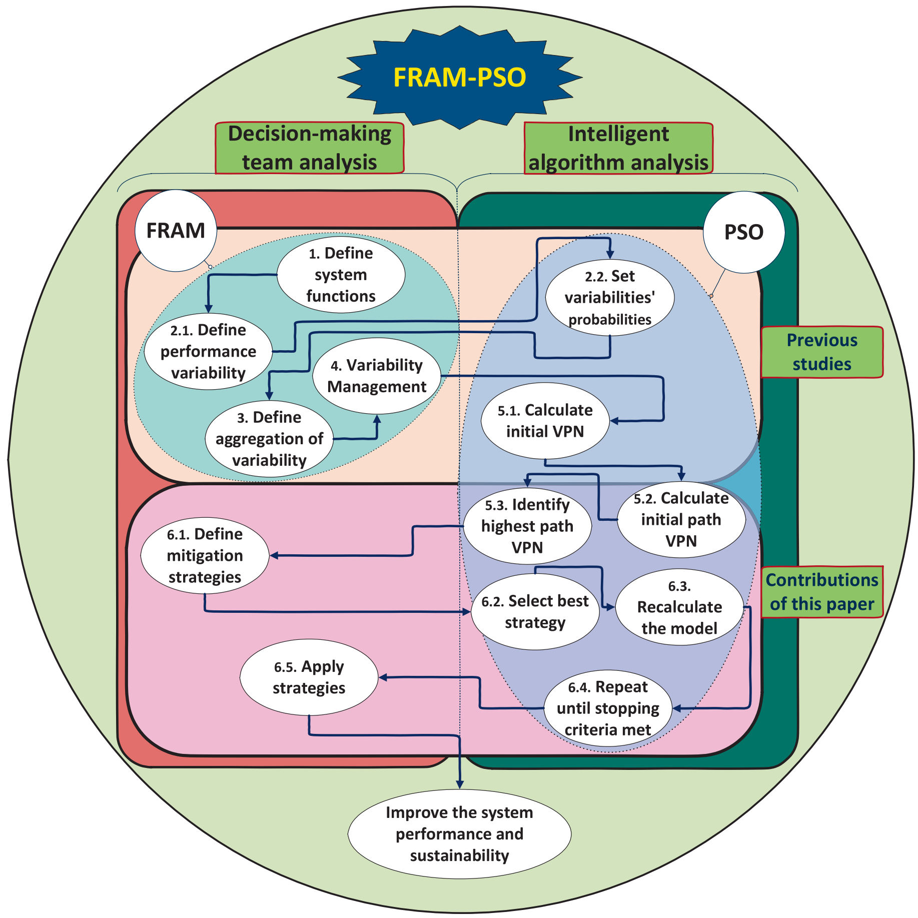

Fig. 1. Methodology process.

one input or one output (Patriarca, Di Gravio, & Costantino, 2017). Identifying background functions helps clarify how different parts of the system interact and affect overall performance and reliability. This distinction allows analysts to focus on key functions while still considering the broader system. The specifications of FRAM functions can be visually represented using a Functional Model Visualizer (FMV) (Mofidi Naeini & Nadeau, 2022). This step is also the first (1) step demonstrated in Fig. 1.

2.2. Identification of performance variability

This step involves analyzing function variability specific to each risk scenario by creating instances of the FRAM model. This includes identifying potential variability under different conditions and examining actual variability in each instance (Kim & Yoon, 2021). Variability in a function can arise due to its connection with upstream functions, where changes or fluctuations in upstream outputs can directly impact the performance and behaviour of downstream functions (Rosa et al., 2015). Function variability arises from three main sources: internal (changes within the function), external (influences from the work environment), and coupling (effects from upstream functions). Understanding these factors helps explain why function outputs differ (Kim & Yoon, 2021).

Variability can be categorized into several types based on characteristics such as timing, precision, speed, distance, sequence, object, force, duration, and direction (Zinetullina et al., 2021). However, most researchers simplify the approach by focusing primarily on timing and precision (Kumar et al., 2024), such as those by (Kaya & Hocaoglu, 2020; Kaya et al., 2021; Mofidi Naeini & Nadeau, 2023; Patriarca, Di Gravio, & Costantino, 2017; Slim & Nadeau, 2019; Yu et al., 2025; Zinetullina et al., 2021).

In this work, we focus on assembly and disassembly operations, where time, precision, force (exerted by the worker), and sequence are key factors. These were selected as they directly map to the primary failure modes and performance enhancements associated with the use of smart wearables in manual tasks. For instance, smart glasses provide visual cues that directly influence the sequence of operations, while smart gloves provide haptic feedback affecting the force and precision of handling components. Time is a critical overarching factor in production line efficiency. Given their interdependence and impact on overall performance, we consider them for further analysis. Table 2 shows the variability values for each characteristic considered in this study.

OV_j is the variability of the upstream output j, which is calculated by equation (1).

Table 2
Proposed variability values.

Characteristic	Variability	Value
Time (V_t)	Too early	1
	On-time	2
	Too late	3
	Not at all	4
Precision (V_p)	Precise	1
	Acceptable	2
	Imprecise	3
	Wrong	4
Force (V_f)	Too low	1
	On Target	2
	Too high	3
	Not at all	4
Sequence (V_s)	Correct order	1
	Wrong order	2

$$OV_j = V_j^T * V_j^P * V_j^F * V_j^S \tag{1}$$

Where V_j^T, V_j^P, and V_j^F represent the variability in timing, precision, and force, respectively, while V_j^S accounts for sequence variability. This equation provides a systematic approach to quantifying how these variations collectively influence system outputs. To improve the reliability of the results, an occurrence probability vector is introduced for each output, considering its timing, precision, force, and sequence.

Since simulated data are used in this study, MCS will be used to estimate the probability distribution of the outputs, which can be used in the design phase analysis; however, in the running cases, the past behavior of these variabilities should be considered. Table 3 provides an example of a probability distribution for a randomly selected function.

2.3. Aggregation of variability

The aggregation of variability is a crucial aspect of analyzing the functional relationships within a system. By using FRAM, the interplay among system functions is graphically modelled to reveal how the variability of upstream functions propagates downstream (Kaya & Hocaoglu, 2020). This variability arises from a combination of a function's inherent characteristics and the input it receives from upstream functions (Patriarca, Di Gravio, & Costantino, 2017). When the variability from upstream functions amplifies, it can create resonant effects within the system, potentially leading to critical paths or cascading failures (Zinetullina et al., 2021).

Examining these couplings highlights the dual nature of variability's impact. On one hand, negative variability can resonate across interconnected functions, magnifying system risks and identifying critical areas of concern, such as accident precursors or key contributors to hazards. On the other hand, positive variability can serve as a stabilizing force, mitigating downstream variability and enhancing system resilience (Zinetullina et al., 2021). A comprehensive understanding of these dynamics is essential for identifying critical couplings and assessing how variability propagates through the system, ultimately improving risk management and system performance (Yu et al., 2025).

The values for these factors, presented in Table 4, were chosen based on their proven reliability in previous studies (Kaya & Hocaoglu, 2020; Kaya et al., 2021; Mofidi Naeini & Nadeau, 2023; Patriarca, Di Gravio, & Costantino, 2017; Slim & Nadeau, 2019; Yu et al., 2025; Zinetullina et al., 2021). Using established values ensures consistency and enables meaningful comparisons with other studies. These parameters could be varied according to each system and industry. The parameters α_{ijn}^T, α_{ijn}^P, α_{ijn}^F, and α_{ijn}^S represent the effect of output n from upstream function j on downstream function i, in terms of time, precision, force, and sequence, respectively. These factors are incorporated to assess their impact on the overall system performance. To quantify the overall impact of timing, precision, force, and sequence on system performance, we define the cumulative interaction effect (CI_{ij}), as demonstrated in equation (2).

$$CI_{ijn} = \alpha_{ijn}^T * \alpha_{ijn}^P * \alpha_{ijn}^F * \alpha_{ijn}^S \tag{2}$$

Table 3
Example of the probability distribution for the variability output of a function.

Characteristic	Too Early / Acceptable / Too Low	On-Time / Precise / On-Target/ Correct Order	Too Late / Imprecise / Too High	Not at All / Wrong
Time (V_t)	0.08	0.80	0.09	0.03
Precision (V_p)	0.15	0.75	0.08	0.02
Force (V_f)	0.20	0.65	0.14	0.01
Sequence (V_s)	–	0.90	–	0.1

Table 4
Damping and amplifying factor values.

Effect type	Value
Damping effect	0.5
No effect	1
Amplifying effect	2

2.4. Management of variability

Managing variability focuses on amplifying positive outcomes and minimizing negative ones by addressing critical couplings identified through functional resonance analysis (Patriarca et al., 2025). Improvement measures aim to prevent accidents or restore the system to optimal functionality in case of disruptions (Zinetullina et al., 2021).

After analyzing the core performance characteristics, the next step is to integrate the influence of external operating conditions on the system's performance. This involves defining a set of Scenario Performance Conditions (SPCs) that capture various internal and external factors, such as environmental influences (e.g., temperature, lighting), equipment reliability, workload variations, etc., that may affect overall performance.

For each function within the system, the impact of each SPC is evaluated by assigning an impact rating, where a value of 1 indicates a high impact, a value less than 1 indicates a moderate impact, and 0 indicates no impact. This method creates a clear relationship between external conditions and the system's functions. These values should be assessed by the decision-making team based on the past system behavior. In a practical application, ensuring the reliability of these subjective inputs would be critical. In a practical application, these values would be established through structured workshops with domain experts, leveraging techniques like pairwise comparison or direct rating scales to ensure consistency and justification for the assigned weights (Afnor, 2024; O'Hagan et al., 2006). Furthermore, prior to integrating assigned impact ratings into the model, calculating inter-rater reliability scores among experts, such as Cohen's kappa or intraclass correlation, is essential to validate the consistency and robustness of their judgments to ensure alignment with structured elicitation protocols (O'Hagan et al., 2006).

Once the influence of the SPCs on the functions is established, distinct operating scenarios are defined by assigning specific ratings to each SPC. Each scenario is characterized by a particular combination of performance condition effects. Decision makers must identify the most critical scenarios which can influence the system. The overall effect of a scenario on a given function is determined by summing the weighted contributions of each SPC, as shown in Equation (3).

$$e_j^z = \sum_{k=1}^{m} SPC_z^k * b_j^k \tag{3}$$

Here, e_j^z is the conditional variability of function j under scenario z, SPC_z^k denotes the rating of the k^{th} condition in scenario z, and b_j^k represents the impact of the k^{th} condition on function j. If a function is not influenced by any external condition (i.e., all b_j^k equal zero), the variability is considered a baseline value of 1 (Patriarca, Di Gravio, & Costantino, 2017).

2.5. Quantifying the risks

The index for each coupling, Variability Propagation Number (VPN) can be derived from equation (4). This index combines the inherent variability of the upstream function j (OV_j), the cumulative interaction effect between upstream and downstream functions (CI_{ij}), and the conditional variability e_j^z, which represents how external factors in scenario z influence the system's performance. By incorporating these elements, this equation provides a detailed and dynamic measure of the coupling's variability, capturing internal performance fluctuations and the effects of external operating conditions.

$$VPN_{ij}^{z} = OV_j{}^{*}CI_{ij}{}^{*}e_j^z \tag{4}$$

In the next step, the data collected through FRAM will be used to apply the PSO algorithm, providing a structured and systematic way to quantify the model. PSO is inspired by the movement of swarms in nature, where candidate solutions are represented as particles navigating a multi-dimensional search space. Each particle has a position $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, a velocity $V_i = (v_{i1}, v_{i2}, \cdots, v_{id})$, and a personal best position $P_i = (p_{i1}, p_{i2}, \cdots, p_{id})$. The algorithm continuously updates each particle's velocity and position to move toward an optimal solution. The velocity update follows equation (5) (Karevan & Vasili, 2018; Marini & Walczak, 2015).

$$V_k(i+1) = V_k(i) + c_1 r_1 \left(P_{best,i}^{k} - X_k(i)\right) + c_2 r_2 \left(g_{best,i} - X_k(i)\right) \tag{5}$$

This update consists of three components: momentum, which helps maintain previous velocity for smoother movement; cognitive influence, which pulls the particle toward its own best-known position; and social influence, which directs the particle toward the global best solution found by the swarm. Once the velocity is adjusted, the particle's new position is calculated as equation (6) (Karevan et al., 2020; Lalwani et al., 2013).

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{6}$$

To initialize the algorithm, the variability values of each output ($V_j^T, V_j^P, V_j^F, V_j^S$) are first defined. Then, the relationships between outputs, including upstream and downstream dependencies, are mapped, creating function paths. A Monte Carlo Simulation is employed to estimate the occurrence probability of each output under four different variabilities. Based on these probabilities, the OV of each output is calculated (Eq.1).

Next, damping and amplifying factors are assigned, applying specific weighting factors to variability aspects such as timing, precision, force, and sequence based on predefined conditions (Eq.2). In real-world applications, these weighting factors can be determined through empirical data analysis, expert elicitation, or human factors and ergonomics (HF/E) assessments. Decision-makers identify the most influential factors by conducting task analyses, observational studies, and data-driven risk assessments. Since this approach relies on measurable inputs and systematic evaluation, it can be readily applied in real-world cases, allowing decision-makers to adjust the factors dynamically to reflect actual operational conditions.

Following this, various SPCs and external influence factors e_j^z are considered. Using these inputs, the VPN is calculated for each function, followed by the computation of the path VPN based on the summation of downstream functions for each function. Then, the initial high path VPN is determined, leading to the identification of the critical path. The objective function is to minimize the path VPN, which results in minimizing the VPN for each function.

2.6. PSO implementation and parameters

For the results presented in this paper, the PSO algorithm was implemented with the following parameters, chosen based on common practices in the literature to ensure stable convergence. The swarm size was set to 50 particles for 500 iterations. An inertia weight (w) was used, linearly decreasing from 0.9 to 0.4 over the course of the iterations, to balance global and local search. The cognitive and social coefficients (c1 and c2) were set to 0.9 and 1.5, respectively. The decision vector for each particle represented a potential set of mitigation strategies to apply.

2.7. Sustainable mitigation strategies

After identifying the highest path VPN, the next step is to systematically mitigate it by selecting sustainable strategies (alternatives). Depending on each case study and industry, decision-makers may identify various sustainable mitigation strategies. These strategies must consider three main pillars of sustainability. Economically, manufacturers can improve cost efficiency through automation and lean practices (Hasanain, 2024), reduce operational costs via process innovation (Martín-Gómez et al., 2024), and simplify assembly processes to minimize downtime while recovering valuable components for cost savings (Machado et al., 2020). Environmentally, initiatives include boosting energy efficiency with energy-efficient machinery and smart systems (Jovanović & Filipović, 2016), utilizing renewable energy at facilities (Machado et al., 2020), optimizing waste reduction (Martín-Gómez et al., 2024), and lowering carbon emissions through process optimization (Foo & Tan, 2016). Socially, efforts focus on investing in employee training (Ciccarelli et al., 2023), enhancing employee satisfaction through better work environments (Hasanain, 2024), and ensuring safe working conditions (Gualtieri et al., 2021).

Decision-making teams need to determine the associated functions and SPCs for each strategy, assess the level of difficulty in implementing each strategy (feasibility), and evaluate the impact of each strategy on the system, and assess its contribution to the three sustainability pillars (environmental, economic, and social). The algorithm then selects the best strategy in each iteration, applies it to the model, and recalculates the overall risk profile from the beginning. Over successive rounds, this iterative process not only reduces high-risk outputs but also progressively transforms the entire model into a sustainable one, balancing risk reduction with long-term environmental, economic, and social benefits. The process involves:

1) Identifying the function with the maximum Path VPN.
2) Selecting the most effective available sustainable mitigation strategy from Table 9 relevant to that function's associated SPCs (with a constraint preventing the immediate re-selection of the same strategy for the same path if alternatives exist).
3) Applying the chosen strategy's impact weight within the model.
4) Recalculating all function VPNs and path VPNs.
5) Repeating the process for a predetermined number of steps (four in this study).

3. Case studies

Case studies serve as a crucial research approach, particularly when investigating complex subjects with limited prior knowledge (Rashid et al., 2019). Also, using multiple case studies allows for comparative analysis across different contexts, facilitating the identification of patterns, trends, and underlying factors that may remain undetected in a single case study. Examining operations such as assembly and disassembly across various settings enhances theoretical generalization (Karevan & Nadeau, 2025).

The case studies presented in this research were originally examined in another paper (Karevan & Nadeau, 2025) and are being reused to validate the proposed methodology. To ensure an extensive perspective, these cases represent different operational environments: an assembly line, a job shop assembly process, and a disassembly line. Each case is briefly summarized below. However, for a deeper understanding of the cases and their details, the authors recommend referring to the paper mentioned.

The first case study looks at an assembly section in a refrigerator manufacturing plant. In this setup, refrigerators move along a conveyor line, and workers perform specific tasks at each station along the way. In this particular assembly section, the worker's role involves selecting and assembling various components from bins. To assist with the task, they wear smart gloves that help with handling the parts more precisely.

Additionally, smart glasses are used to display assembly instructions, guiding the worker step-by-step through the process.

In the second case study, the focus is on a job shop assembly process where the assembler is equipped with smart glasses and smart gloves to assist with the work. The workstation is organized with a tool cabinet containing the necessary tools for the task and seven bins of required parts positioned in front of the assembler. A dolly is used to transport the assembly structure, allowing the worker to move the parts and components easily. Work instructions are accessed through a computer, guiding the assembly process.

In the third case study, the focus is on a refrigerator disassembly process, where the worker's main job is to remove parts like the refrigerant for recycling, along with the freezer door, process pipe, and dry filter. The workstation is equipped with a tool cabinet and storage bins to sort the disassembled components. The smart glasses provide step-by-step instructions, visually guiding the worker on what needs to be removed. The smart gloves help the worker apply the right amount of force and even detect hazardous components.

This combination of wearables simplifies the workflow, ensuring that workers can follow instructions accurately and efficiently while minimizing the chances of errors. The use of these technologies enhances both the speed and accuracy of the assembly and disassembly processes and also improves sorting efficiency and enables real-time communication with supervisors.

4. Results

This section details the application of the proposed FRAM-PSO methodology to assembly and disassembly processes case studies, focusing on function identification, risk assessment via VPN calculation, and the impact of targeted mitigation strategies. The initial step involved identifying and characterizing the core functions essential to the system.

These functions, derived from analysis of the case study operations, are listed and described in Table 5. This table also indicates the specific case studies where each function is relevant.

Each function was examined based on six key attributes. Additionally, the FVM software was used to visually map these functions in Fig. 2 for the first case study, Fig. 3 for the second case study, and Fig. 4 for the third case study. Table 6 presents a mapping of these outputs and their related downstream functions, illustrating the system's interconnected nature.

To evaluate system variability and potential vulnerabilities, we identified three key SPCs critical to the case studies:

- **Wearable Performance (WP):** Evaluates the effectiveness of smart wearables like gloves and glasses in terms of calibration, functionality, and accuracy.
- **Worker Condition (WC):** Encompasses the worker's physical, physiological and cognitive state in response to task demands, drawing upon the Stress-Strain Model (Rohmert, 1973). This model distinguishes between stress (external demands such as task complexity, workload, and shift duration) and strain (the worker's response, influenced by factors like skill, fatigue, cognitive load, posture, and training). Maintaining a balance between these factors is crucial for efficiency, efficacy, safety, and well-being in assembly tasks (Djefour et al., 2024).
- **Resource Availability (RA):** Refers to the availability of essential components, tools, wearables, and devices required for the assembly process.

The potential impact of suboptimal performance in each SPC on system functions was categorized using a standardized scale (Table 7), ranging from no impact (0) to high impact (1). These values are used based on the literature to have a more robust framework (Patriarca, Di Gravio, & Costantino, 2017). Applying this scale, we assessed the

Table 5
Identified functions.

Code	Function	Description	Related case study 1	2	3
F-1	To train workers	Workers must be trained to use the wearables effectively, ensuring that they understand how to interact with the smart devices during assembly.	*	*	*
F-2	To manage resources	Restock bins and ensure components/tools/wearables are available to prevent stoppages.	*	*	*
F-3	To calibrate and maintain	Calibration and maintenance of the wearables and devices to avoid any inaccuracy and stoppage.	*	*	*
F-4	To program wearables	Programming ensures that the smart gloves and smart glasses provide accurate feedback and guidance to the worker.	*	*	*
F-5	To verify stock levels	Workers use smart glasses to check stock levels to ensure that sufficient parts are available to avoid assembly stoppage.	*	*	*
F-6	To verify the product map	Before assembly, the worker verifies the correct components using the product map to ensure the right parts are being used.	*	*	*
F-7	To select and handle components	The worker uses smart gloves to select and handle components with precision and correct pressure.	*	*	*
F-8	To assemble the product	The worker assembles the product.	*	*	
F-9	To supervise workers	The supervisor remotely monitors the assembly process, ensuring adherence to quality and production standards.	*	*	*
F-10	To monitor and report production in real time	The production process is continuously monitored online. Data is collected in real time to track assembly performance and to ensure quality.	*	*	*
F-11	To move the product using a conveyor/ dolly	The product transfers between the stations using a conveyor or a dolly.	*	*	*
F-12	Next station	The assembled product moves to the next station.	*	*	*
F-13	Human resource planning	Hiring new workers.	*	*	*
F-14	Production and resource planning	Providing the plan of the production and resources.	*	*	*
F-15	To receive and analyze data	Collect and analyze data from wearables.	*	*	*
F-16	To access work instructions (via computer)	The worker retrieves and views procedural guidance for the task using a workstation computer interface.		*	
F-17	To manage the tool cabinet	Ensure necessary tools are available, organized, and accounted for within the designated tool cabinet.		*	*
F-18	To disassemble the product	The worker takes apart the product, removing specific components according to the process requirements			*
F-19	To detect hazardous components	Use smart gloves and smart glasses to identify potentially dangerous materials or parts during handling or disassembly.			*
F-20	To sort disassembled components	Place removed parts into designated storage bins based on material type, destination, or other criteria.			*
F-21	To manage storage bins	Ensure storage bins are available, correctly labelled, and emptied or replaced as needed to facilitate sorting and storage.			*

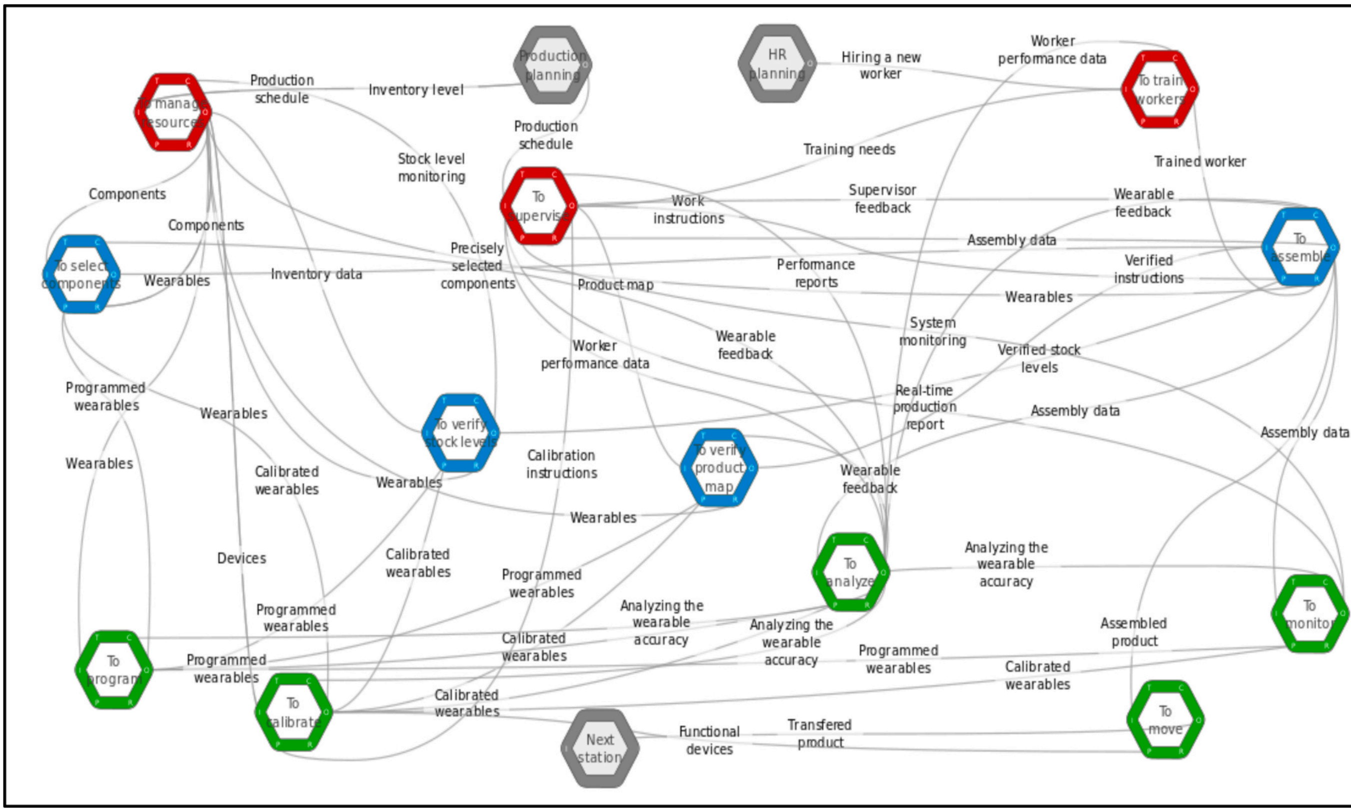

Fig. 2. The FRAM model of the first case study.

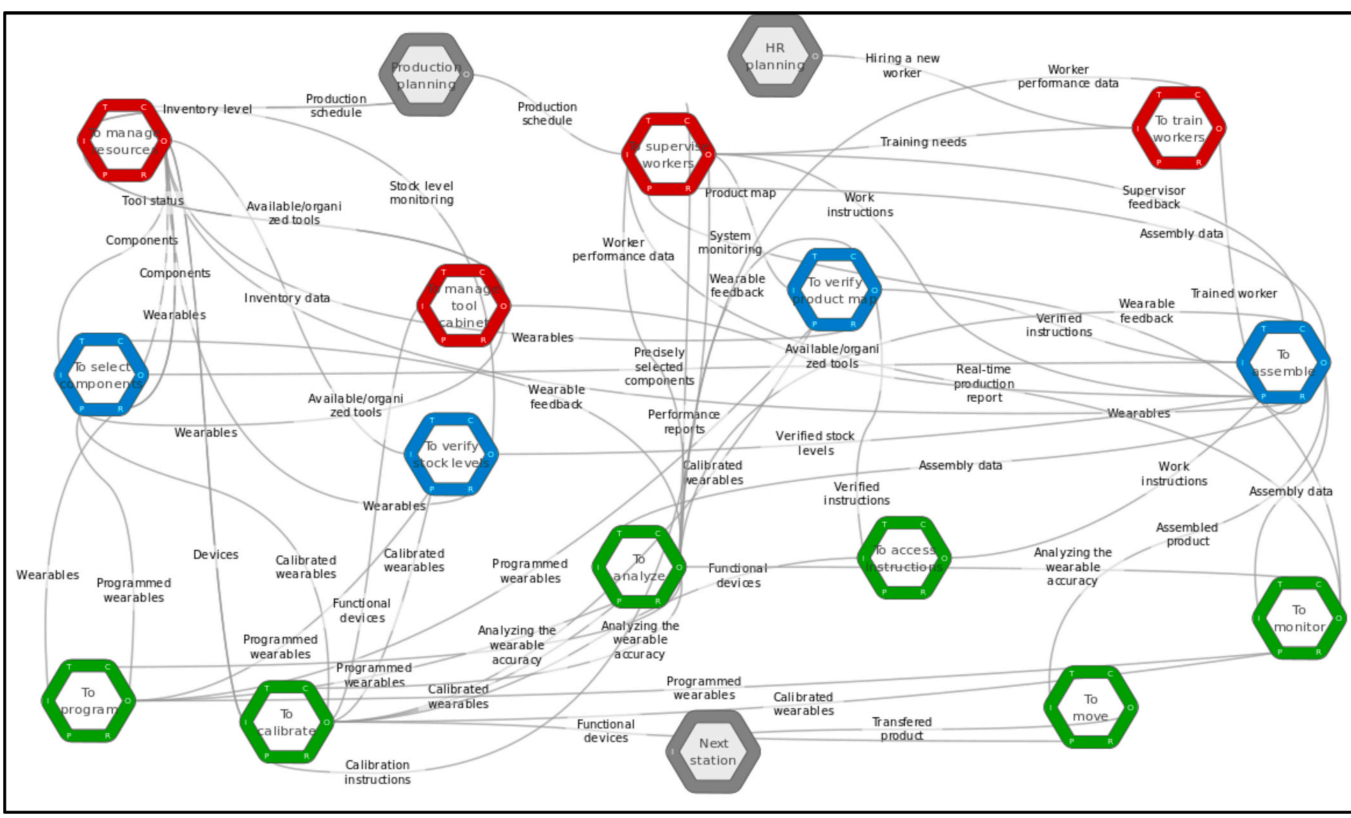

Fig. 3. The FRAM model of the second case study.

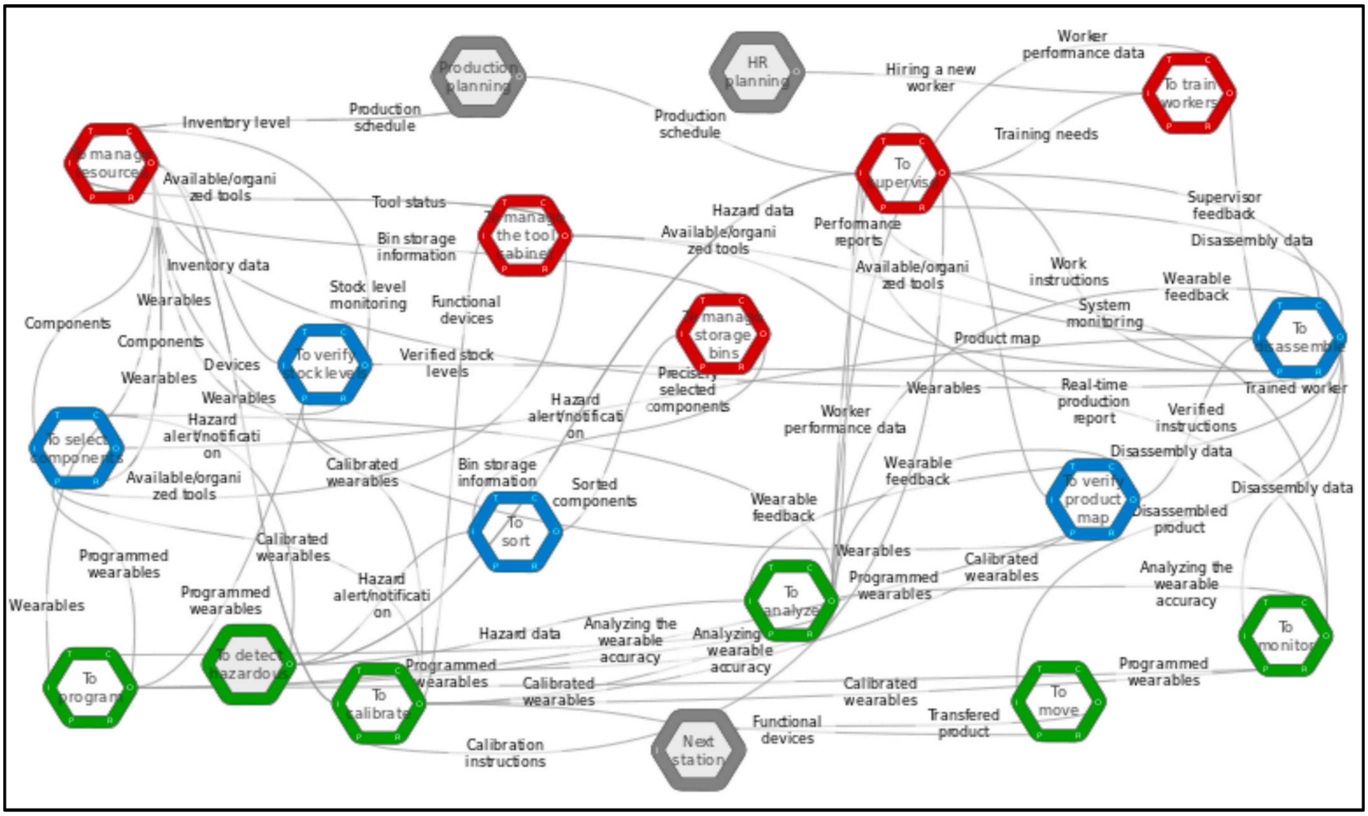

Fig. 4. The FRAM model of the third case study.

specific impact of each SPC on every identified function, based on the operational context of the case studies. The results of this assessment are presented in Table 8. For instance, 'To Assemble the Product' (F-8) and 'F-18: To disassemble the product' (F-18) are highly impacted by all three SPCs, while 'To Move the Product' (F-11) is unaffected under the defined conditions. Herein, the authors used arbitrary values based on their perspective; however, in real case studies, it should be determined by the decision-making team.

To simulate varying operational contexts and assess system resilience, four distinct scenarios were defined, modulating the impact level of the SPCs:

Normal conditions: Assumes moderate variability across all SPCs.
Wearable malfunction: Represents high variability in Wearable Performance (WP).
High fatigue: Simulates high variability in Worker Condition (WC).
Resource shortage: Introduces high variability in Resource Availability (RA).

By using the established function network, SPC impacts (Table 8), and scenario definitions, we employed the PSO algorithm integrated within the FRAM framework (FRAM-PSO) to calculate the VPN for each function. The VPN quantifies the potential variability or risk associated with each function under the defined scenarios.

From the individual function VPNs (Eq.4), the Path VPN is calculated for each function, representing the cumulative variability propagated through its downstream dependencies. The initial state of the system, depicting the calculated Path VPNs before any mitigation, is visualized in Fig. 5. In this graph, the intensity or thickness of the connections can represent the magnitude of the Path VPN, emphasizing critical pathways.

For this study, the algorithm's objective is to reduce the path VPNs, which results in the reduction of the function VPNs and improvement of the overall model. We defined a set of potential sustainable mitigation actions (Table 9), each linked to specific SPCs and associated functions.

For each strategy, we assigned illustrative values for implementation feasibility (from easy to difficult), impact weight (from low to high improvement), and contribution to sustainability pillars (environmental, economic, social – rated from low to high impact). To provide a clear perspective on how to use this methodology, the authors base these values on their assessment when assigning values to these variables. In a practical application, these values would be established through structured workshops with domain experts, leveraging techniques like pairwise comparison or direct rating scales to ensure consistency and justification for the assigned weights (Afnor, 2024; O'Hagan et al., 2006). Additionally, based on the level of importance for each industry, the sustainable aspects can be weighted to demonstrate their significance for each specific industry (Karevan & Vasili, 2018). However, this study assumes equal weight for each aspect.

The FRAM-PSO algorithm was used in an iterative mitigation process. In the interest of conciseness, the main body of this paper includes graphs and figures pertaining only to the first case study. The results derived from the other case studies can be found in the Appendix. The initial assessment performed showed that the sum of all path functions was 8736. The algorithm then starts by identifying the highest path VPN. The function with the highest initial path VPN was F-2 (to manage resources), which had a value of 1726.

Then, the four-step mitigation process unfolds as follows:

- **Step 1:** F-2 (to manage resources) was targeted as the highest path VPN. Then the algorithm selected and applied the most suitable mitigation strategy across all the options, "Digital inventory management".
- **Step 2:** F-15 (to receive and analyze data) was identified as the next highest path VPN. The "Wearable maintenance program" strategy was selected and applied.

Table 6
Functions and their outputs.

Function Code	Output	Downstream functions
F-1	Trained worker	F-8
F-2	Inventory data	F-5
	Wearables	F-3, F-4, F-5, F-6, F-7, F-8, F-10, F-15
	Components	F-7
	Devices	F-3, F-11
F-3	Calibrated wearables	F-5, F-6, F-7, F-10, F-11, F-15
	Functional devices	F-11
F-4	Programmed wearables	F-5, F-6, F-7, F-10, F-15
F-5	Verified stock levels	F-8
	Stock level monitoring	F-2
F-6	Verified instructions	F-8
F-7	Precisely selected components	F-8
F-8	Assembled product	F-11
	Assembly data	F-9, F-10, F-15
F-9	Product map	F-6
	Work instructions	F-8
	Training needs	F-1
	Supervisor feedback	F-8
	Calibration instructions	F-3
F-10	Real-time production report	F-9
	System monitoring	F-9
F-11	Transferred product	F-12
F-13	Hiring a new worker	F-1
F-14	Production schedule	F-2, F-9
	Inventory level	F-2
F-15	Wearable feedback	F-6, F-7, F-8
	Analyzing the wearable accuracy	F-3, F-4, F-10
	Worker performance data	F-1, F-9
	Performance reports	F-9
F-16	Work instructions	F-8
F-17	Available/organized tools	F-2, F-7, F-8, F-18
	Tool status	F-2
F-18	Disassembled product	F-11, F-12, F-20
	Disassembly data	F-9, F-10, F-15
F-19	Hazard alert/notification	F-7, F-9, F-20
	Hazard data	F-9, F-15
F-20	Sorted components	F-21
F-21	Bin storage information	F-2, F-20

Table 7
SPC impact definition.

The impact of SPCs	Value	Wearable Performance (WP)	Worker Condition (WC)	Resource Availability (RA)
No impact	0	Wearables do not affect the function	The worker's physical and cognitive state does not significantly affect the function	Resource availability does not significantly affect the function
Moderate impact	0.5	Wearables are useful but have limitations or occasional malfunctions	The worker's physical and cognitive state affects performance, but not critically	Limited resources may cause some delays or inefficiencies
High impact	1	Wearables are critical for functional success	The worker's physical and cognitive state is crucial for successful performance	Lack of resources causes significant delays or stoppages

- **Step 3:** F-3 (to calibrate and maintain) emerged as the next target, and the "Worker-centric wearable design" strategy was implemented.

Table 8
SPC impact on the process.

Function	WP	WC	RA
F-1: To train workers	0	1	0
F-2: To manage resources	0.5	0.5	1
F-3: To calibrate and maintain	1	0	1
F-4: To program wearables	1	0	1
F-5: To verify stock levels	0.5	1	1
F-6: To verify the product map	1	1	0
F-7: To select and handle components	1	1	1
F-8: To assemble the product	1	1	1
F-9: To supervise workers	0.5	1	0
F-10: To monitor and report production in real-time	1	0.5	0
F-11: To move the product using a conveyor/dolly	0	0	0
F-12: Next station	0	0	0
F-13: Human resource planning	0	1	0
F-14: Production and resource planning	0	0.5	1
F-15: To receive and analyze data	1	0.5	0
F-16: To access work instructions (via computer)	0.5	1	0.5
F-17: To manage the tool cabinet	0.5	0	1
F-18: To disassemble the product	1	1	1
F-19: To detect hazardous components	1	1	0
F-20: To sort disassembled components	1	0.5	0.5
F-21: To manage storage bins	0.5	0	1

- **Step 4:** In the last step, F-8 (to assemble the product) was selected, and the "Wellness monitoring and breaks" strategy was applied.

While the Path VPN provides a robust internal metric for quantifying systemic risk within the model, its direct managerial relevance can be enhanced by linking it to tangible Key Performance Indicators (KPIs). The mitigation strategies selected by the FRAM-PSO algorithm can be directly mapped to expected improvements in operational metrics that decision-makers track.

Table 10 provides an illustrative mapping for the four mitigation strategies applied in the first case study. This demonstrates how the concept of "risk reduction" can be translated into a practical performance monitoring plan. For example, the "Worker-centric wearable design" strategy, which reduced the Path VPNs, would be expected to yield measurable improvements in KPIs such as a lower human error rate and a reduction in reported musculoskeletal discomfort (Alenjareghi et al., 2025). This translation is a critical step in bridging the gap between systemic modeling and practical, data-driven management.

After these four mitigation steps, for the first case study, the total sum of path VPNs in the methodological prototype decreased significantly to 6207. This represents an overall risk reduction of approximately 28.9 % within the model's illustrative scenario. The maximum path VPN observed was reduced to 1241. It is critical to note that this figure is not a prediction of real-world performance but a demonstration of the framework's mechanics and its ability to quantify the systemic impact of targeted interventions. The progression of this risk reduction is illustrated in Fig. 6. The second and third case studies showed similar improvements within their respective models (see Appendix).

Fig. 7 provides insight into the systemic impact of each applied strategy, mapping which functions were affected by each strategy. For example, implementing "Worker-centric wearable design" influenced the VPNs of six distinct functions (F-1, F-3, F-7, F-8, F-10, F-13). This occurs because an ergonomic and intuitive wearable (the mitigation strategy) directly improves the physical and cognitive aspects of tasks like handling components (F-7) and assembling the product (F-8). It also reduces the training burden (F-1) and makes it easier for supervisors to monitor work (F-10), a finding consistent with the work of Valdesse Eko'ola & Nadeau (2025).

A direct comparison of the initial and final Path VPNs for each function is presented in Fig. 8. This figure highlights the percentage reduction achieved for each pathway. Notably, while mitigation efforts directly targeted only F-2, F-15, F-3, and F-8 in these steps, the

Table 9
Sustainable mitigation strategies.

Strategy	Description	Related functions	Related SPC	Feasibility level	Weight	Sustainability aspects Envi.	Econ.	Social
Worker-centric wearable design	Use wearables with ergonomic features (e.g., lightweight, easily adjustable)	F-1, F-3, F-7, F-8. F-10, F-13, F-18	WC, RA	Difficult	High	Low impact	Medium impact	High impact
Low-power sensors	Use wearables with energy-efficient sensors powered by kinetic energy or solar cells	F-2, F-3, F-19, F-21	WP, RA	Difficult	Medium	High impact	Medium impact	Low impact
Wearable maintenance program	Regular calibration and repair using recycled parts	F-3, F-4, F-6, F-9, F-11, F-15, F-16, F-18, F-19	WP, RA	Medium	High	High impact	Medium impact	Low impact
Wellness monitoring and breaks	Equip wearables with real-time health tracking to trigger mandatory breaks and reduce physical strain	F-8, F-9, F-13, F-18	WC	Easy	High	Low impact	Medium impact	High impact
Tool sharing optimization	Use wearables to track and optimize tool-sharing across workers, reducing idle resources	F-2, F-9, F-14, F-17	WP, RA	Easy	Medium	High impact	Medium impact	Low impact
Reusable tool systems	Shift to modular, reusable tools with wearables for maintenance tracking	F-2, F-14, F-17	RA, WP	Medium	Medium	High impact	High impact	Low impact
Digital inventory management	Use wearables to monitor and optimize material stock digitally, reducing over-ordering	F-2, F-5, F-11, F-14, F-17, F-20, F-21	RA	Medium	High	Medium impact	High impact	Medium impact

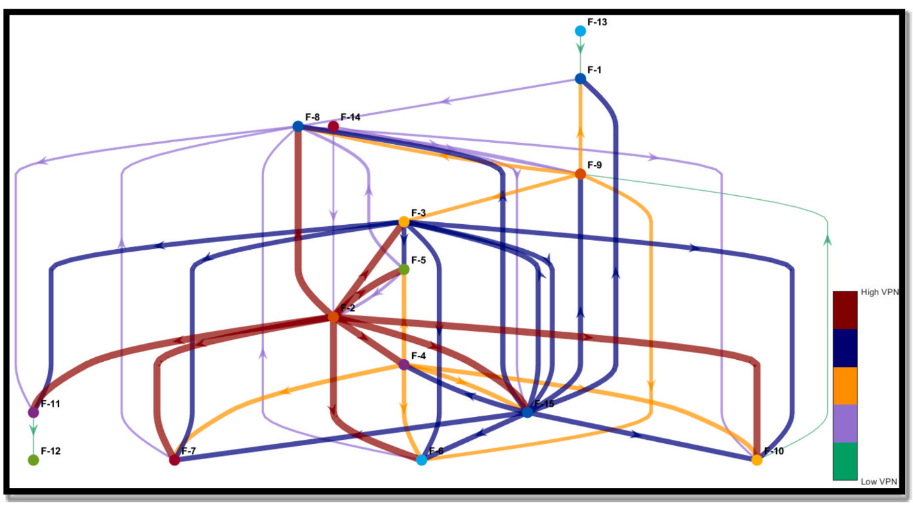

Fig. 5. Path Graph with VPN-Weighted Connections (first case study).

interconnected nature of the system led to significant indirect improvements in other functions. For instance, the path VPN for F-1 (to train workers) decreased by 37.3 %, demonstrating the cascading benefits of the applied strategies. This significant indirect improvement is because the implementation of more ergonomic and easier-to-use wearables (a mitigation for F-8) reduces the complexity and duration of the required training. Conversely, some functions like F-11 (To move the product), which had low initial VPN and weak connections to the targeted areas, only improved by 14.9 %.

These results demonstrate the effectiveness of the FRAM-PSO approach in identifying critical risk paths and quantifying the system-wide impact of targeted, sustainable mitigation strategies. The significant reduction in overall path VPN, achieved through just four strategic interventions, underscores the value of this methodology for enhancing system resilience and sustainability.

5. Discussion

Resilience is gaining growing importance in modern manufacturing environments (Chari et al., 2023). The resilience engineering community has successfully applied FRAM as both a retrospective and prospective method, explaining that system outcomes are shaped by how different functions vary and interact, often leading to unexpected results known as functional resonance (Lundblad et al., 2008; Yousefi et al., 2019; Zheng et al., 2024). However, FRAM is inherently qualitative, prompting numerous efforts to enhance its objectivity and quantification capabilities (Patriarca, Di Gravio, & Costantino, 2017). This study directly engages with this challenge within the context of modern industrial systems incorporating smart wearables.

The successful application of this novel FRAM-PSO framework resulted in a substantial 28.9 % reduction in the overall system risk through four targeted sustainable mitigation steps (first case study). This highlights the methodology's effectiveness in not only modelling variability but also guiding practical interventions. Furthermore, the findings illustrate the systemic effects central to FRAM. While mitigation directly targeted functions F-2, F-15, F-3, and F-8, significant improvements propagated to interconnected functions, such as the 34.1 % risk reduction observed in F-5 (to verify stock levels) (Fig. 8). This demonstrates how targeted interventions can yield broader system resilience benefits.

Addressing the known challenge of FRAM quantification (Patriarca, Di Gravio, & Costantino, 2017), the integration of PSO offers a distinct contribution. Unlike other quantification methods (e.g., MCS, BN), PSO actively optimizes, allowing the framework not only to quantify variability (VPN) but also to search for and select optimal sustainable mitigation strategies to maximize risk reduction. To the best of our

Table 10
Illustrative Mapping of Selected Mitigation Strategies to Managerial KPIs.

Mitigation Step	Primary Path VPN Reduction	Selected Mitigation Strategy	Illustrative Managerial KPIs to Monitor
Step 1	F-2 (to manage resources)	Digital Inventory Management	• Reduction in line stoppages due to part shortages • Improvement in inventory turnover rate • Decrease in ordering errors
Step 2	F-15 (to receive and analyze data)	Wearable Maintenance Program	• Reduction in wearable failure rate • Decrease in maintenance costs • Improvement in data accuracy from wearables
Step 3	F-3 (to calibrate and maintain)	Worker-Centric Wearable Design	• Reduction in human error rate • Decrease in reported musculoskeletal discomfort • Reduction in task completion time
Step 4	F-8 (to assemble the product)	Wellness Monitoring and Breaks	• Decrease in fatigue-related incidents • Improvement in employee satisfaction scores • Increase in adherence to mandatory break protocols

knowledge, this combination of FRAM and PSO for risk quantification and optimized mitigation represents a novel contribution to the field.

This study also tackles the specific gap concerning systematic risk assessment for smart wearables (Karevan & Nadeau, 2023). Moving beyond prior qualitative (Mofidi Naeini & Nadeau, 2023) or STPA-based analyses (Karevan & Nadeau, 2024a, 2025), the FRAM-PSO approach provides a quantitative, systemic, and mitigation-oriented framework for these technologies. Another contribution is the explicit integration of sustainability (environmental, economic, and social factors) into the risk mitigation process. This integration addresses the critical need, highlighted by Karwowski et al. (2025) in their grand challenges, for human factors and ergonomics to contribute towards sustainability, including enhancing system resilience and developing ethical principles for sustainable futures (Karwowski et al., 2025; Valette et al., 2023). Also, achieving sustainable production is a key objective in today's manufacturing industry (Ma et al., 2024; Zhang et al., 2024). By adopting Industry 5.0 principles, this work introduces an integrated approach to understanding risk that fills a gap we identified in existing systemic risk frameworks through a literature review.

An additional contribution is the framework's alignment with emerging regulatory and reporting standards for sustainability. Global frameworks, such as the International Sustainability Standards Board (ISSB) standards, the European Sustainability Reporting Standards (ESRS), and the Global Reporting Initiative (GRI) standards, increasingly require organizations to implement robust processes for identifying, assessing, and mitigating sustainability-related risks (Elidrisy, 2024; Krivogorsky, 2024). Our FRAM-PSO model provides a tangible, operational-level methodology to meet these requirements. By systematically linking system functions to environmental, social, and economic impacts, the model makes sustainability risks traceable and mitigation efforts transparent. This strengthens its utility for decision-makers who must navigate evolving regulatory landscapes while managing operational risk.

While the results are promising, limitations must be acknowledged.

- The findings are based on three specific case studies, necessitating further applications for broader generalizability. While the methodology is designed to be adaptable, its performance and the specific critical functions identified might differ in other industrial contexts or systems with different structures and technologies. The methodology can be generalized to other complex socio-technical domains such as aerospace, healthcare, and logistics by redefining the system functions, performance variabilities, and SPCs to match the specific operational context.

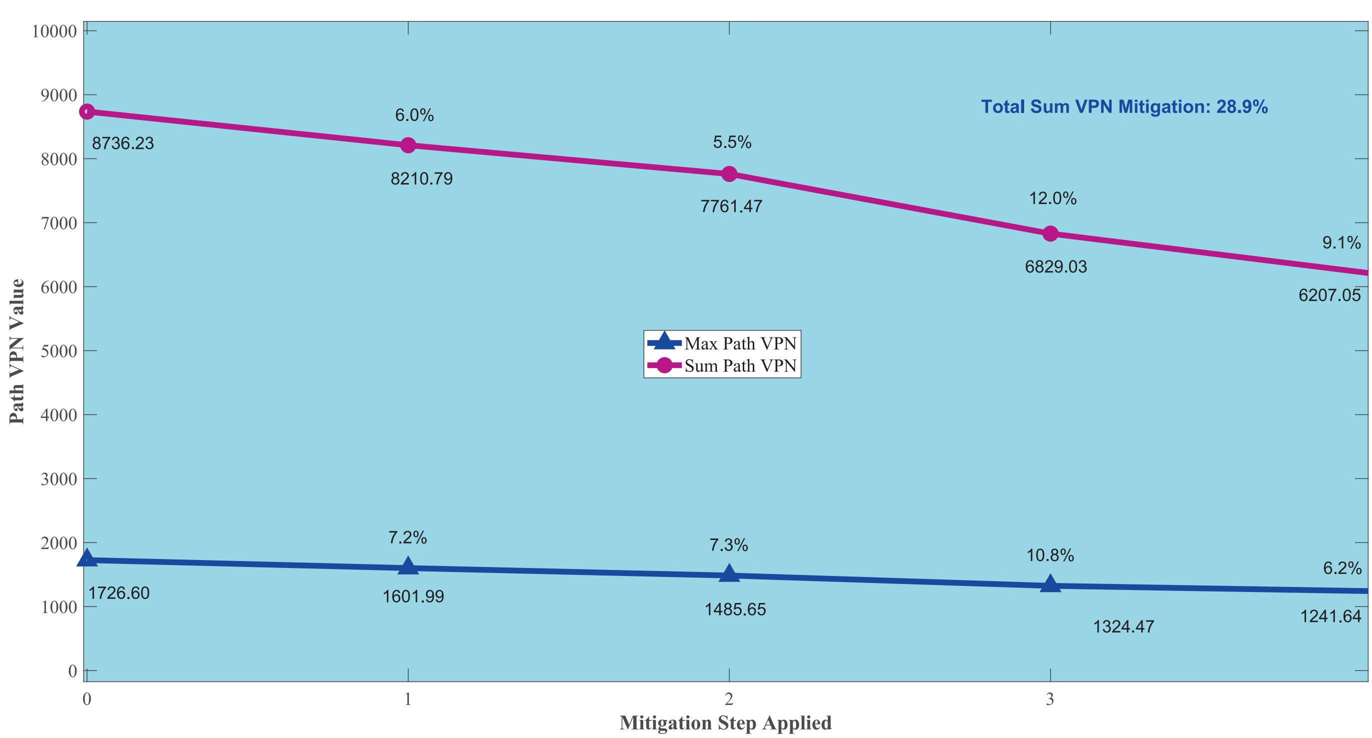

Fig. 6. Mitigation Progress: Risk Reduction Over Steps (first case study).

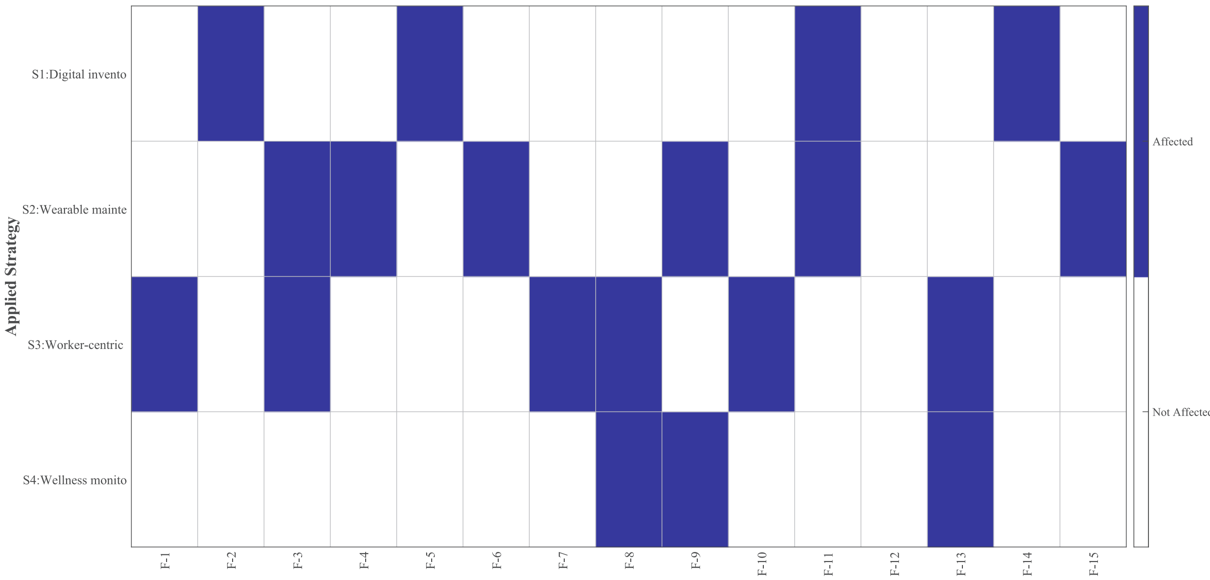

Fig. 7. Functions Affected by Each Applied Strategy (first case study).

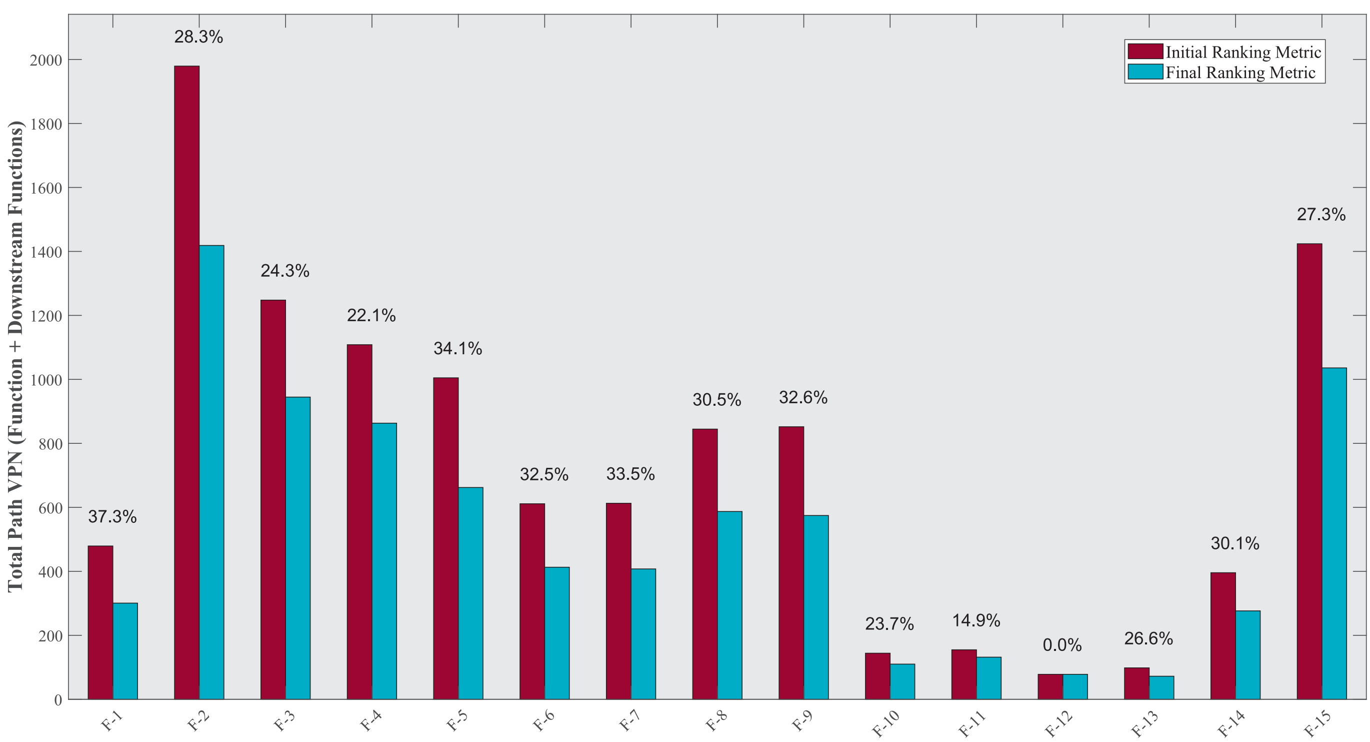

Fig. 8. Path VPN Comparison: Initial vs. Final Mitigated (first case study).

- The initial assessment of SPC impacts and the characterization of mitigation strategies (feasibility, weight, and sustainability impacts) relied on illustrative values. This approach was intentionally chosen to demonstrate the mechanics and viability of the FRAM-PSO framework as a methodological prototype. As is common in foundational studies that propose new models, the primary goal is to establish the framework's internal logic and potential before undertaking extensive, context-specific empirical validation. We fully acknowledge that for a real-world application, gathering these data and inputs from domain experts and empirical assessments is crucial for ensuring the practical reliability and robustness of the results.
- Furthermore, the assessment of sustainability contributions remains at a semi-quantitative level. To increase its practical utility, the framework would need to be enhanced to operationalize these dimensions with fully quantitative metrics, such as measured energy savings, specific cost reductions, or validated changes in worker satisfaction surveys.

6. Conclusions

This paper addresses the need for semi-quantitative, systemic risk assessment in complex industrial systems, particularly those utilizing smart wearables, while simultaneously integrating sustainability considerations. We developed and demonstrated a novel methodology integrating the FRAM with PSO. FRAM-PSO model applied in three case studies of the assembly and disassembly systems, which use smart gloves and smart glasses. We demonstrated that this is a powerful model to systematically identify, quantify, analyze and mitigate the risks with sustainable strategies. The results demonstrate that applying this model can improve the system by reducing the risk of the model by more than 22 % after four steps of mitigation for all three case studies.

The core contributions of this research are the synergistic integration of FRAM and PSO for quantitative risk analysis and optimized mitigation, and the pioneering incorporation of multi-dimensional sustainability criteria (environmental, economic, social) directly within this systemic risk management process. This work represents a valuable advancement towards building more resilient, efficient, and responsible industrial operations, in line with the goals of Industry 5.0. This method equips practitioners with a structured tool to identify vulnerabilities, quantify risks, and prioritize sustainable mitigation investments in complex, wearable-integrated systems. Theoretically, it advances quantitative FRAM approaches and pioneers the integration of sustainability within systemic operational risk management.

Future research should prioritize broader application and validation across diverse industrial contexts, along with refining methods for robust input elicitation. Specific directions for future work include:

- Validating the model using real-time operational data from industrial partners to confirm its predictive accuracy and practical utility. This would also involve refining input elicitation methods through structured expert judgment or fuzzy logic techniques.
- Exploring the integration of alternative optimization algorithms to compare their effectiveness and computational efficiency in identifying optimal mitigation strategies.
- Developing a software-based decision-support tool to facilitate the practical application of the FRAM-PSO framework enabling industry practitioners to conduct systemic risk assessments more easily and effectively.

CRediT authorship contribution statement

Ali Karevan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sylvie Nadeau:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

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

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Appendix

I. Case study 2 results

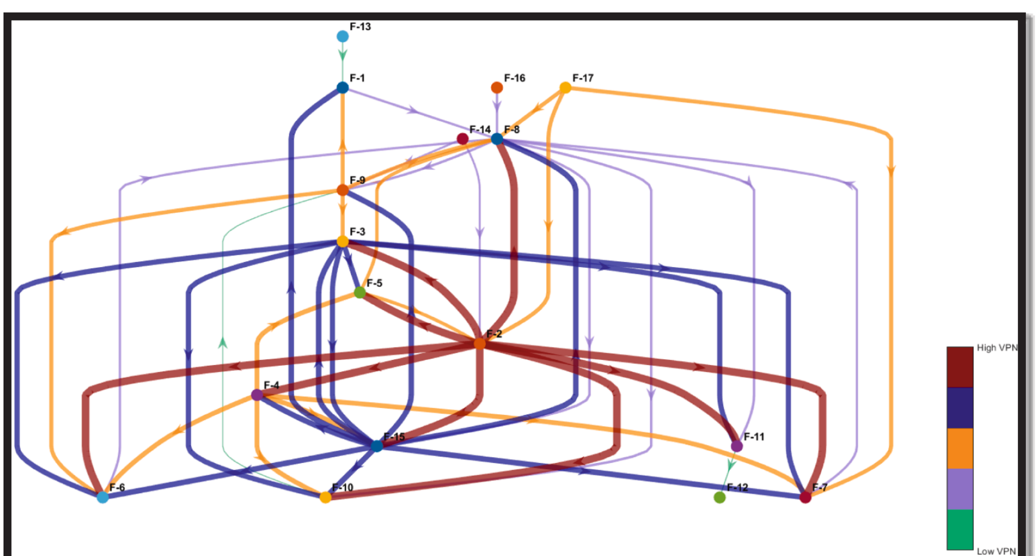

Fig. 9. Path Graph with VPN-Weighted Connections (second case study)

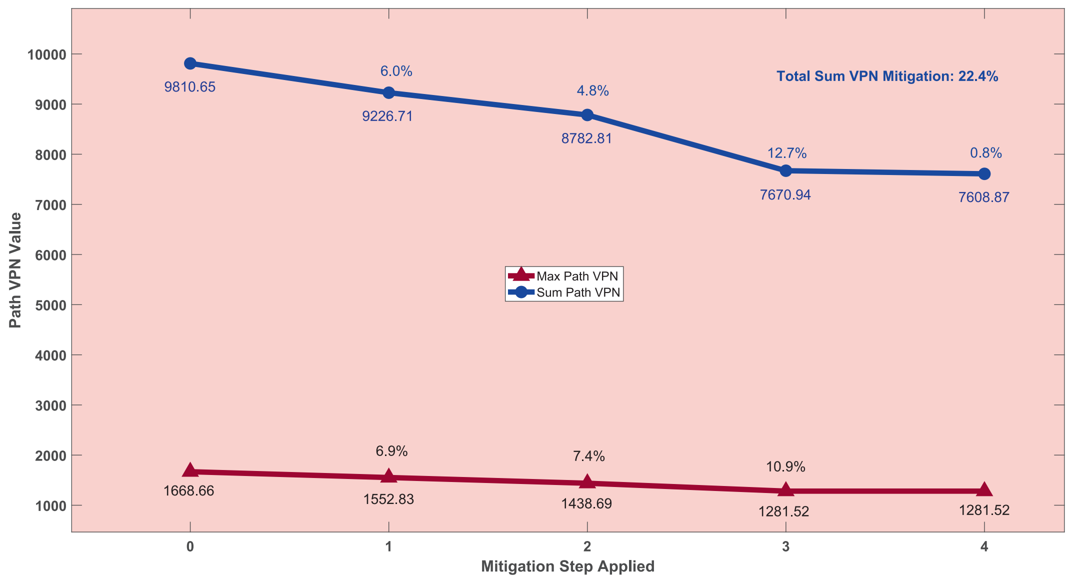

Fig. 10. Mitigation Progress: Risk Reduction Over Steps (second case study)

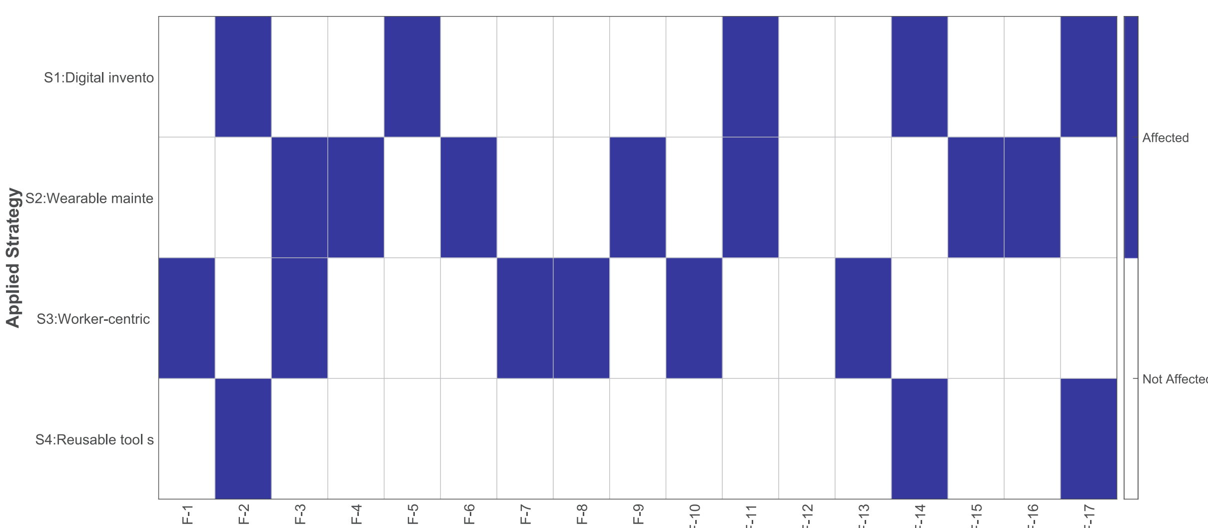

Fig. 11. Functions Affected by Each Applied Strategy (second case study)

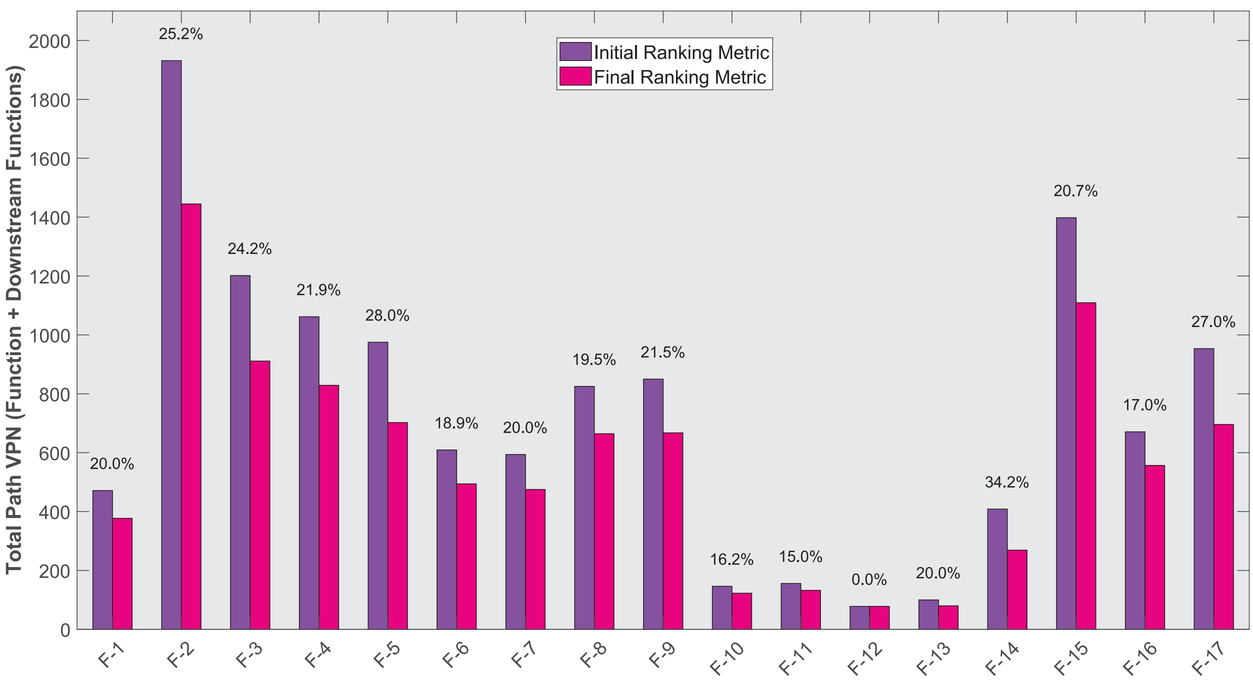

Fig. 12. Path VPN Comparison: Initial vs. Final Mitigated (second case study)

II. Case study 3 results

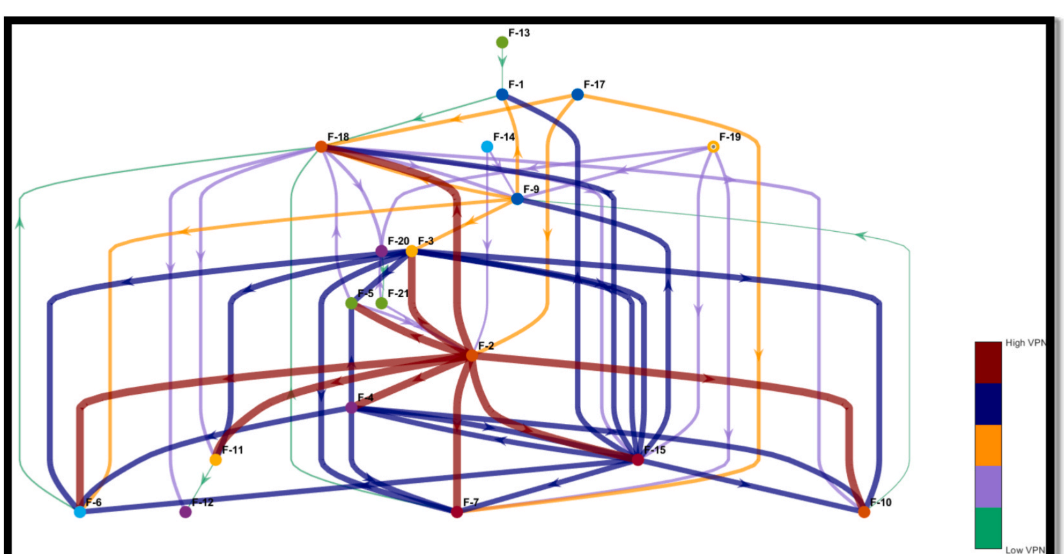

Fig. 13. Path Graph with VPN-Weighted Connections (third case study)

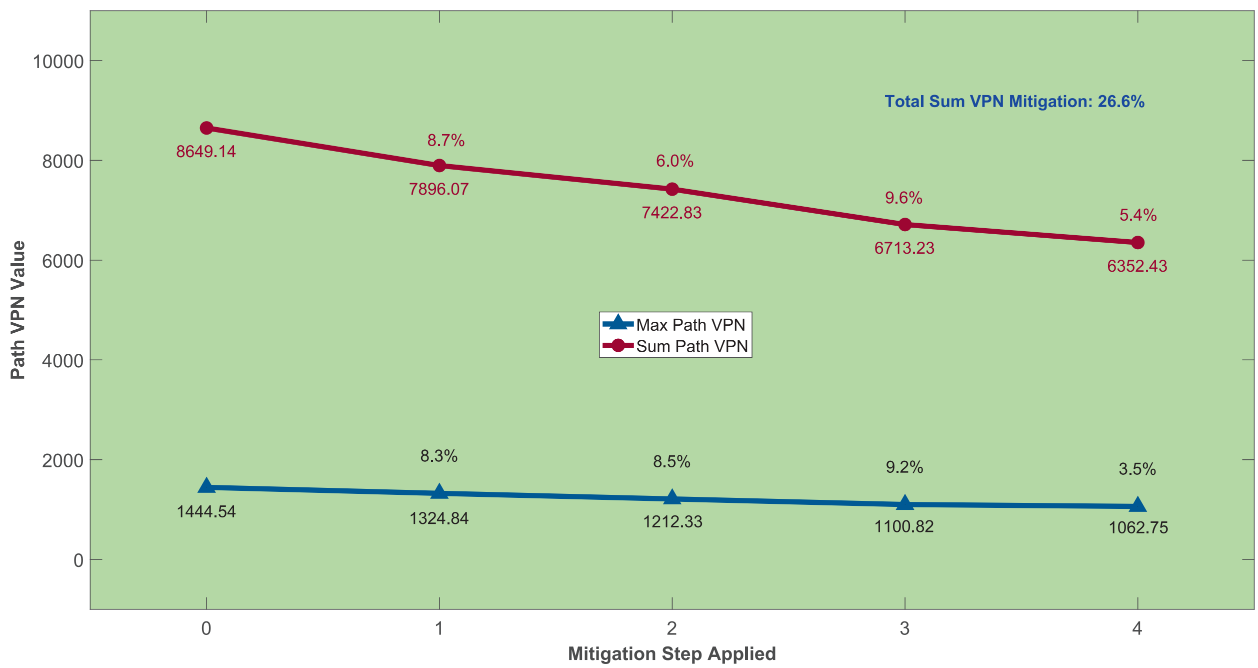

Fig. 14. Mitigation Progress: Risk Reduction Over Steps (third case study)

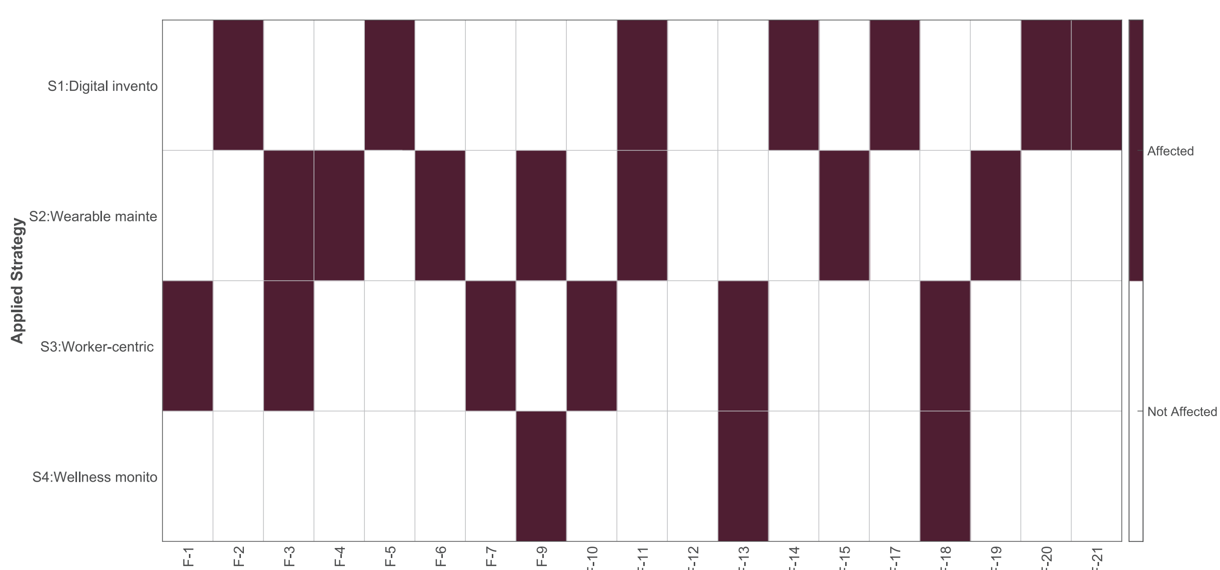

Fig. 15. Functions Affected by Each Applied Strategy (second case study)

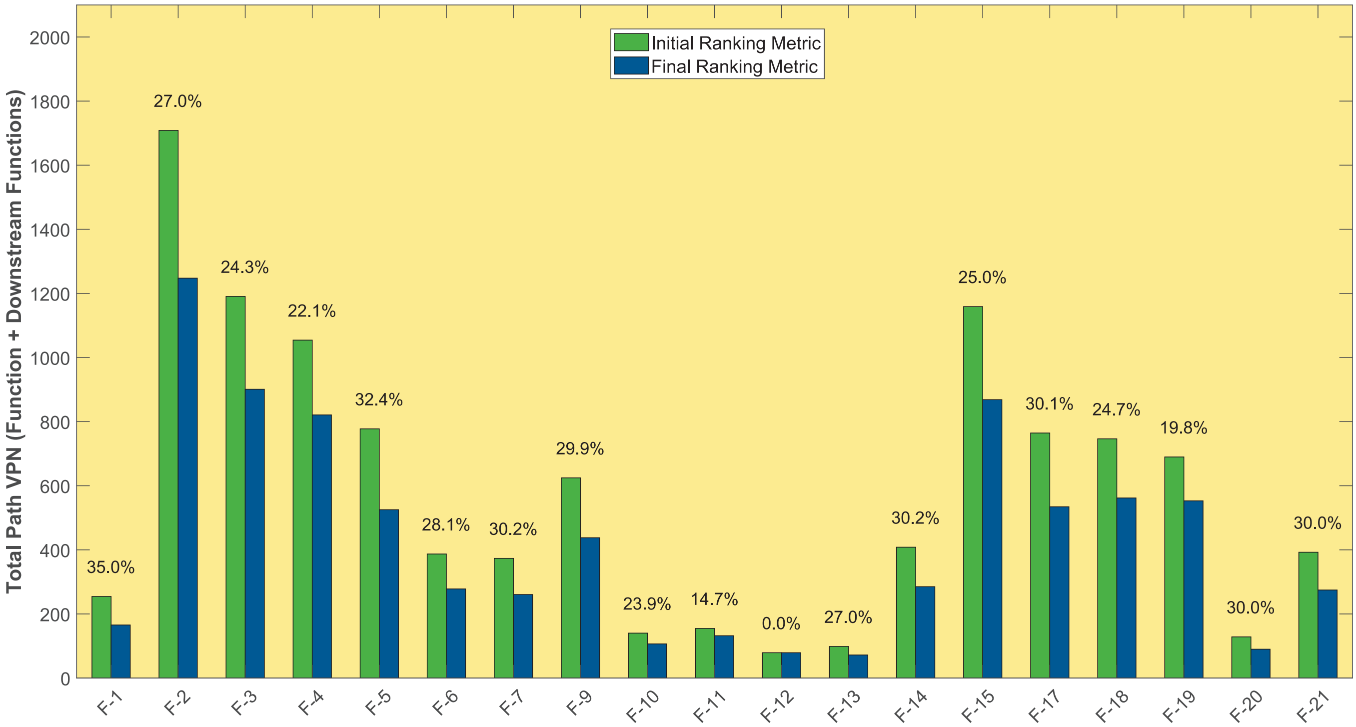

Fig. 16. Path VPN Comparison: Initial vs. Final Mitigated (third case study)

Data availability

The data that support the findings of this study are openly available on GitHub at: https://github.com/Alikarevan-code/FRAM-PSO-Sustainability-Risk-Framework/blob/main/README.md.

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