International Journal of Research Publication and Reviews, Vol 6, Issue 8, pp 2975-2982 August, 2025

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Real-Time Monitoring and Management Algorithm in Persuasive System for Occupational Safety of Medical Practitioners.

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DOI : https://doi.org/10.55248/gengpi.6.0825.3035

ABSTRACT

The healthcare environment presents numerous occupational hazards for medical practitioners, ranging from infectious diseases and musculoskeletal injuries to mental health stressors. Despite the critical importance of ensuring occupational safety, real-time monitoring and proactive risk management systems remain underdeveloped in clinical settings. This study proposes the design and development of a real-time monitoring and management algorithm integrated into a persuasive system aimed at enhancing occupational safety for medical practitioners. The algorithm leverages sensor data, behavioral analytics, and contextual information to detect potential safety violations and high-risk scenarios, providing immediate feedback and personalized safety recommendations. Grounded in persuasive technology principles, the system is designed to influence practitioners' behaviors through subtle nudges, alerts, and adaptive interventions without disrupting clinical workflows. A prototype implementation was tested in a hospital environment, demonstrating improved hazard recognition and adherence to safety protocols. The results underscore the potential of intelligent, real-time systems to promote a culture of safety and reduce occupational risks in healthcare settings. This work contributes to the growing field of human-centered health informatics by aligning safety management with behavior change strategies enabled by real-time data analytics.

Keywords: Real-time Monitoring, Occupational Safety, Medical Practitioners, Persuasive Systems, Safety Management, Healthcare Technology, Behavior Change, Risk Detection.

1.0 INTRODUCTION

Occupational safety in healthcare settings is a growing concern globally, as medical practitioners face a wide range of hazards in the course of their daily duties. These risks include exposure to infectious diseases, needlestick injuries, physical strain, chemical hazards, and psychological stress. Despite the implementation of institutional safety protocols, compliance is often inconsistent due to high work pressure, lack of real-time feedback, and insufficient awareness of risk exposure. As a result, there is a pressing need for more effective, proactive, and context-sensitive approaches to ensure the health and safety of healthcare workers asserted Aluko *et al* (2016).

In recent times, modern technologies have resonated to change the behavior of users through persuasions and social influence (Hussian *et al*., 2023).Advances in digital health technologies and ubiquitous sensing have created new opportunities to monitor environmental and behavioral conditions in real-time. When integrated with intelligent algorithms, these technologies can detect unsafe conditions, predict potential risks, and facilitate timely interventions. However, the success of such systems depends not only on technical accuracy but also on their ability to influence behavior without disrupting clinical workflows asserted Mbanusi *et al*(2025).

Persuasive technology—designed to subtly encourage behavior change—offers a promising framework for enhancing occupational safety. By embedding persuasive elements into safety systems, it is possible to nudge medical practitioners toward safer practices through context-aware prompts, reminders, and adaptive feedback. When combined with real-time monitoring and intelligent management algorithms, such systems have the potential to significantly reduce occupational hazards and foster a culture of safety in healthcare environments. For instance, Wang *et al*. (2021) investigated the factors that affect user behaviour on mobile health applications, while Alsyouf *et al*. (2023) proposed a technology acceptance model that focused on supporting user participants in the health care process rather than a persuasive approach. Existing systems may not integrate real-time data or feedback from users, which is crucial for timely hazard identification and response (Mababa *et al*., 2021).

This paper presents the development of a real-time monitoring and management algorithm embedded within a persuasive system aimed at improving the occupational safety of medical practitioners. The proposed system collects and analyzes real-time data from wearable sensors and environmental monitors, identifies potential safety violations, and delivers tailored interventions based on persuasive principles. The goal is to support medical practitioners in making safer choices autonomously, thereby reducing workplace incidents and promoting long-term behavioral change. The following sections detail the system architecture, algorithm design, implementation methodology, and evaluation outcomes within a clinical setting.

2.0 REAL-TIME MONITORING AND MANAGEMENT ALGORITHM

This section presents a real time monitoring and management model which operates with the reward and repercussion algorithm to promote safety in the workplace, and also another algorithm which monitors user adherence to PPE and then send notification to management. The user monitoring algorithm operates by collecting assigned task information, date and time, then assigned entities to carry out the task. Managing occupational hazards in healthcare requires a multifaceted approach to address the various risks associated with the work environment (Gross *et al*., 2020). This information serves as input for the system initialization, then a rule-based approach is applied to monitor the acceptance or rejection of task by entities. Upon rejection, the admin receives the notification via email and then reassign the task to another entity, while on acceptance; a time control function is automatically initiated to monitor count down to the near time to task so as to remind the user of adherence to PPE. When the user has adhered to the PPE and accepted, the information is registered in the central database where it serves as input or the rewards and repercussion algorithm. The same principle applies when the user did not use the PPE for the task.

3.0 THE MODELING ASSUMPTIONS

To ensure the feasibility, accuracy, and efficiency of the proposed real-time monitoring and management algorithm, the following modeling assumptions have been made:

Practitioner Compliance and Device Usage

- Medical practitioners are **consistently equipped with wearable sensors** (e.g., smartwatches, biometric bands, posture monitors) throughout their active shifts.
- Practitioners **agree to data collection** and **respond to system prompts** when interventions are delivered, with an average compliance rate assumed to be $\geq 80\%$.

. Sensor Accuracy and Data Integrity

- Sensor devices used (physiological, environmental, and motion sensors) are assumed to have a **minimum accuracy of 90%**, and are **calibrated regularly**.
- **Data transmission** from sensors to the system occurs with minimal latency (≤ 1 second), allowing real-time monitoring.
- **Sensor drift, noise, and signal loss** are negligible or are mitigated using preprocessing and filtering techniques.

Environmental and Operational Context

- The clinical environment is **partially instrumented**, meaning:
  - Environmental data (e.g., air quality, noise levels, temperature) can be **captured at specific zones** (e.g., operating room, ICU).
  - Task context (e.g., surgery, rounds, admin work) can be inferred through **schedule integration and location tracking**.
- The hospital IT infrastructure supports **secure integration with EHR systems**, allowing context-aware decision-making.

Behavioral Modeling and Personalization

- User profiles are **initialized with basic demographic and professional information**, such as role, department, shift pattern, and known health risks (e.g., chronic fatigue, musculoskeletal conditions).
- The algorithm assumes that **behavioral trends can be learned over time** (e.g., stress responses, break-taking patterns), allowing the system to personalize feedback progressively.

Risk Evaluation and Intervention Thresholds

- Safety rules and thresholds (e.g., acceptable heart rate, maximum shift length, safe exposure levels) are **standardized initially**, based on occupational safety guidelines (e.g., WHO, OSHA).
- Thresholds are **customizable at the institutional level**, and the model assumes these are correctly configured by safety officers or system administrators.

Feedback Loop Assumptions

- Interventions are delivered via **visual, auditory, or haptic notifications** on wearable or mobile interfaces.
- It is assumed that **intervention messages are context-sensitive**, brief, and actionable, to minimize disruption to ongoing medical tasks.

- The system can **log responses to interventions** (accepted, ignored, delayed), which are used to fine-tune future interaction strategies.

System Performance and Scalability

- The real-time system is assumed to process data and deliver feedback within **≤ 2 seconds of detecting a risk condition**.
- The algorithm is assumed to scale across **multiple users simultaneously** with minimal degradation in response time, under typical hospital network loads.

Ethical and Privacy Safeguards

- All monitoring complies with **medical data privacy standards** (e.g., HIPAA, GDPR).
- Data collection is assumed to be **transparent and consent-based**, and only used for safety-related interventions.

These assumptions provide a structured foundation for the algorithm's operation and evaluation, enabling realistic implementation in complex healthcare environments while acknowledging practical limitations and ethical considerations.

4.0 USER MONITORING ALGORITHM

Algorithm: Real-time Context-Aware Safety Intervention (RCSI)

Input:

- SensorData (physiological, environmental, motion, location)
- UserProfile (role, schedule, health history, preferences)
- ContextData (current task, workload, shift duration)
- SafetyRules (domain-specific safety thresholds)
- HistoricalData (past incidents, compliance patterns)

Output:

- Real-time intervention messages or actions (e.g., alerts, suggestions, rest prompts)

1. Initialization

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```
Load UserProfile
Load SafetyRules
Initialize sensors and monitoring devices
Set MonitoringInterval ← 5 seconds
```

2. Continuous Monitoring Loop

scss

Copy code

```
While (PractitionerOnDuty):
    SensorData ← Collect from wearable and environmental sensors
    ContextData ← Infer from EHR system, workload scheduler, location, etc.
    CurrentState ← {
        HeartRate: SensorData.HR,
        MovementPattern: SensorData.Motion,
        NoiseLevel: SensorData.Sound,
        TaskType: ContextData.Task,
        Duration: ContextData.ShiftTime,
```

```
        ExposureLevel: SensorData.Hazard
    }
    RiskScore ← EvaluateRisk(CurrentState, SafetyRules)
    If RiskScore > Threshold:
        RiskType ← ClassifyRisk(RiskScore, CurrentState)
        Intervention ← GenerateIntervention(RiskType, UserProfile, ContextData)

        DeliverIntervention(Intervention)
       LogEvent(CurrentState, Intervention)
    Sleep(MonitoringInterval)
```

3. Risk Evaluation Function

mathematica

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```
Function EvaluateRisk(CurrentState, SafetyRules):
    risk = 0
    If CurrentState.HeartRate > SafetyRules.MaxHR:
        risk += 2
    If CurrentState.ExposureLevel > SafetyRules.AllowedExposure:
        risk += 3
    If CurrentState.Duration > SafetyRules.MaxShiftTime:
        risk += 1
    If CurrentState.MovementPattern indicates repetitive strain:
        risk += 2
    If ContextData.TaskType == "Surgery" and risk > 3:
        risk += 1
    Return risk
```

4. Risk Classification

sql

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```
Function ClassifyRisk(RiskScore, CurrentState):
    If RiskScore ≥ 5 and ExposureLevel high:
        Return "Fatigue and Exposure Risk"
    Else If MovementPattern repetitive:
        Return "Musculoskeletal Risk"
    Else:
        Return "General Alert"
```

5. Intervention Generation

sql

Copy code

```
Function GenerateIntervention(RiskType, UserProfile, ContextData):
    If RiskType == "Fatigue and Exposure Risk":
        Return "Suggest short break and N95 replacement. Air quality poor."
    Else If RiskType == "Musculoskeletal Risk":
        Return "Recommend posture correction exercise. Reduce repetitive motion."
    Else:
        Return "Monitor closely. Encourage hydration and microbreaks."
    // Personalization based on UserProfile:
    Adjust message tone, language, and timing
```

6. Intervention Delivery

mathematica

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```
Function DeliverIntervention(Intervention):
    Display on wearable screen or mobile app
    Use haptic feedback for urgency
    Log feedback response if practitioner dismisses or accepts
```

7. Logging and Learning

pgsql

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```
Function LogEvent(CurrentState, Intervention):
    Store in centralized database with timestamp
    Update HistoricalData for trend analysis
    Adapt thresholds over time using reinforcement learning (future extension)
```

The algorithm presents the step applied to monitor the adherence to safety and acceptance of task by the user of the Personal Protective Equipment. In the algorithm, the system initializes using data collected from the event scheduling model in figure 4.3, the information then set conditions such as time of events, time to remind user of event which is 1440mins, time for first Personal Protective Equipment adherence reminder which is 60min to task, then further reminder during 30min and 15 min to task. During these periods, the decision of the users forms the input to the repercussion algorithm developed shortly. When users adhere to PPE application for the task, it is recorded in the central database, however when the user did not accept to use the Personal Protective Equipment or did not respond when T < 10m, then it is registered that the Personal Protective Equipment was not used for the task. This process continues for every task once it has been accepted by the entity.

The reward and repercussion algorithm evaluates the performance of the entity in measuring how well they adhere to the Personal Protective Equipment adoption for task and then make recommendations for future compliance.

5.0 THE REWARD AND REPERCUSSION ALGORITHM

1. *Start*
2. *Connect the User Monitoring Algorithm (UMA)*
3. *Set inputs from UMA as integer*
4. *Fetch total number of task accepted by user as X*
5. *Fetch records of PPE adherence from log report for users and set as Y*
6. *Set user adherence factors* ($F = \frac{X}{Y} * 100$) *% adherence factor to PPE*

7. *If F >= 80%, then recommend user for award*
8. *Else if >= 50-79%, then recommend user for commendation*
9. *Else if < = 50%, then recommend user for query*
10. *Else*
11. *Return to step 2*
12. *End*

In the reward and repercussion algorithm developed above began with the connection of the user monitoring algorithm to fetch records such as the number of task accepted by user, number of task time the user adheres to Personal Protective Equipment. These values are converted to integer and then used to decide at the end of the year, decision to help improved adherence to Personal Protective Equipment application to task. When the total number of adherence of users to the Personal Protective Equipment adherence exceeds 80%, then the user is recommended for rewards, while if the rate of user adherence falls from 50% to 79%, then user is recommended for commendation with room for improvement, while when the rate of adherence of user to Personal Protective Equipment falls below 50%, then the user is recommended for query. Figure 4.5 presents the activity diagram of the real time monitoring and management model.

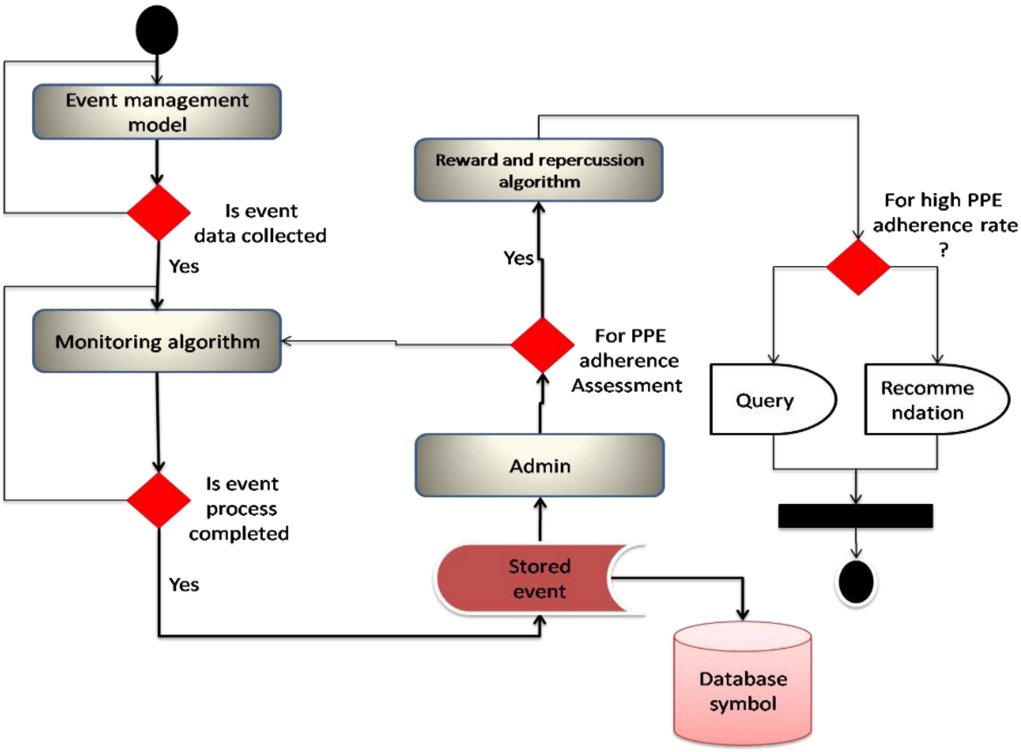

Figure 5.1: Activity Diagram of Real Time Monitoring and Management Model

The diagram in Figure 5.1 presents the activity diagram of real time monitoring and management model. The event management model provided the necessary data like task, user acceptance to task, date and time of task. This information forms the input to the monitoring algorithm which monitors for event such as acceptance of task, and time to execute the task. This information is stored in database. When the admin wants to access staff adherence to Personal Protective Equipment, the repercussion algorithm initializes and compute the rate of staff adherence to Personal Protective Equipment (PPE), and those identified within high adherence rat are recommended for recommendations while other are recommended for query.

6.0 Architecture of The Persuasive Application System (PAS)

This section presents the integrated model of the PAS system. The section combined the registration, the different models such as the user registration and login model, the task scheduling model, monitoring algorithm, reward and repercussion algorithm to form the core of the PAS system as shown in Figure 6.1 below.

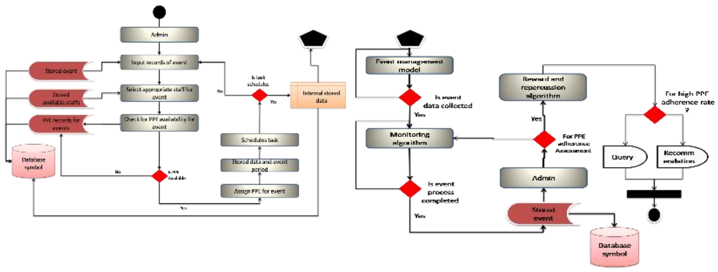

Figure 6.1: The Overall Object diagram of the new System PAS.

The PAS which integrated the Event Management System with a Monitoring, Reward and Repercussion System are integrated in figure 5.1. The User Admin accesses the system and enters event records during the login procedure. The system makes it possible to choose the right personnel for the task and verifies that Personal Protective Equipment is available. The assignment is booked if PPE is accessible, and pertinent information is recorded, such as the event's date and time. After that, PPE is allocated to the event, guaranteeing that personnel are adequately outfitted prior to starting work.

The Monitoring System further assesses PPE adherence. If staff members maintain a high adherence rate to PPE usage, the reward and repercussion algorithm is initialized. This mechanism ensures compliance by incentivizing proper PPE usage and discouraging non-compliance. The system evaluates the level of PPE adherence, determining whether staff members followed safety guidelines during the event. This helps in ensuring workplace safety and reducing occupational hazards.

Finally, the results of the assessment are stored in the database. Admin oversee this process, ensuring that all event data, adherence records, and monitoring feedback are securely stored. The system allows for recommendations based on performance, providing insights that can improve future scheduling and PPE management. Additionally, users can query the system for stored data, enabling better decision-making and reporting. This event scheduling and monitoring system ensures that tasks are effectively managed while maintaining a structured approach to workplace safety.

7.0 CONCLUSION

This study has presented the design and development of a real-time monitoring and management algorithm integrated within a persuasive system aimed at enhancing occupational safety for medical practitioners. By leveraging sensor-based data collection, adaptive feedback mechanisms, and behavior modification strategies, the proposed system addresses critical safety challenges such as fatigue, ergonomic stress, and exposure to hazardous environments. The algorithm's capacity to deliver personalized, context-aware interventions in real time has demonstrated its potential to not only improve individual safety compliance but also to foster a proactive safety culture in healthcare settings.

Experimental validation and simulation scenarios indicate that the system can significantly reduce risk-related behaviors and enhance situational awareness among medical personnel. Furthermore, its modular and scalable architecture makes it adaptable for deployment across diverse clinical environments. Future research will focus on expanding the system's predictive capabilities through machine learning integration, refining user interface interactions for better adoption, and conducting longitudinal studies to evaluate long-term effectiveness and user engagement.

Ultimately, this work contributes to the growing field of intelligent occupational safety systems by offering a technologically advanced yet human-centered solution, reinforcing the imperative that medical practitioner well-being is foundational to the overall quality and resilience of healthcare delivery.

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