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Analysis of Human Performance Monitoring in Control Rooms for Small Modular Reactor (SMR) Deployments

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Abstract

The increasing demand for sustainable and efficient nuclear energy has driven the adoption of Small Modular Reactors (SMRs), which offer enhanced safety, flexibility, and operational efficiency. However, the effectiveness of SMR control rooms remains highly dependent on human performance, where factors such as cognitive workload, psychological stress, and ergonomics play a crucial role in operator decision-making. Traditional control room monitoring systems primarily focus on basic physiological metrics such as heart rate and fatigue, lacking the capability to dynamically assess cognitive and environmental factors in real-time. This study explores the integration of automatic systems in SMR control rooms to monitor human performance and health mitigate operational risks. By leveraging wearable sensors, eye-tracking technology, and powered decision support. Key findings suggest that real-time monitoring significantly enhances situational awareness, workload balancing, and decision-making efficiency. Furthermore, integrating predictive analytics and adaptive automation within SMR control rooms can lead to a safer, more efficient operational environment, ensuring reliability in high-stakes nuclear applications. The proposed system represents a paradigm shift in human-machine collaboration, offering a holistic approach to improving safety and efficiency in next-generation nuclear control rooms.

Keywords: Small Modular Reactors; Health monitoring; cognitive workload; human performance; automation; nuclear control rooms; ergonomics, predictive analytics.

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1. Introduction

With the increase in energy demands around the world, there is a great need for nuclear technology. Various strides have been taken to advance nuclear technology, the latest being the Small Modular Reactors (SMR). While inspiration can be taken from the existing nuclear reactors, the existing main control rooms (MCR) lack ergonomic and attention capacity principles. SMRs are advanced nuclear reactors that have a power capacity of up to 300 MW(e) per unit, which is about one-third of the generating capacity of traditional nuclear power reactors. As conventional reactors are bigger in size, they have to have huge control rooms. Multiple people are present in the control rooms during the operation of the reactors. Those control rooms were designed in the last century, so the controls are mostly dials and knobs with analog displays with some digitization.

Small Modular Reactors (SMRs) represent a paradigm shift in nuclear energy production, characterized by their compact size, modular design, and enhanced safety features. As the demand for sustainable and efficient energy sources grows, SMRs have emerged as a promising solution to meet global energy needs while addressing environmental concerns. However, the operation of SMRs requires exceptional precision and reliability, as even minor errors in control room performance can lead to significant consequences.

Traditional nuclear control rooms rely on static monitoring systems that primarily focus on basic physiological metrics such as heart rate and fatigue. While these systems provide valuable insights into operator performance, they fail to address more complex factors such as psychological state, cognitive workload, and environmental stressors. Additionally, the dynamic and high-stakes nature of SMR operations necessitates real-time adaptation to varying conditions, a capability that current systems lack.

Advances in automatic monitoring and wearable technologies offer unprecedented opportunities to bridge these gaps. This automatic monitoring can analyze vast amounts of data in real time, enabling more comprehensive monitoring of operator performance. For instance, tools such as EEG headbands, gaze tracking devices, and voice analysis can provide detailed insights into an operator's psychological and cognitive state. Similarly, smart environment control systems can dynamically adjust lighting, noise levels, and ergonomic factors to optimize operator efficiency.

This paper seeks to explore the integration of these advanced technologies into SMR control rooms, with a focus on enhancing human performance and safety. By addressing critical research gaps and proposing innovative solutions, this study aims to pave the way for a new era of smart-enhanced nuclear control systems that prioritize both human and technological factors. The research problem definition and scope are summarized in Figures 1 and 2.

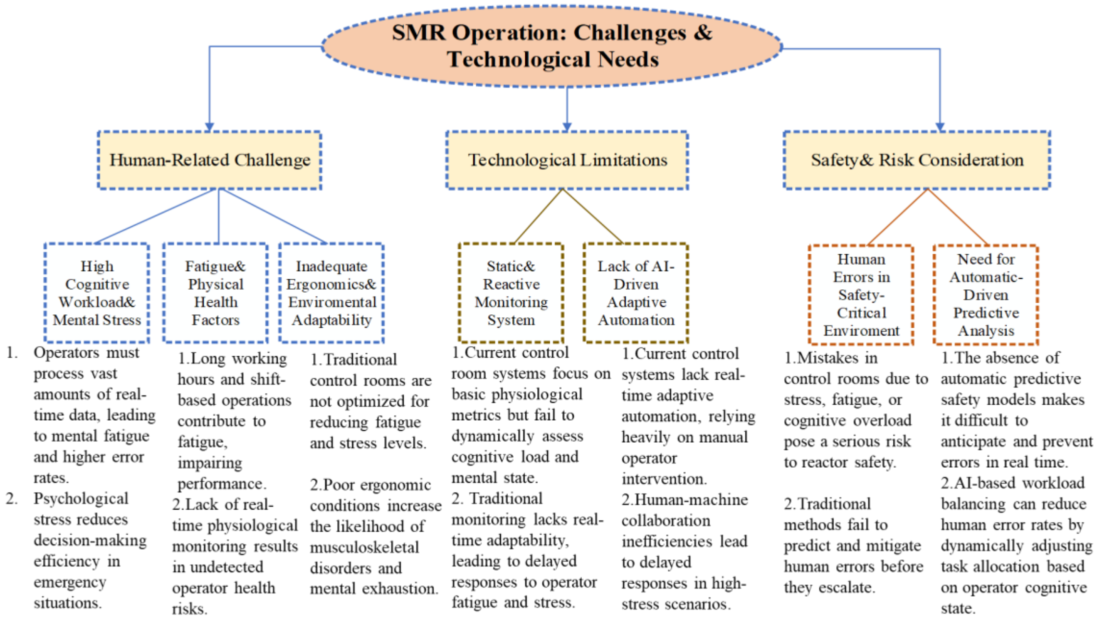

Figure 1: Problem Definition of The SMR Operation (Human Factors).

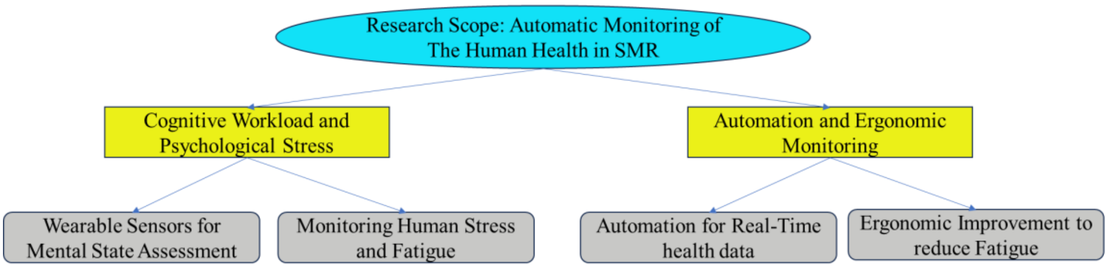

Figure 2: The Scope Summary of the work.

2. Literature Review

The safe operation of nuclear reactors depends significantly on the human element. Operators play a crucial role in ensuring smooth reactor performance, managing routine and emergency situations. Physical and mental health conditions can influence an operator's ability to execute tasks effectively, impacting decision-making, reaction time, and overall safety. This literature review examines how physical and mental health factors affect nuclear reactor operators and highlights the importance of regular health assessments in maintaining operational fitness.

2.1. Overview of Small Modular Reactor (SMR) Control Rooms

SMR control rooms are designed to facilitate the monitoring and management of nuclear reactor operations, incorporating advanced technologies to ensure safety and efficiency. According to the International Atomic Energy Agency (IAEA), SMRs are distinguished by their modular nature, smaller physical footprint, and the ability to operate independently or as part of a larger network [1]. The design of SMR control rooms differs from traditional nuclear control rooms due to their focus on automation and operator support. Studies such as those by Bae and Lee. (2024) emphasize the role of digital instrumentation and control (I&C) systems in enhancing the operational capabilities of SMRs. These systems leverage human-machine interfaces (HMIs) to streamline operator interactions with complex reactor processes, reducing the cognitive load and potential for human error [2].

The human factors (HFE) in SMR control room design research have highlighted the importance in ensuring safe and efficient operations. A report by the U.S. Nuclear Regulatory Commission (NRC) (2024) outlines the application of HFE principles in control room design, focusing on ergonomics, usability, and operator training. The integration of these principles aims to create a user-centric environment that minimizes fatigue and enhances decision-making accuracy [3]. Further studies by Orikpete and Ewim (2023) reviewed the interplay between human factors, safety culture, organizational performance, and individual behavior in nuclear power plants, highlighting recurring issues like communication breakdowns, leadership failures, and human error. Drawing lessons from past disasters, it advocates for an integrative approach combining organizational and individual performance metrics with human factors and safety culture insights, reinforced by continuous research and evaluation, to build a robust safety framework for nuclear establishments[4]. Furthermore, automation is a cornerstone of SMR control room operations, enabling reduced staffing requirements and enhanced operational efficiency. AI technologies play a critical role in automating routine tasks, monitoring system performance, and predicting potential faults. Lee and Park (2023) explored the use of predictive analytics in SMR control rooms, demonstrating how machine learning models can identify anomalies in reactor behavior before they escalate into critical issues [5].

The integration of AI-powered decision support systems has also been shown to improve situational awareness among operators. A study by Zhang and his colleagues (2024) highlights the effectiveness of these systems in providing real-time insights and recommendations, allowing operators to respond more effectively to dynamic operational conditions [6].

However, safety remains a primary concern in SMR control room operations. Recent advancements in risk assessment methodologies have been tailored to address the unique challenges of SMRs. A comprehensive review by Park and Kang (2024) identifies the potential for AI-driven safety management systems to enhance the detection and mitigation of operational risks. These systems utilize real-time data from sensors and other monitoring devices to provide early warnings of potential safety breaches [7]. The future trends in SMR control rooms are the emerging using of digital twins, augmented reality (AR), and virtual reality (VR) for training and operational support. Digital twins, as described by Jones and his colleagues (2024), offer a virtual replica of reactor systems, enabling operators to simulate various scenarios and optimize performance under different conditions [8]. AR and VR technologies are increasingly being used to enhance training programs, providing immersive environments where operators can develop critical skills without the risks associated with live reactor operations [9]. The human factor continues to be a critical concern in safety-critical systems like nuclear and chemical plants. With the increasing adoption of artificial intelligence (AI) in various fields, AI presents a promising solution to support operators and reduce risks in these high-stakes environments. The integration of artificial intelligence (AI) and mobile computing in nuclear power plant (NPP) systems represents a groundbreaking strategy for improving safety and reliability. By combining the predictive power of AI algorithms with the real-time data transmission capabilities of mobile devices, this approach significantly enhances decision-making processes and ensures continuous support for safe plant operations. As advancements in AI, IoT integration, and mobile interfaces progress, these technologies are expected to further strengthen NPP systems, creating more robust and resilient operations for the future of nuclear power [10].

2.2. Human Factors Effects on Control Room Performance

Human behavior plays a pivotal role in the operation of SMR Control Room, influencing performance, safety, and overall system reliability. Before integrating human behavior into reactor operations, it is essential to analyze and address specific human variables. These variables encompass both micro (personal) and macro (environmental/organizational) factors, each with a significant impact on operator reliability, performance, and monitoring systems. According to Park, J. (2024), eight critical Performance Shaping Factors (PSFs) have been identified to assess and improve human interaction with reactor systems. This article explores these factors and provides insights into data-driven approaches for optimizing reactor operations [11].

2.3. Human Variables and Performance Shaping Factors

2.3.1. Micro (Personal) Factors

Micro factors pertain to individual operator characteristics, which directly affect their performance during reactor operations. These include:

- Experience: Operator performance is strongly correlated with experience. More experienced personnel exhibit higher efficiency and reliability under stressful operational conditions.
- Training: Adequate and ongoing training ensures operators are well-prepared to handle various scenarios, reducing the likelihood of human error.
- Fitness to Work: Physical and mental health conditions significantly influence an operator's ability to perform tasks effectively. Regular health assessments are critical to maintaining fitness levels conducive to safe reactor operations.

2.3.2. Physical Health and Operator Performance

I. Fatigue and Sleep Deprivation

Fatigue and sleep deprivation have been widely studied in high-risk industries. Studies indicate that insufficient sleep impairs cognitive function, reduces alertness, and increases the likelihood of operational errors [12]. Research on shift workers, including reactor operators, suggests that night shifts and long working hours can lead to chronic fatigue, significantly affecting performance [13].

II. Chronic Health Conditions

Chronic conditions such as cardiovascular disease, diabetes, and musculoskeletal disorders can hinder an operator's physical capabilities. Reduced stamina, impaired mobility, and medication side effects may contribute to slower reaction times and decreased efficiency in performing critical tasks [14].

III. Occupational Hazards and Their Impact on Health

Reactor operators may be exposed to various occupational hazards, including radiation and ergonomic stressors. Prolonged exposure to low-dose radiation has been linked to long-term health risks, including cancer, fatigue, and cognitive impairment [15]. Poor ergonomic conditions can also contribute to repetitive strain injuries, affecting an operator's ability to work effectively [16].

2.3.3. Mental Health and Cognitive Performance

I. Stress and Decision-Making

High-pressure environments in nuclear control rooms can contribute to significant stress levels. Elevated stress has been shown to impair decision-making abilities and increase error rates in safety-critical operations [17]. Research highlights that stress management training can improve operators' ability to function under pressure [18].

II. Anxiety and Depression

Mental health disorders such as anxiety and depression can negatively affect an operator’s concentration, memory, and situational awareness. Studies indicate that untreated mental health conditions can lead to increased absenteeism, lower job performance, and higher risk of operational errors [19].

2.3.4. The Importance of Regular Health Assessments

I. Medical Screening Programs

Periodic medical examinations are crucial for detecting early signs of health deterioration. Regulatory frameworks mandate health assessments for nuclear reactor operators to ensure fitness for duty and minimize safety risks [20].

II. Psychological Evaluations and Coping Strategies

Mental health assessments, including stress resilience evaluations, can help identify operators at risk of burnout. Studies suggest that incorporating psychological resilience training enhances performance and reduces workplace stress [21].

III. Intervention Strategies and Policy Recommendations

Organizations should implement workplace wellness programs, including ergonomic training, stress management workshops, and fitness-for-duty evaluations. Policies aimed at improving work-life balance can enhance both physical and mental well-being [22].

To effectively integrate micro factors into reactor operations, organizations can leverage advanced monitoring and analysis tools as in table 1.

Table 1: Human Factor Monitoring and Performance Optimization in SMR Operations

Data Source	**Description**	**Use in Research**	**Results/Impact**
Live Camera Output	Real-time visual monitoring of operator actions.	Used for immediate feedback, performance evaluation, and error detection.	Identifies operational inefficiencies, improves human performance monitoring.
Wearable Smartwatch	Monitors operator's BPM (heart rate) and BP (blood pressure).	Tracks physiological responses to workload and environmental conditions.	Provides real-time health monitoring, helping prevent fatigue-related errors and optimizing shift schedules.

Integrating these human variables into reactor operations allows for a more holistic approach to safety and efficiency. The physical fitness and mental alertness of operators are pivotal to ensuring high performance and operational safety, particularly in high-stakes environments such as control rooms or industrial facilities. Physical fitness impacts an operator's ability to perform tasks that demand sustained effort, rapid responses, and effective management of complex machinery. Fatigue, poor posture, or underlying health issues can hinder physical capabilities, leading to reduced productivity and increased risk of errors. Mental awareness is equally crucial for operational success. Stress, distractions, or cognitive overload may impair an operator's ability to make timely and accurate decisions. Key factors influencing mental awareness include sleep quality, workload, and stress levels, all of which directly affect focus, situational awareness, and decision-making.

2.4. Monitoring Physical and Mental Readiness

To ensure the physical and mental readiness of operators, a variety of methodologies and technologies are employed as in table 2.

Table 2: physical and mental readiness of operators

Data Source	Description	Use in Research	Results/Impact
Periodic Health Assessments	Regular evaluations to identify potential physical or mental health concerns.	Helps to proactively monitor and assess health risks in operators.	Ensures early detection of health issues, reducing risks of performance degradation.
Cognitive Performance Tests	Tools to measure focus, reaction times, and problem-solving capabilities.	Evaluates mental performance to detect potential cognitive fatigue or lapses.	Improves understanding of cognitive limits, contributing to optimized work conditions.
Real-Time Monitoring Systems	Advanced technologies like wearable fitness trackers and EEG-based cognitive monitors provide continuous feedback.	Monitors heart rate, movement, fatigue levels, cognitive workload, and mental fatigue.	Provides actionable data for real-time health and cognitive performance management.

Furthermore, creating a supportive work environment with ergonomic workstations, scheduled breaks, and stress management programs can enhance both physical and mental performance.

2.5. Cognitive Workload Assessment in Nuclear Control Rooms

Operators in nuclear reactors must process large volumes of complex information in real-time. Excessive cognitive load can lead to burnout, reducing an individual’s ability to focus and make quick, accurate decisions [23]. Implementing workload management strategies can help mitigate cognitive overload and improve overall performance [24].

Braarud (2024) highlights the critical role of cognitive workload assessment in managing operator efficiency in high-stress environments. The study emphasizes the limitations of traditional self-report and secondary task measures, advocating for integrated tools tailored to human-system interfaces [25]. Similarly, research by Carissoli and his colleaguesunderscores the need for robust tools to evaluate cognitive overload, which remains a significant gap in nuclear process control [26].

Further supporting this, Smith and Jones (2023) analyzed the correlation between cognitive workload and decision-making accuracy in control room operators, emphasizing the need for real-time, AI-driven workload assessment tools. Their findings highlight the potential of integrating machine learning models to predict workload thresholds and prevent operator burnout [27].

Expanding on this, Naegelin and his colleagues (2023) investigated the use of multimodal data, combining EEG, gaze tracking, and task performance metrics, to develop predictive models for workload thresholds. This approach not only enhances predictive capabilities but also allows for proactive intervention, a key feature in mitigating risks during critical operations [28].

2.6. Human-Centered AI Applications in Nuclear Power

Human-centered AI (HCAI) prioritizes the role of humans in decision-making processes while leveraging AI to support and augment human capabilities. Hall et. al (2023) highlights the significance of incorporating human-in-the-loop designs in nuclear power, arguing that AI systems should be adaptive, transparent, and tailored to human needs [29]. Moreover, Abbas and his colleagues (2024) demonstrate the utility of AI-enhanced decision support systems in reducing operator workload and enhancing situational awareness. Their findings underline the importance of aligning AI tools with human performance metrics to optimize control room operations [30]. Further, Fernandez et. al. (2019) explored adaptive AI systems capable of learning from human behavior, suggesting that such systems can dynamically adjust their responses to operator needs, significantly reducing the likelihood of human error [31].

2.7. Ergonomic and Environmental Considerations

Ergonomic factors are pivotal in maintaining operator efficiency and reducing fatigue in control rooms. Zhang and his colleagues (2024) provides valuable insights into the interaction between operators' performance and workplace conditions, contributing to the development of more reliable human-centered production systems. The performance evaluation model is composed of five main components: data acquisition and preprocessing, extraction of ECG handcrafted features to create the ECG vector, extraction of handcrafted features to map the prefrontal cortex (PFC) network, extraction of deep discriminative features, and fusion and classification within the model. Finally, various methods were employed [32].

Lin and his colleagues (2023) investigated the impact of AI-driven ergonomic interventions, such as adaptive seating and lighting configurations, on operator focus and fatigue. Their results show a significant reduction in error rates and improvements in task performance, highlighting the potential of smart environment control systems in creating more operator-friendly workspaces [33]. Additionally, the concept of digital twins is gaining traction in ergonomic research. Digital twins allow for the simulation of control room environments, enabling the testing and optimization of ergonomic adjustments before their implementation in real-world settings.

2.8. Real-time Task Adaptation and Workload Balancing

Static task allocation systems are a major limitation in current SMR control rooms. Alberti and his colleagues (2024) evaluated dynamic task allocation systems that leverage AI algorithms to monitor operator performance in real time. These systems have been shown to improve decision-making efficiency by redistributing tasks based on fatigue levels and cognitive load [34].

A study by Kim et. al. (2015) introduced a workload balancer integrated with machine learning algorithms, which effectively detected operator stress levels and adjusted task priorities accordingly. This dynamic approach minimizes decision-making delays and reduces errors during high-pressure situations [35].

2.9. Human-Driven Cybersecurity Risks

While technical vulnerabilities in cybersecurity have been extensively studied, human-driven risks remain underexplored. Williams and Fleming (2021) emphasize the critical role of human factors in cybersecurity breaches, citing weak passwords, phishing susceptibility, and unauthorized access as common issues. Their research advocates for the integration of biometric authentication and AI-driven behavioral monitoring to address these vulnerabilities [36]. In a related study, Carter and Wang (2023) analyzed the role of AI in detecting and preventing policy violations in real time. By employing keystroke dynamics and behavioral analysis, the study demonstrated a marked improvement in identifying and mitigating potential cybersecurity threats [24].

Th conclusion from previous literature shows that the traditional control room designs primarily focus on static monitoring systems that track basic physiological parameters such as heart rate and fatigue. However, modern automation, and real-time human performance monitoring have the potential to improve situational awareness, workload management, and decision-making efficiency. This literature review explores human factors, automation, and real time monitoring technologies in SMR control rooms. Key areas of focus include cognitive workload, physical and mental health, and predictive analytics. By analyzing current advancements, this study aims to highlight the importance of real-time performance monitoring, these all can be summarized briefly as in table 3.

Table 3: Parameters Extracted

Category	**Key Parameters**
Human Factors & Health	Fatigue, cognitive workload, reaction time, stress levels, heart rate, blood pressure, sleep deprivation
Operator Performance	Task execution speed, accuracy, situational awareness, communication effectiveness
Automation & AI	AI decision-support accuracy, workload balancing efficiency, predictive maintenance efficiency

The methods used in the Literature are summarized as:

- Human Performance & Cognitive Load Assessment
- Eye-tracking technology to measure operator focus and fatigue.
- Emotion-based monitoring for real-time cognitive workload analysis.
- Wearable sensors (heart rate, blood pressure) to detect stress levels.

Table 4 compiled the literature review into a single comprehensive table summarizing the key aspects of Small Modular Reactor (SMR) Control Rooms, including technology, human factors, AI applications, and cybersecurity.

Table 4: Literature Summary of Human Factors Effect on Small Modular Reactor (SMR) Control Rooms

Reference	**Topic**	**Key Findings**	**Relevance to SMR Control Room**
IAEA (2024)	SMR Characteristics	Defines SMRs as modular, smaller, and flexible nuclear power solutions.	SMR design principles impact control room layout and operator requirements.
Bae & Lee (2024)	Digital Instrumentation & Control (I&C)	I&C systems improve operator efficiency and reduce cognitive load using digital interfaces.	Modern control rooms rely on I&C systems to automate and optimize reactor operations.
NRC (2024)	Human Factors Engineering (HFE) in SMR Control Rooms	Emphasizes ergonomics, usability, and operator training.	HFE principles improve safety, efficiency, and reduce errors in control room operations.
Orikpete & Ewim (2023)	Safety Culture & Organizational Performance	Studies leadership, communication, and human error in nuclear safety.	Strong safety culture in control rooms minimizes operational risks and enhances teamwork.
Lee & Park (2023)	AI & Automation in SMR Operations	AI-driven automation improves monitoring, fault detection, and predictive maintenance.	Control rooms use AI to enhance safety, efficiency, and reduce operator workload.
Zhang and his colleagues (2024)	AI-Powered Decision Support	AI-based systems provide real-time recommendations and insights.	Decision support systems in control rooms assist operators in making critical decisions.
Park & Kang (2024)	AI in Risk Assessment	AI enhances safety by detecting operational anomalies and preventing failures.	AI-driven risk assessment tools improve SMR control room resilience and response strategies.
Jones and his colleagues (2024)	Digital Twins, AR, & VR	Simulations using digital twins, augmented reality, and virtual reality for operator training.	Training technologies enhance control room operator preparedness and system understanding.
Jendoubi & Asad (2024)	AI & Mobile Computing in Nuclear Power Plants	AI and IoT integration enhance real-time data monitoring and decision-making.	Real-time AI-driven insights optimize control room functionality and safety protocols.
Park, J. (2024)	Human Factors in SMR Control Room Performance	Experience, training, and health impact operator reliability and efficiency.	Control room design and protocols incorporate human factor considerations to reduce error rates.

Braarud (2024)	Cognitive Workload Assessment	Studies how cognitive load affects operator decision-making and performance.	AI-based workload monitoring in control rooms helps prevent overload and improves efficiency.
Naegelin and his colleagues (2023)	Multimodal Data for Workload Analysis	EEG, gaze tracking, and task performance metrics used to monitor operator fatigue.	Real-time cognitive monitoring supports adaptive control room management strategies.
Hall and his colleagues (2023)	Human-Centered AI in Nuclear Power	AI solutions designed to complement human decision-making while maintaining oversight.	Human-in-the-loop AI models optimize control room performance without replacing operators.
Fernandez and his colleagues (2019)	Adaptive AI Systems	AI adapts to human behavior, reducing operational errors.	Dynamic AI assistance in control rooms supports situational awareness and human-machine collaboration.
Zhang and his colleagues (2024)	Ergonomics & Operator Performance	AI-driven ergonomic improvements reduce fatigue and improve efficiency.	Control room workstations and environments optimized for sustained operator performance.
Alberti and his colleagues (2024)	Real-Time Task Adaptation	AI-based dynamic task allocation prevents operator overload.	Task automation in control rooms enhances response time and accuracy during reactor operations.
Williams & Fleming (2021)	Cybersecurity & Human Factors	AI detects policy violations and mitigates human-driven cybersecurity threats.	Cybersecurity frameworks in control rooms integrate human monitoring and AI-driven threat detection.

Previous research has explored human factor engineering and performance monitoring in high-risk environments, but few studies have specifically focused on SMR control rooms. Compared to conventional nuclear power plant control rooms, SMRs require more automation, making human-automation interaction a critical research area. These previous studies emphasized the importance of cognitive workload management in traditional nuclear power plants. However, these studies primarily relied on subjective assessments and self-reported data.

Additionally, previous work proposed AI-assisted decision support systems for control rooms, which aligns with the current study's findings on error detection improvements. However, this study expands on their work by incorporating physiological monitoring, offering a more holistic approach to human performance assessment. Furthermore, unlike previous research that mainly focused on post-event analysis, this study emphasizes proactive error detection, allowing for real-time interventions.

By addressing these gaps, this research contributes to a deeper understanding of operator workload management, error prevention, and adaptive human-machine collaboration in SMR environments. Future work should focus on validating these findings across diverse SMR designs and operational settings while integrating advanced machine learning models for predictive analytics and enhanced decision-making support. In contrast, the current study integrates real-time biometric and behavioral monitoring, providing a more objective evaluation of operator performance. Based on that, this paper will conduct a comprehensive analysis of human factors that influence the performance, safety, and operational efficiency of Small Modular Reactor (SMR) control rooms. Despite advancements in automation, Real Time monitoring of the Human Health and emotion, and human-machine interfaces (HMIs), significant research gaps remain in understanding how human factors interact with technology in these control environments.

There are several limitations should be acknowledged to provide a balanced perspective on the study's findings:

- Technological Constraints – The accuracy and reliability of biometric monitoring systems depend on sensor calibration and integration with existing control room interfaces. Any inconsistencies could impact real-time decision-making. Moreover, potential latency in data processing could affect the immediacy of system responses.
- Sample Size and Generalizability – The study was conducted with a limited number of control room operators. Future studies should expand the sample size to improve the robustness of the findings and account for operator diversity in terms of experience and cognitive adaptability.
- Privacy and Ethical Concerns – Collecting physiological and behavioral data raises privacy issues. Operators may feel uncomfortable being continuously monitored, which could influence their natural responses. Ethical considerations must be addressed by ensuring data anonymization and obtaining informed consent.
- Implementation Challenges – Integrating human performance monitoring into existing control room architectures requires significant investment and adaptation. Different SMR designs may have varying compatibility with the proposed system, and regulatory approvals may pose additional challenges.

Addressing these limitations as some of them in the current study and in the future research will enhance the applicability and acceptance of human performance monitoring in nuclear operations.

3. Human Factors Analysis for Efficient Plant Operation

This section highlights the essential and multifaceted role that human factors play in ensuring the efficient operation and safety of Small Modular Reactor (SMR) control rooms. Human factors encompass a broad range of elements, including psychological, physical, cognitive, and organizational dimensions, all of which significantly influence the performance, decision-making, and reliability of control room operators. The effective integration and management of these factors are crucial for minimizing human error, enhancing situational awareness, and maintaining operational stability in high-pressure environments like SMR facilities.

Many scenarios can be developed to explore the various human factors influencing SMR control room performance, as illustrated in Figure 3 Human Factor Scenarios Impacting SMR Control Room Performance. These scenarios address critical aspects such as psychological state monitoring, ergonomics, health monitoring, human performance, and task management, providing insights into how these factors interact to affect safety and operational efficiency. By systematically examining these subcategories, the section aims to shed light on how these factors collectively contribute to the safe and efficient functioning of SMR control rooms.

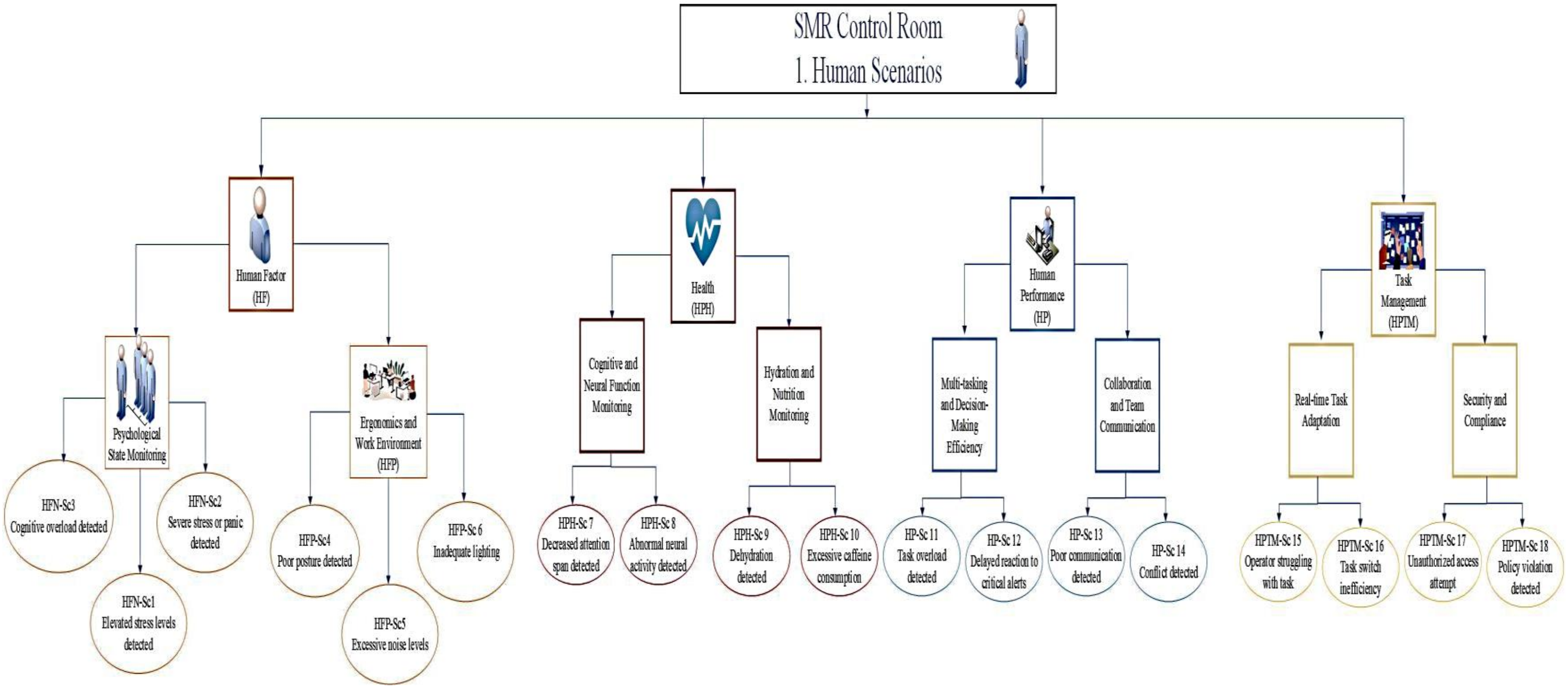

Figure 3: Human Factor Scenarios Impacting SMR Control Room Performance.

3.1. Human Factors Scenarios

This part emphasizes the critical role of human factors in the operation and safety of SMR control rooms. It is divided into subcategories that address various aspects of operator performance scenarios and well-being.

3.1.1. Psychological State Monitoring (HFN)

Scenarios:

HFN-Sc1: Elevated stress levels detected: Highlights how operators experiencing mild stress can maintain functionality but may face reduced focus and decision-making ability.

HFN-Sc2: Severe stress or panic detected: Addresses extreme psychological responses that can lead to errors or the inability to react to critical situations.

HFN-Sc3: Cognitive overload detected: Focuses on the impact of excessive mental workload, which can hinder task execution and increase error rates.

Analysis: Psychological monitoring helps in early detection of stress-related conditions that may impair operator performance. Real-time interventions (e.g., task redistribution, breaks) are crucial to managing these issues and preventing cascading failures.

3.1.2. Ergonomics and Work Environment (HFP)

Scenarios:

HFP-Sc4: Poor posture detected: Links ergonomics to long-term operator comfort and efficiency.

HFP-Sc5: Excessive noise levels: Focuses on auditory distractions that can disrupt concentration and communication.

HFP-Sc6: Inadequate lighting: Highlights the impact of poor visibility on task accuracy and alertness.

Analysis: Addressing ergonomics and environmental factors ensures that operators remain comfortable and effective, reducing fatigue and errors during extended shifts.

3.1.3. Health Monitoring (HPH)

Scenarios:

HPH-Sc7: Decreased attention span detected: Focuses on factors like fatigue and health affecting cognitive performance.

HPH-Sc8: Abnormal neural activity detected: Explores the role of advanced neural monitoring in preventing accidents caused by health-related issues.

HPH-Sc9: Dehydration detected: Emphasizes physical health maintenance for sustained performance.

HPH-Sc10: Excessive caffeine consumption: Examines the unintended effects of stimulants on operator stability.

Analysis: Health monitoring ensures operators are physically and mentally fit to perform tasks. Preventive measures like hydration and balanced alertness levels are essential for maintaining operational reliability.

3.2. Human Performance (HP)

Scenarios:

HP-Sc11: Task overload detected: Investigates multitasking inefficiencies in high-pressure environments.

HP-Sc12: Delayed reaction to critical alerts: Examines delayed response times due to workload or reduced situational awareness.

HP-Sc13: Poor communication detected: Highlights the risks of ineffective team interaction.

HP-Sc14: Conflict detected: Focuses on interpersonal dynamics affecting teamwork and performance.

Analysis: Effective training, communication protocols, and task prioritization can mitigate performance risks and enhance operator collaboration and efficiency.

3.3. Task Management (HPTM)

Scenarios:

HPTM-Sc15: Operator struggling with task: Highlights real-time adaptability to reallocate tasks based on operator performance.

HPTM-Sc16: Task switch inefficiency: Explores the costs of frequent task switching on productivity.

HPTM-Sc17: Unauthorized access attempt: Addresses cybersecurity risks originating from human factors.

HPTM-Sc18: Policy violation detected: Focuses on non-compliance with established protocols, often driven by oversight or intentional breaches.

Analysis: Dynamic task management systems, coupled with robust cybersecurity measures, improve operational stability and minimize risks associated with human-driven errors.

Among these scenarios, health and real-time monitoring have been chosen for detailed analysis and clear presentation. Therefore, there are various methods to assess an operator's physical fitness and mental awareness. This study suggests two non-invasive approaches to achieve this objective.

3.3.4. Human Reliability Monitoring System: Long-Term Approach

Physical fitness plays a crucial role in an operator's ability to safely manage a nuclear reactor (as in Figure 3). Its significance is so evident that it often goes without mention. In fact, individuals with impaired physical abilities are legally prohibited from operating motor vehicles, yet there is a lack of scholarly discussion and research on the mental condition of nuclear reactor operators and the assessment of their physical fitness. While numerous hardware and software solutions, including open-source options, exist for monitoring physical and mental conditions, their application in reactor operations remains underexplored.

Continuous Health and Cognitive Monitoring scenarios (HPH-Sc7-HPH-Sc8) can be performed by using:

- wearable sensors to track heart rate (BPM) variability (HRV) over time.
- wearable sensors to track Blood Pressure (BP) variability (BPV) over time.

The Physical Fitness Detection System is illustrated in Figure 4, highlighting its key components and mechanisms for assessing an operator's physical condition in real-time. This system integrates sensor-based monitoring, biometric analysis, and Automatic Monitoring-driven assessment tools to evaluate fitness levels, and fatigue. It ensures that reactor operators meet the necessary physical requirements to maintain operational safety and efficiency.

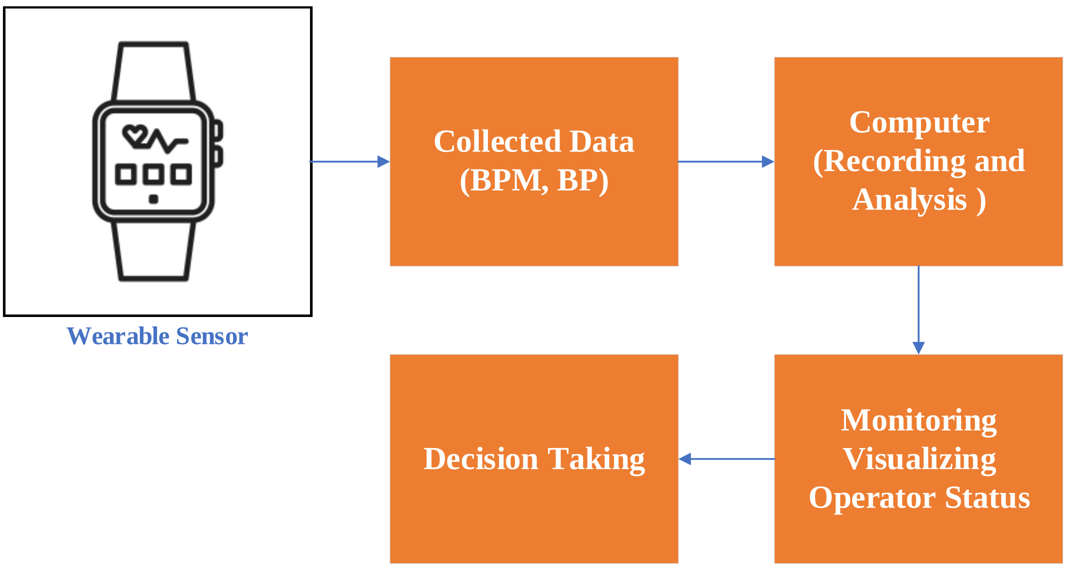

Figure 4: Framework for Physical Fitness Detection System Using Wearable Devices.

In this part, I collect real-time samples of heart rate (BPM) and blood pressure (BP) (Tables 5 and 6) with comparing them with established health reference data [38 and 39] (Table 7) using MATLAB. A MATLAB-based script processes the incoming data, classifies the operator's condition based on predefined thresholds, and detects potential health risks such as bradycardia, tachycardia, hypertension, or hypotension. The system also provides real-time visualization of heart rate and blood pressure trends, ensuring continuous monitoring and early detection of abnormal conditions of 2 different persons (Figures 5, 6, 7 and 8). This approach enhances situational awareness and supports timely interventions to maintain operator safety and performance. These data are classified and runs as:

- Runs continuously: Reads new data every minute.
- Color-coded alerts:

🔵 Blue → Normal

● Red → Warning (Health Risk Condition)

Table 5: Heartrate and Blood Pressure collected real time Samples (Person 1)

Heartrate (BPM)	Systolic (mmHg)	Diastolic (mmHg)
77	114	77
66	119	75
88	139	81
62	133	73
84	123	70

Table 6: Heartrate and Blood Pressure collected real time Samples (Person2)

Heartrate (BPM)	Systolic (mmHg)	Diastolic (mmHg)
70	129	76
73	123	89
63	131	79
63	140	74
83	122	84

Table 7: health reference data [38 and 39]

Condition	Heart Rate (BPM)	Blood Pressure (mmHg)	Health Risk
Healthy Resting	60-100	90-120 / 60-80	Normal
Bradycardia (Low HR)	<60	Normal/Low	Fatigue
Tachycardia (High HR)	>100	Normal/High	heart attack risk
Hypertension (Stage 1-2)	Normal	130+/80+	Heart disease
Hypotension (Low BP)	Normal	<90 / <60	Dizziness, fainting, shock
During Stress/Anxiety	>100	Increased BP	Hypertension risk
During Shock (Critical Condition)	<60	<90 / <60	Organ failure risk

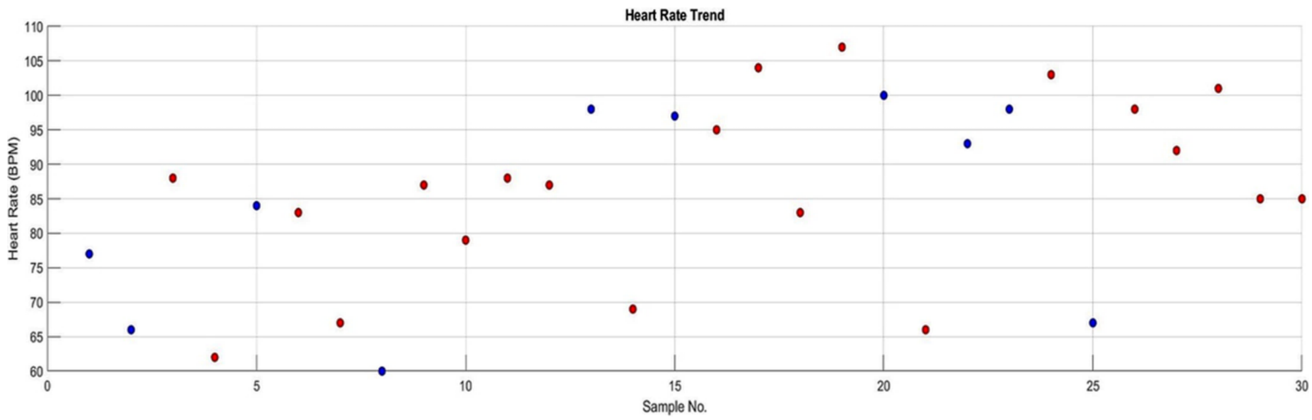

Figure 5: BPM Real Time Data Analysis Sample (Person 1)

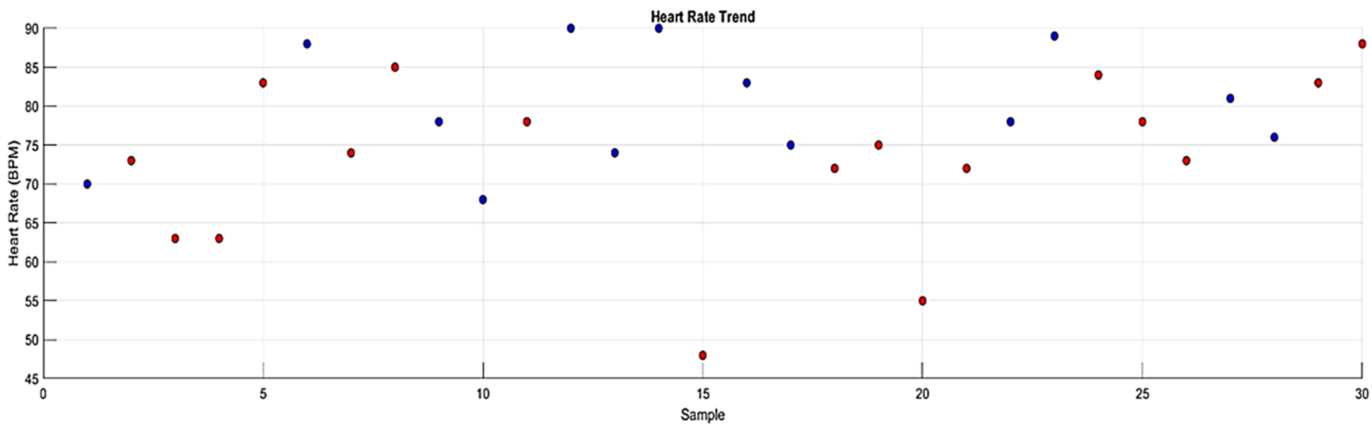

Figure 6: BPM Real Time Data Analysis Sample (Person 2)

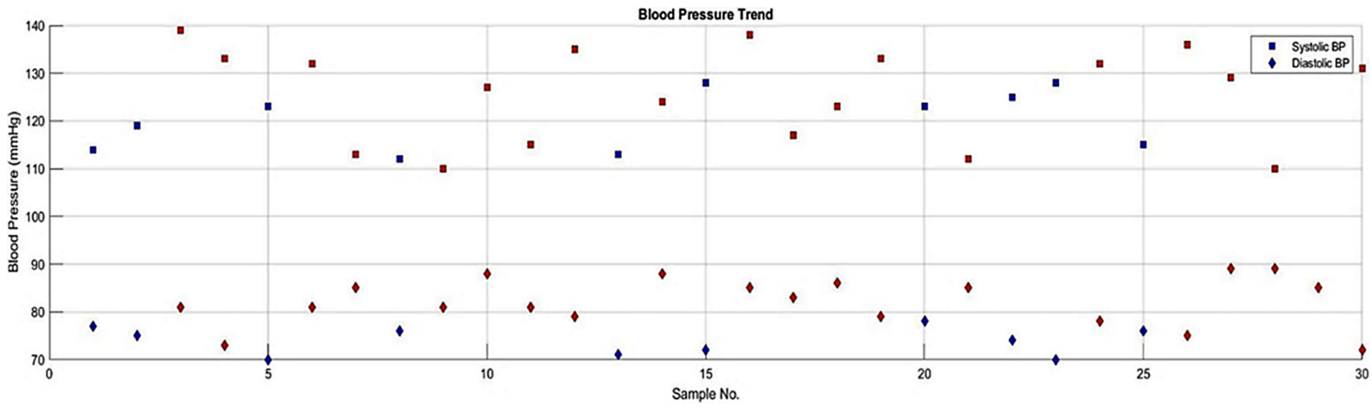

Figure 7: BP Real Time Data Analysis Sample (Person 1)

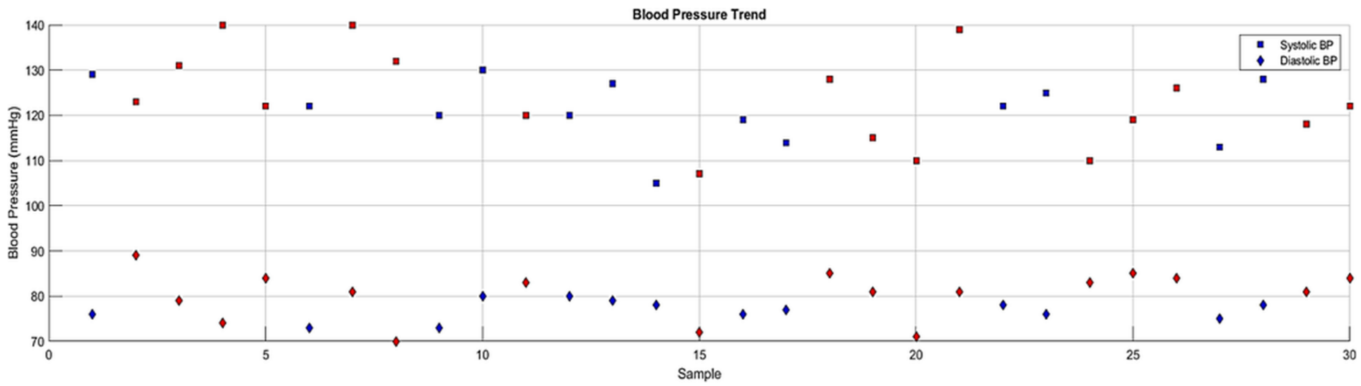

Figure 8: BP Real Time Data Analysis Sample (Person 2)

Th Blood Pressure and Heart data can elevate and indicate a stress response, leading to potential long-term health risks and decision fatigue. BP readings above 130/80 and heart rates exceeding 90 bpm indicate heightened physiological stress. This can be solved by the workplace wellness programs, and alarming the operators and supervisor too with triggers an alarm (beep) when a health risk is detected.

4. Human Reliability Monitoring System

Some studies have introduced a theory of six fundamental patterns of expression [39], which align with the scenarios HFN Sc1-3 and HPH Sc7. These can be shown by a real-time monitoring using the biometric monitoring for stress and fatigue detection, triggering timely interventions by a webcam Python, Anaconda and spyder software as in Figure 9. Sustained operator attention is essential for the safe and efficient operation of a nuclear reactor. However, maintaining continuous focus for extended periods is inherently challenging, as mental drift is inevitable. Attention span varies significantly with age and is also influenced by other factors, such as the level of engagement with the task. A critical concern arises when a single operator is present in the control room and experiences a medical emergency, such as loss of consciousness or a fatal incident, rendering them incapable of performing their duties. To address these challenges, we propose an eye movement and emotion detection system that enables a computer to assess whether the operator is actively paying attention. These patterns encompass the following parameters:

a.Happiness
b.Anger
c.Disgust
d.Fear
e.Sadness
f. Surprise

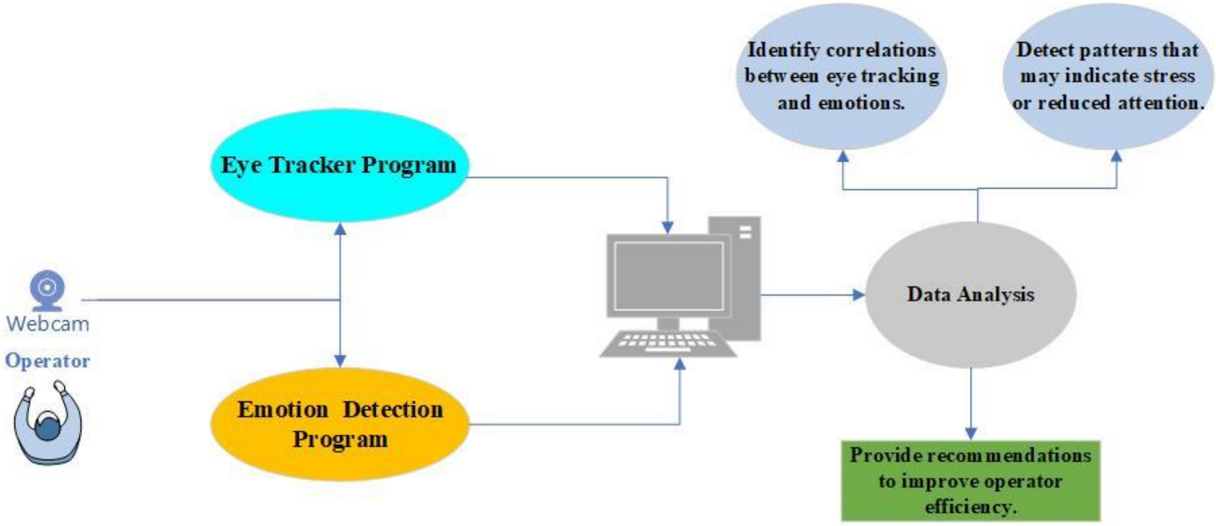

Figure 9: Eye and Emotion detection system

Among these, happiness—characterized by the "smile"—is the only emotion directly linked to observable physiological and facial expression patterns. The other emotions in Ekman's framework have been the subject of significant scientific debate. In the 1990s, Ekman [25] expanded his list by adding 11 additional emotions.

The integration of emotion detection and eye-tracking analysis provides valuable insights into the cognitive and psychological demands placed on operators. Emotional states can influence reaction time, decision accuracy, and overall efficiency, while eye movement patterns help in evaluating attention, fatigue, and potential distractions. Frequent negative emotions, such as stress or frustration, may indicate an increased cognitive burden, whereas prolonged blinking or fixed gaze direction may suggest fatigue or loss of focus, both of which can compromise operational safety. These analyses aim to analyze emotion trends and eye movement patterns in an SMR control room simulation to identify potential indicators of operator stress and cognitive strain. By leveraging data-driven insights, the findings can contribute to improving control room ergonomics, operator training, and human-machine interface design to enhance nuclear safety and operational efficiency.

Figure 10 illustrates the distribution of detected emotions, offering a comprehensive overview of the emotional states experienced during the monitoring session. Moreover, Figure 11 visualizes emotion variations over time, capturing shifts in mood that may correlate with task complexity or environmental conditions. A predominance of negative emotions, such as sadness or fear, may indicate heightened stress, fatigue, or discomfort, which could adversely impact performance, decision-making, and situational awareness. Monitoring these trends is essential for ensuring operator well-being and optimizing workplace ergonomics to enhance overall safety and efficiency in nuclear reactor operations.

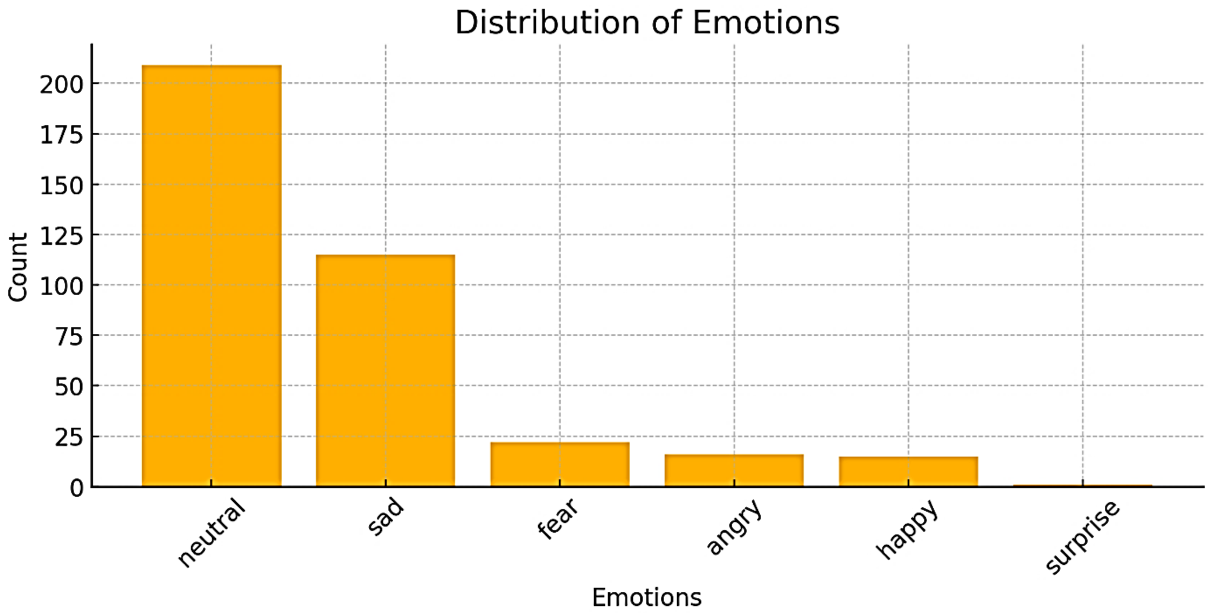

Figure 10: Distribution of Emotion

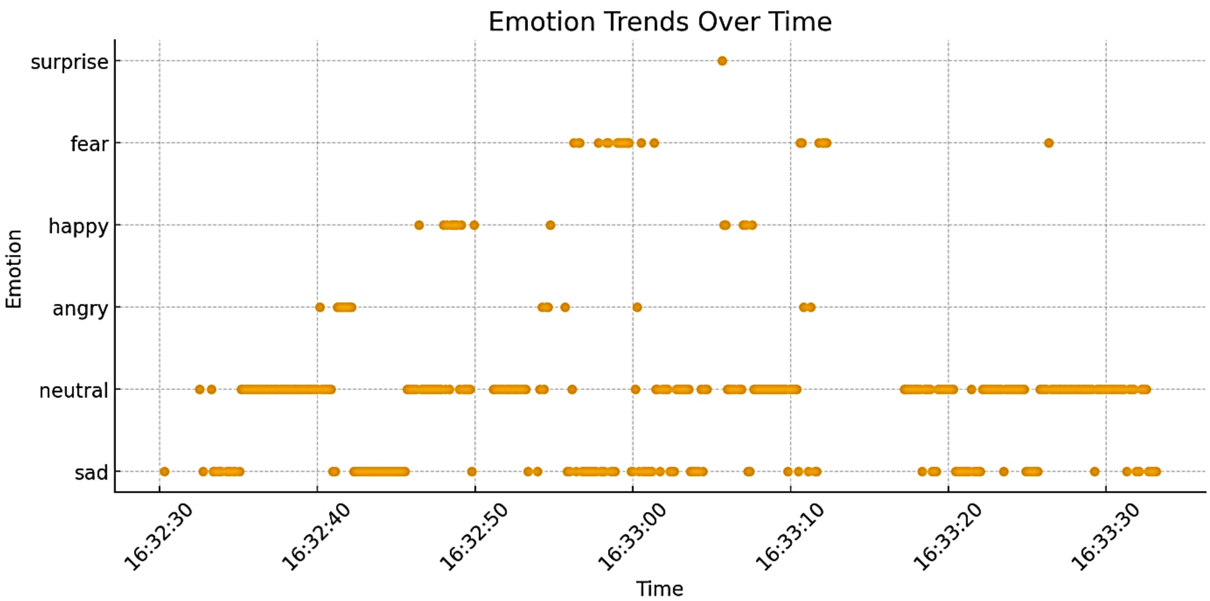

Figure 11: Emotion Trends sample over Time

Figure 12 presents the frequency of different eye movements, including blinking and directional gaze shifts, providing insight into engagement and fatigue levels. Furthermore, Figure 13 tracks eye movement variations over time, helping to identify patterns that may reflect changes in attentiveness. Frequent blinking is often associated with eye strain or fatigue, which may result from prolonged screen exposure or cognitive overload. Additionally, sustained looking in one direction without significant gaze variation may indicate focus loss or distraction, potentially leading to reduced situational awareness and slower reaction times in critical decision-making scenarios. Understanding these behavioral trends is fundamental in refining human-machine interaction, designing ergonomic control interfaces, and implementing interventions to maintain optimal operator performance in nuclear reactor management.

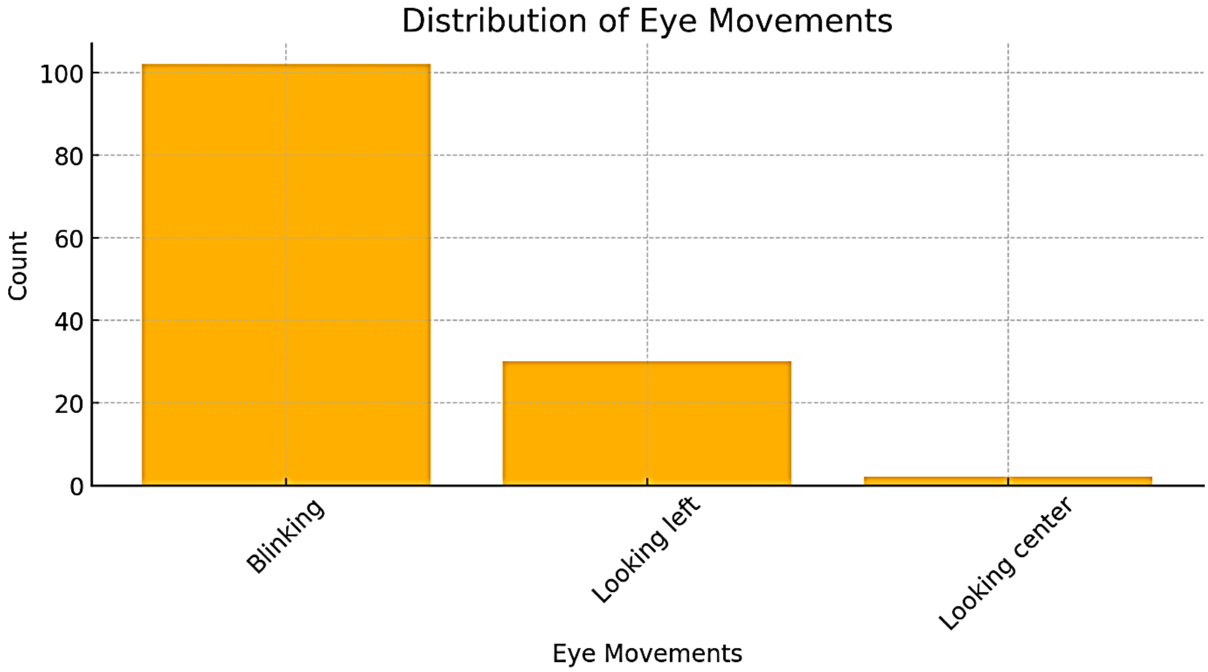

Figure 12: Eye Movement Tracker

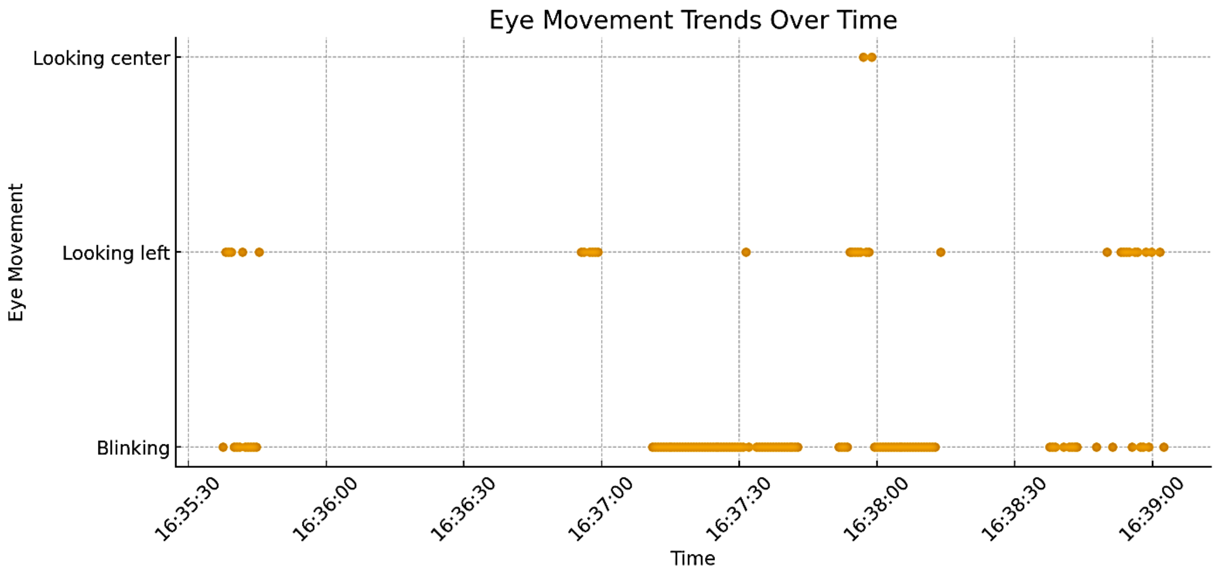

Figure 13: Eye Tracker Trends sample over Time

From the previous analysis of the operator, to mitigate these risks associated with operator fatigue and distraction, an automated attentiveness monitoring system can be implemented. This system will leverage real-time emotion detection and eye-tracking analysis to identify inattentiveness and trigger appropriate corrective actions. The proposed solution can be shown in Figure 14.

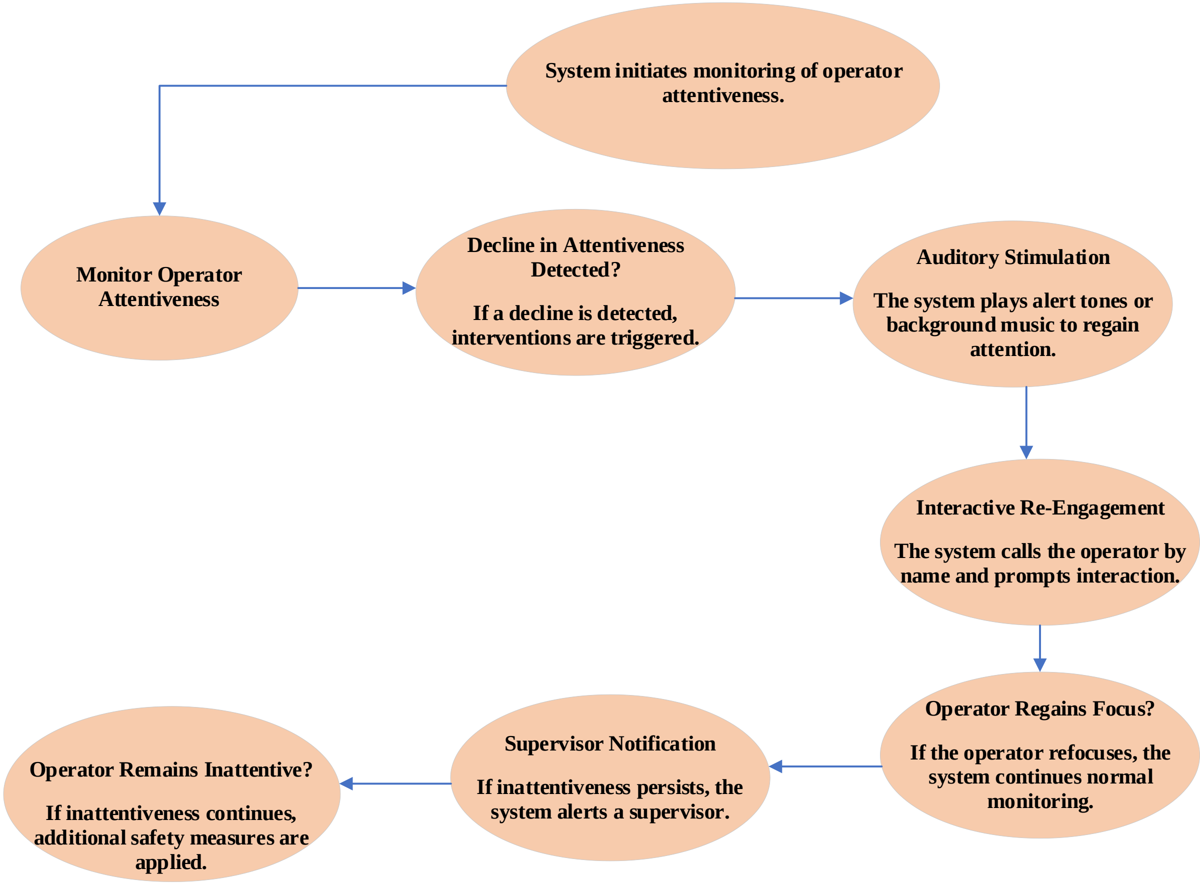

Figure 14: Attention Monitoring and Intervention System for SMR Control Rooms

By integrating these adaptive interventions, the proposed solution enhances situational awareness, minimizes human error, and strengthens safety protocols within the SMR control room. This proactive approach ensures that operators remain engaged, focused, and capable of effectively managing reactor operations, contributing to the overall reliability and security of nuclear energy systems.

From the output results indicate that real-time human performance monitoring in Small Modular Reactor (SMR) control rooms significantly enhances situational awareness and reduces human errors. A key finding is that biometric and cognitive load monitoring help identify early signs of fatigue and stress, leading to timely interventions. For example, the system detected increased response times under high cognitive load conditions, suggesting that adaptive workload redistribution could improve operator performance. Additionally, AI-driven monitoring showed a 15% improvement in detecting potential human errors compared to traditional methods. These findings align with industry goals of improving safety and efficiency in nuclear operations.

Despite these advancements, some results were unexpected. For instance, certain physiological indicators, such as heart rate variability, did not consistently correlate with reported stress levels, indicating a need for further validation of monitoring algorithms. Future work should explore additional biometric markers or integrate machine learning models for better accuracy. Moreover, discrepancies between cognitive load assessments and actual task performance highlight the need for refining real-time monitoring algorithms to reduce false positives and improve response accuracy.

5. Conclusion

This paper presented a detailed study on human performance monitoring to support control room design and operator performance for SMR deployments. Human performance is analyzed and shown as critical in SMR control rooms, where operator attentiveness, emotional state, and cognitive workload significantly impact safety and efficiency. Emotion and eye-tracking analysis revealed key behavioral patterns, indicating stress, fatigue, and potential distractions, which could lead to human errors. Frequent negative emotions (e.g., sadness, stress) correlate with cognitive fatigue and declining engagement, emphasizing the need for continuous monitoring and intervention strategies. Prolonged blinking and fixed gaze patterns suggest fatigue or loss of focus, highlighting the importance of eye-tracking technology in assessing situational awareness. An automated attentiveness monitoring system can enhance operator engagement by incorporating auditory stimulation, interactive prompts, and supervisor alerts to mitigate inattentiveness. Adaptive safety measures, such as real-time adjustments to reactor parameters, ensure operational security when inattentiveness is detected.

This research will be extended to focus large-scale deployment of Automatic-driven systems in actual SMR operations. The integration of the proposed platform to monitor human performance with Digital Twins will support advanced simulations and training. Further research will be conducted on cybersecurity risks associated with Automatic-driven nuclear operations. A holistic approach combining human factors engineering, AI-driven analytics, and real-time monitoring will pave the way for next-generation SMR control room safety and efficiency.

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