Edge AI for Real-Time ICU Alarm Fatigue Reduction: Federated Anomaly Detection on Wearable Streams

Kawaljeet Singh Chadha
University of the Cumberlands, Williamsburg, KY, USA
Email: kawaljeetsinghchadha99@gmail.com

Abstract
ICU alarm fatigue is a serious problem in the healthcare sector since healthcare practitioners are overwhelmed by the number of alarms that are triggered, and most of them are false positives. It causes desensitization, a delay in response, and compromises patient safety. Federated learning and Edge AI present a viable solution to curbing alarm fatigue through optimization of alarm management systems and effective real-time patient monitoring. Edge AI enables data processing on wearable devices, ensuring that alerts occur promptly and with minimal delay. Federated learning allows machine learning models to be learned on decentralized and secure patient data without direct access to protected health information, maintaining privacy and customizing alarm limits. This paper discusses the possibilities of federal anomaly detection in wearable devices relating to ICU patients, in the context of real-time detection of health anomalies like abnormal heart rates and oxygen saturation. The objective is to evaluate how these technologies can streamline alarm systems by minimizing false alarms, while focusing on the important event. Important insights show the potential of Edge AI to enhance healthcare processes and deliver insights capable of driving interventions with minimal input. Federated anomaly detection is an innovative solution that can improve the work of an ICU, both in terms of operational efficiency and patient safety. This analysis seeks deeper research and the application of these technologies to clinical practice to reach their full potential.

Keywords: ICU Alarm Fatigue, Edge AI, Federated Learning, Anomaly Detection, Wearable Devices

1. Introduction

Intensive Care Units (ICUs) have experienced alarm fatigue, a hazard that further threatens patient safety and the well-being of healthcare providers. Monitoring patients requires the use of alarms, which warn the staff about a change in vital signs, including heart rate, oxygen saturation, blood pressure, and respiration rate. The high rate and number of alarms, however, confuse the employees, who cannot distinguish between life-threatening and inconsequential alerts. Alarm fatigue is a condition in which repeated exposure to alarms can result in desensitization of the healthcare worker, reduced response delay, missed alerts, and, in extreme cases, patient-care failures. Patients in the ICU may face hundreds or thousands of alarms in a given day, and most are false positives indicating nonexistent issues. This persistent sound causes stress, lower alertness, and an increased risk of making errors. Long-term, it leads to burnout and compassion fatigue, decreasing efficiency and resiliency in the critical care teams.

The issue is serious, and statistics reflect it. The average ICU has more than 300 alarms per patient per day, which equates to thousands in a high-trafficked hospital. Studies indicate a false positive rate of about 72 per cent on ICU alarms, with 12 per cent being actual emergencies. In certain environments, the false alarm rates can be as high as 90 per cent, breaking down and undermining trust in the alarm itself and resulting in desensitization. It can slow reaction to actual crises and cause life-endangering lapses. Its psychological effects are a prominent cause of alarm fatigue among nurses and doctors, leading to them ceasing work in the ICU or leaving the profession altogether.

Measures to curb the effect of alarm conditions are the readjustment of alarm thresholds, device reprogramming, and the introduction of management protocols. False alarms can be minimized by adjusting the sensitivity of an alarm, but this is a fine balance, as a setting that is too sensitive will miss important changes. A setting that is too insensitive will produce many more alarms. Alarm prioritization systems by severity can assist, but are still quite heavy on manual work, and may be too slow to respond to the needs of an ICU. Such solutions are also costly to invest in, train, and maintain, making them, to an extent, not scalable.

There exists a good option for incorporating Edge AI and federated learning on wearable medical devices. Edge AI operates the data on-site and can serve real-time alerts with low latency, triggering only when needed, which results in a low number of irrelevant alarms. Federated learning involves training of AI models on local devices and sharing just model updates, so federated learning improves known confidentiality and regulations such as HIPAA. Collectively, these technologies produce smarter, patient-specific alarm systems that can predict emergencies more precisely and keep data secure. The implementation of wearable devices with Edge AI and the federated learning technology can change ICU alarm management, leading to enhanced patient safety, reducing stress for healthcare staff, and promoting their productivity. With alarm fatigue still rampant, these smart, privacy-watching solutions pave the way for safer, more sustainable critical care.

2. Literature Review

2.1 Alarm Fatigue in ICU: A Growing Problem

Alarm fatigue in Intensive Care Units (ICUs) is a growing issue that greatly affects healthcare professionals and patient safety (11). The problem arises due to consistent alarms produced by medical equipment used to monitor the vital signs of a patient. The sheer volume of these alarms, which are intended to warn staff of potential problems and protect patients, has rendered them quite overwhelming. Even in a regular ICU, hundreds, and possibly thousands, of alarms can sound over a 24-hour cycle. Alarm fatigue is the syndrome in which healthcare workers develop tolerance to the alarming noise, delaying their response and missing some alarms that should be taken seriously for patient safety. The high number of false alarms is the main cause of alarm fatigue. Research has found that up to half of ICU alarms are not emergencies concerning the patient. For example, it is estimated that as many as 72% of ICU alarms are false, often triggering despite the patient being stable. Such frequent false alarms can stem from factors such as inaccurately calibrated medical equipment or the use of generic alarm thresholds that fail to account for patient-specific variations. These limitations reduce clinicians' likelihood of responding promptly to alarms, even when urgent intervention is required (7).

The healthcare providers have been affected significantly by alarm fatigue. The alarms are tiring nurses and doctors since they cause emotional and physical fatigue, which would result in phone burnout. Alarm fatigue syndrome is related to increased burnout, which is a consequence of mental, emotional, and physical exhaustion due to constant work-related stress. The problem of ICU alarm fatigue can make health care professionals less effective where the stakes are very high, which contributes to the ratings of human error and, in turn, considerably impairs patient outcomes. One research study published in the Journal of Clinical Nursing discovered that alarm fatigue is a key aspect that leads to burnout amongst ICU nurses, leading to high turnover rates in such units. When nurses develop alarm fatigue, they will tend to ignore crucial alarms or even respond to the alarms only after the patient develops complications. Other effects of alarm fatigue are not only limited to their employees, but also the safety of the patients (16). Alarm fatigue may ultimately lead to missed diagnoses of poor patient conditions and delays in treatment, which can ultimately cause poor patient outcomes. Take the case, there was a research study published in JAMA that stated that alarm fatigue was associated with delays in identifying life-threatening conditions, including sepsis and cardiac arrest. Alarm fatigue, hence, becomes a significant risk to patient safety because it is linked with reduced trustworthiness of systems meant to ensure the security of the patient against any form of harm.

As shown in the image below, alarm fatigue in ICU settings is influenced by several factors, including equipment programming errors, excessive workload or staffing issues, unclear delineation of responsibility, competing priorities, desensitization to alarms, lack of contingency or escalation plans, and inefficient alarm design.

Figure 1: Combating Alarm Fatigue

2.2 Technology-based Interventions

Alarm fatigue has led to the emergence of several technological solutions that would help address alarm management in ICUs. Some of the early alarm systems, which initially were mainly meant to provide staff with alerts of changes in patient vital signs, were not sophisticated enough to priorities alarms or to differentiate between which events were critical and which were not. This led to inundation of ICUs with the number of alarms, and the healthcare staff became overwhelmed with the level of alarms. Subsequently, alarm management technologies started to develop to counter this problem by filtering, prioritizing, and even inhibiting alarms based on their priorities and the relevance to patient safety. Over the last decade, there have been major evolutionary contributions towards alarm management, especially with the use of computerized decision support systems (CDSS). These systems are designed to process patient data in real-time and evaluate a clinical situation to prioritise alarms based on the state of emergency. As another example, CDSS can ensure which alarms are non-critical, e.g. generated by transient changes in vitals, and prioritize on more important needs, e.g. poor breathing or arrhythmia. This assists in preventing alarm fatigue since the staff would only get alarmed when there is a need to attend to it. As AI continues to improve alarm management, ensuring the Shift Left Security approach within healthcare IT systems prevents vulnerabilities before they can be exploited (31).

The latest developments in alarm systems still depend on predefined thresholds and centralized servers. Although CDSS can screen and prioritized alarms, they do not always give true indications of the situation occurring in specific patients. An illustration is that a heart-rate threshold will suit the general ICU population but fail with patients with particular cardiovascular diseases. Consequently, there is a possible occurrence of unnecessary alarms, or rather, alarm fatigue.

The use of artificial intelligence (AI) has become one of the most promising prospects for improving the development of alarm management systems. Machine learning models have been applying AI algorithms to improve alarm accuracy using large datasets of patient data. AI systems may process enormous amounts of real-time data provided by several sensors and make predictions regarding the condition of a patient. Another example would be the use of machine learning algorithms to predict possible conditions or acute cases of patients based on changes in vital parameters, which can be an early indicator of such conditions as sepsis or cardiac arrest. Such systems can dynamically respond to real-time data by adjusting alarm conditions to lessen the chance of false alarms, and only raise alarms when truly warranted.

Along with the AI-based solutions, wearable health monitoring devices have also contributed greatly to the enhancement of alarm-related systems in the ICUs. Wearable sensors (continuous glucose monitors, wearable ECG devices, smart watches) provide real-time information about a patient, which can be processed either locally on the device or sent to central monitoring systems. These gadgets constantly measure vital measurements, providing denser and more frequent measurement data than traditional monitoring systems, which are based on measurements made at specific intervals. Real-time detection of anomalies can be achieved with wearable devices connected to AI models. For example, a portable ECG can identify irregular heart rates and immediately alert the medical team. These devices not only enhance patient surveillance but also reduce alarm fatigue by providing healthcare professionals with patient-specific data rather than generic alerts. Furthermore, wearables can support early intervention by detecting subtle signs of deterioration before the patient develops critical conditions (20:21).

With the further development of the healthcare industry, the combination of AI and wearable technologies is likely to help find more efficient and effective ways of addressing alarm fatigue. Through AI and wearable technology, ICU-based alarm management systems can become more intelligent, tailored, and eventually more effective at safeguarding patients and medical practitioners.

2.3 Federated Learning and Edge AI

The current work is an Edge AI that is revolutionizing real-time healthcare decision making, especially in ICUs, where fast action is essential. Edge AI prevents the use of cloud servers, overcoming transmission lags, as with wearables and monitors, processing patient data locally and allowing it to occur in real-time. In wearable units, Edge AI could potentially analyze live, every second, vital signs, heart rate, respiratory rate, blood pressure, oxygen saturation, and alert upon early signs of sepsis, arrhythmias, or respiratory failure, thus at the right time. It also improves predictive algorithms to foresee researchers such as cardiac arrest or ARDS so that early intervention is possible. Still, excessive data need not be sent, which is essential in low bandwidth setups.

Federated learning is a complementary technology to Edge AI: it is possible to train machine learning models without moving patient data through federated learning (17). Data is stored in the device, and only model updates are shared, which will not breach privacy and regulatory laws like HIPAA. This enables collaboration by various institutions to share in advancing AI models with different data and maintain confidentiality. Google Health, as an example, used federated learning in the radiology setting, where it assisted in increasing diagnostic accuracy across different hospitals without transferring image data, and Philips Healthcare in wearables, where its use predicted the risk of heart failure in a secure manner. In the same regard, multi-hospital federated systems have improved the detection of sepsis. These applications demonstrate how Edge AI and federated learning can enhance accuracy, alleviate alarm fatigue, and facilitate real-time ICU decisions, using federated learning that preserves privacy.

As shown in the image below, privacy challenges in healthcare are multifaceted, involving aspects such as legibility, robustness, ethical considerations, scalability, adaptability, security, confidentiality, and integrity.

Figure 2: Privacy-preserving artificial intelligence in healthcare

3. Methodology

3.1 Data Sources

The major sources of data for monitoring patients in an ICU can be found in several types of wearable health devices that can collect real-time and continuous data about patients. These are non-invasive devices that monitor several vital signs, including heart rate, oxygen saturation, breathing rate, body temperature, and blood pressure, which are essential in monitoring the health condition of patients in the ICU. As an example, continuous electrocardiograms (ECGs) would be used to monitor the electrical activity of the heart, pulse oximeters would measure oxygen content of the blood, and wearable thermometers would monitor changes in body temperature. Such data plays an important role in early indication of patient deterioration, which includes the issue of arrhythmias, respiratory failures or sepsis. Data is obtained by the wearables present in an ICU setting, and the transmission of data may be wireless or via a wired connection to a central control monitoring system (12). In some instances, data is run locally on the device (Edge AI), and in some situations, the data is uploaded to the cloud-based servers to be further analyzed. To ensure that patients are updated with the current patient information, the data must be collected in a continuous and real-time process so that interventions can be made during critical events. The devices are mainly non-invasive, and they ensure continuous monitoring without interfering with the patient's comfort.

3.2 Design of Edge AI Model

Edge AI is the means of doing computations at the device level, in the case of wearables, instead of utilizing cloud-based servers. Edge AI is especially useful in ICU environments since it minimizes latency on alarm events. The use of traditional cloud-based platforms is also likely to lead to some delays in data transmission, a fact that can be deadly in time-constrained cases. Given that Edge AI operates on wearables using local data processing, it can detect and alert changes in the vital signs of a patient the moment they become significant, thus signaling immediate actions taken by the healthcare providers. Edge AI in wearable devices typically includes lightweight neural networks. These neural networks are best suited for performing complex functions like anomaly detection in a computationally efficient manner. The networks are fed with physiological data to learn to detect patterns of interest that may suggest impending medical events (like abnormal heart rhythms or oxygen saturation levels falling below a critical level). On the advantage side: lightweight models can be deployed on devices with less processing power, meaning that they can be used by smartwatches or patch sensors and at the same time convey fast, actionable insights.

As shown in the image below, designing Edge AI models involves balancing privacy needs, memory constraints, and latency requirements

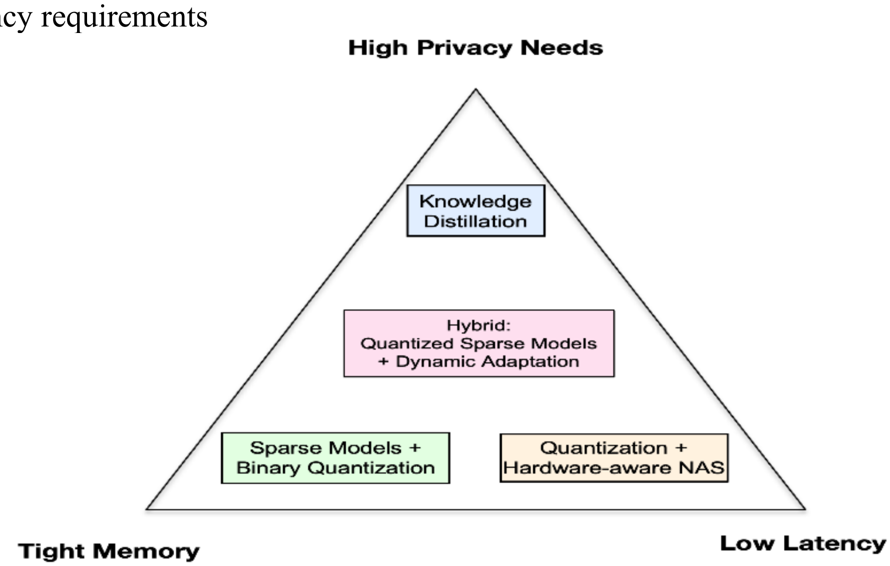

Figure 3: Decision framework for edge intelligence techniques.

3.3 Setup of Federated Learning

Federated learning is a form of machine learning where many devices or institutions collaborate to train a machine learning model, without sharing confidential patient data. Federated learning processes patient data locally, ensuring data security through models such as Zero Trust Architecture to prevent unauthorized access while maintaining privacy (32). Such an approach is especially useful in healthcare because data privacy is essential. Each machine or health establishment learns the model locally from its patient data. The data is not transmitted directly, but the learned parameters (the model updates) are sent to a central server, where they will be aggregated to enhance the global model.

Such an approach would guarantee that patient data will not leave the device or healthcare facility, thereby protecting patient privacy and ensuring compliance with privacy regulations such as HIPAA (23). In addition, federated learning can be used to build personalized models that are trained on local data to enhance the performance of the model on a sub-population of patients. As an example, a federated model may pick up on different sepsis detection patterns in hospital A, as opposed to hospital B, which can translate into the local differences in patient demographics, disease progression or treatment regimens.

As shown in Table 1 above, the key advantages of Edge AI and Federated Learning include local data processing for real-time alerts with Edge AI, which helps reduce latency.

Table 1: Key Advantages of Edge AI and Federated Learning

Technology	**Advantage**
Edge AI	Local data processing for real-time alerts, reducing latency.
Federated Learning	Data privacy maintained by not sharing patient data, only model updates.
Combined Use	Smarter, patient-specific alarms that enhance patient safety and efficiency.

3.4 Anomaly Detection

One of the components of the system is anomaly detection, which helps to reduce alarm fatigue and enhance patient monitoring in the ICU. In real-time care patterns, anomaly detection algorithms detect the continuous stream of information sent by wearables to locate any relevant deviations in the normal health trends of a patient. As an example, an abnormality recognition algorithm could warn of an abnormal heart rate or a sudden decrease in oxygen saturation as a possible indication of a deeper-lying health problem. Anomaly detection is done in real time using machine learning models that have been trained on what constitutes normalcy in a particular patient. Trained, these models could easily identify such deviations that would signal a significant health event. To provide another example, a sharp decrease in oxygen saturation can be an indicator of a respiratory failure. In contrast, arrhythmia or the beginning of a cardiac episode is identified with irregular heartbeat signals.

When developing anomaly detection systems in machine learning, a trade-off often exists between recall and precision. Precision measures the percentage of true positive alarms out of all alarms raised, whereas recall measures the percentage of true positive alarms out of all actual issues (true positives + false negatives). In healthcare, balancing these metrics is critical, as excessive false positives can contribute to alarm fatigue, while excessive false negatives can lead to missed opportunities for timely intervention. This balance can be improved by incorporating clinical thresholds—such as age, pre-existing conditions, or treatment plans—into anomaly detection models, ensuring that alarms are both accurate and actionable (2: 19).

4. Federated Anomaly Detection on Wearable Streams

4.1 How Federated Learning Works in Anomaly Detection

In a federated learning configuration, anomaly detection in ICUs can be improved as the machine learning model is trained on many different, decentralized devices without the need to exchange sensitive patient information. In conventional centralized machine learning, data must be transported to a central server, which is a major privacy issue. Instead, by using federated learning, each device (e.g., wearable monitor) will locally analyze and learn on its local data. These learned parameters or model updates are then transmitted to a central server, which is aggregated into a global model to enhance its level of accuracy and performance without revealing any raw data about the patient. This approach enhances the capability of detecting anomalies among decentralized devices through the contributions of several healthcare institutions or wearable devices as members of a shared learning model (18). Indicatively, any wearable device in the ICU can identify abnormalities such as irregular heart rate, changes in breathing rate, or variations in oxygen saturation levels. The model can also become increasingly capable of detecting fine patterns or changes in patient health indicators as it is improved using federated learning, and generate more accurate predictions and fewer false positives or negatives.

Anomaly detection tasks can be used in monitoring vital signs, including heart rate, oxygen saturation level, and respiratory rate. As an example, an ECG monitor can be worn to identify the onset of arrhythmia, and a pulse oximeter can be used to detect declines in oxygen levels, which could indicate the onset of respiratory distress. Having identified such anomalies early enables healthcare providers to act quickly, which may save a life and prevent further deterioration in its condition.

As shown in Table 2 above, federated learning in anomaly detection for ICU wearables involves monitoring various health parameters such as heart rate, oxygen saturation, respiratory rate, and glucose levels.

Table 2: Federated Learning in Anomaly Detection for ICU Wearables

Anomaly Detection Task	**Device Used**	**Health Parameter Monitored**	**Anomaly Detected**	**Impact of Early Detection**
Heart Rate Irregularities	ECG Monitor	Heart Rate	Arrhythmia or irregular heartbeats	Enables early intervention in cardiac issues
Oxygen Level Decline	Pulse Oximeter	Oxygen Saturation	Respiratory distress or hypoxia	Prevents respiratory failure and improves survival rates
Respiratory Rate Changes	Wearable Respiratory Monitor	Respiratory Rate	Difficulty in breathing, potential respiratory failure	Allows timely intervention to prevent complications
General Health Deterioration	Continuous Glucose Monitor	Glucose Levels, Vital Signs	Potential signs of sepsis, hypoglycemia, or infection	Early identification of systemic issues like sepsis

4.2 Real-Time Data Streaming

Wearables in the ICU continuously measure patients' vital signs and transmit the data to local Edge devices for localized analysis. This real-time data flow allows the monitoring system to receive constant updates, such as heart rate and oxygen saturation levels. Edge AI processes this information on a local wearable or nearby server, enabling faster anomaly detection and timely alert issuance (8). Edge AI is also an important feature since it enables real-time data processing by analyzing data instantaneously. Sudden drops in oxygen saturation, which may be noticed in a few seconds, can be identified, and the system can inform healthcare personnel to take action. This local processing would make the system very quick, as there is negligible delay, unlike in the cloud-based solution, where they have a dependency on transmission of data and processing in the core.

As shown in the image below, real-time data streaming from wearables in healthcare systems, such as smart watches and patches, utilizes IoT sensors to monitor physical activity and vital signs. The data is transmitted to cloud and edge computing systems for analysis.

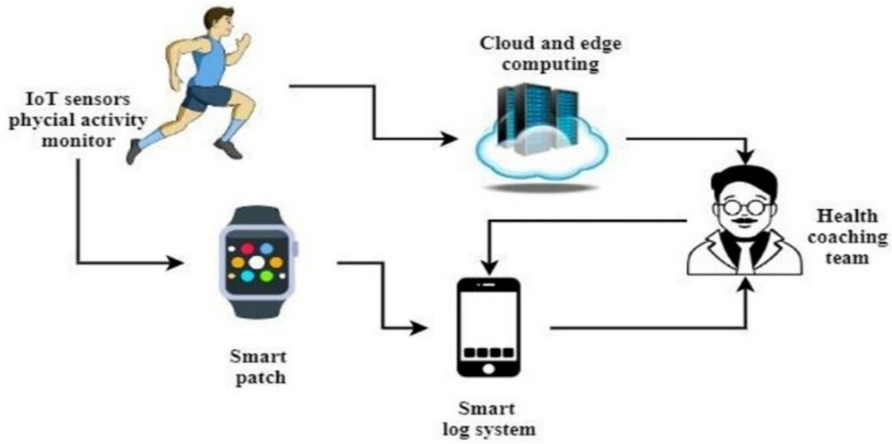

Figure 4: The architecture of the proposed intelligent m-Health monitoring system (Im-HMS).

4.3 Federated Learning Advantages in ICUs

Privacy preservation is one of the key advantages of federated learning in ICU settings. Patient data collected by wearable devices is securely stored locally, minimizing exposure to unauthorized parties. In healthcare, this is particularly critical given strict data privacy regulations such as HIPAA, which are designed to safeguard sensitive health information (15). Federated learning also eliminates the transfer of data to centralized servers and is thus capable of minimizing bandwidth consumption (1). In an ICU with many patients and a large volume of real-time data, the less data is transferred, the more efficiently and faster the system will work, so that the serious notification can be delivered in time. Moreover, federated learning makes it possible to tailor models of anomaly detection to the individual patient. As every single healthcare facility or wearable device may train its model on the local data on patients, the system will be better at identifying the unique health patterns and identifying anomalies particular to the condition of the patient. This individualization enhances the collective efficiency of the system by giving more precise warnings and more aligned care tailored to the individual.

5. Case Study: Implementation of Edge AI and Federated Learning in ICU Wearables

5.1 Description of a Pilot Study or Real-World Example

An intensive urban hospital with a large healthcare facility conducted a pilot that aimed to evaluate the efficiency of federated anomaly detection on wearable devices on ICU patients (4). This work was intended to assess the potential impact of integrating Edge AI with federated learning on the overall alarm management, leading to reduced alarm fatigue and overall patient care. The facility was equipped with different types of wearable devices, such as continuous glucose monitors (CGMs) and smartwatches, as well as pulse oximeters that helped monitor the critical health data of the patients in the ICU. Wearables recorded real-time data on some of the vital signs: blood oxygen levels, heart rate, glucose levels, and respiratory rate. This information was then relayed to Edge devices at a local level to be processed in real-time. In the example of CGMs, the glucose level data was always connected to identify possible instances of hypo- or hyperglycemia. Patients with breathing difficulties had pulse oximeters that constantly showed them their oxygen saturation levels. On the smart watch, they monitored their heart rate for any signs of irregularity, suggesting the possibility of arrhythmia or cardiac event.

Data collection was conducted over a three-month period by monitoring the health status of ICU patients. The cohort included individuals with chronic conditions such as diabetes, heart failure, and respiratory diseases, as well as post-surgical patients. This diverse demographic provided the machine learning models with a broad range of health information, enabling them to learn from various patient profiles. The study also assessed the accuracy and detection rate of anomaly detection algorithms under real-world, high-stress ICU conditions (23: 28).

As shown in the image below, Generative AI in healthcare has a wide range of applications, including enhancing patient care, improving AI diagnostic capabilities, predicting patient outcomes, and personalizing treatment plans

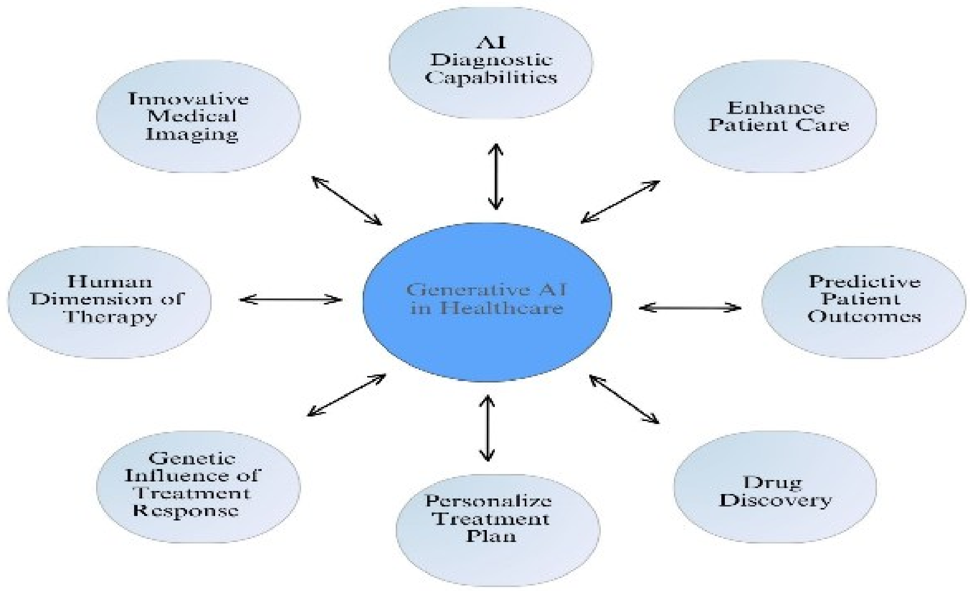

Figure 5: Key applications and benefits of generative AI in healthcare

5.2 Results

The pilot study yielded some encouraging findings, both quantitative and qualitative.

Quantitative outcomes

Adoption of federated anomaly detection also led to a notable decrease in fatigue (22). There were decreases in the number of non-urgent alarms reported by healthcare staff as false positives could be filtered more effectively. Alarm notifications per patient had decreased by almost 40 per cent. This decrease in instances of noisepins enabled medical professionals to concentrate on the alarms that needed immediate attention. Besides this, the reduction of false alarms also enhanced the monitoring system of the ICU as a whole, since the actual alarms were identified promptly and were responded to accordingly.

There is an enhancement in response times. The process of notifying healthcare providers about critical situations occurred in shorter periods due to the relatively small period between the detection of an anomaly and the alert by the anomaly detection system. Edge-AI-enabled real-time processing guaranteed that alerts were sent within seconds, enabling timelier actions, especially where patients are at risk of developing sepsis or cardiac arrest.

Qualitative outcomes

Physicians and other health practitioners reported greater satisfaction with the new system, noting that the reduced alarm load made it easier to stay attentive during shifts and increased their confidence in the system's ability to recognise critical issues in real time. Operational efficiency also improved, as staff spent less time responding to false alarms and more time providing direct patient care. Patient outcomes showed notable improvement, particularly in early interventions for cardiac and respiratory problems. The ability of nurses and doctors to act earlier in cases of deterioration led to shorter recovery times and fewer adverse events (25).

As shown in Table 3 below, the pilot study on federated anomaly detection yielded significant results. Alarm fatigue was reduced by a 40% decrease in false alarms per patient, improving healthcare provider satisfaction and reducing stress and burnout.

Table 3: Results of Pilot Study on Federated Anomaly Detection

Outcome	**Quantitative Result**	**Qualitative Outcome**
Alarm Fatigue Reduction	40% decrease in false alarms per patient	Healthcare provider satisfaction, reduced stress and burnout
Response Time Improvement	Faster alerts (within seconds)	Improved operational efficiency and reduced response delays
Patient Outcomes	Early intervention in cardiac/respiratory issues	Quicker recovery and fewer adverse events

5.3 Problems

Although the pilot study proved to be successful, it also revealed several challenges that were experienced in the implementation.

Technical challenges

Using federated anomaly detection incorporated in the existing ICU architecture was not straightforward (6). The existing system of monitoring used in the hospital was not originally conceived to work in decentralised frameworks such as the Edge AI. Consequently, the integration process presented significant challenges to align the legacy systems with the new wearable devices. Also, there were constraints on real-time processing. The Edge AI models needed to analyse large quantities of data on patients in real-time, which occasionally caused delays in response or necessitated increased computing power. This necessitated a succession of adjustments to ensure that the system could meet the requirements of a bustling ICU setting.

Legal and moral dilemma

Federated learning, in its design, maintains the privacy of patients since it does not centralise data. Nevertheless, it was paramount to adhere to the rules of data privacy, including HIPAA in the States. There were also challenges in obtaining informed patient consent to participate in the study, especially at the ICU, where a patient could be in critical condition, making it impossible to give consent. Also, questions of the algorithm's transparency were present. Since the machine learning models improved with time due to feed-forward feedback learning, healthcare providers had to ensure that they could understand how the system was making decisions, particularly in high-stakes settings. This necessitated transparent models of AI that are easily understandable by the healthcare staff.

6. Discussion

6.1 Impact on Alarm Fatigue

Federated anomaly detection aims to handle alarm fatigue, a significant ICU problem due to an inordinate number of false alarms that desensitize staff and slow critical responses (13). When AI is used to prioritise alerts based on their severity, the system removes anything but critical fluctuations to only trigger critical life-threatening negatives. Based on real-time data of wearables, AI models are personalized to achieve specific thresholds according to the profile of each patient. An example is a chronic heart patient compared with a post-surgery patient. Frequent and ongoing learning with federated models is what keeps the alarms relevant, minimizing noise and improving concentration, as well as patient outcomes and reducing stress and burnout among healthcare providers.

6.2 Scalability

The federated anomaly detection is, by its nature, scalable to suit hospitals of both small and large sizes. Its distributed architecture enables each institution to keep control of the data as it adds to a worldwide model. The models can be trained at large hospitals on several ICUs, whereas smaller facilities respond without significant infrastructure modifications. Nevertheless, the variety of patients with differences in age, conditions, and severity implies that the models need to be localised to be correct. This is supported by federated learning, which enables personalized training, but the variations in the data collection and processing must also be treated carefully to avoid becoming brittle across populations.

As shown in the image below, federated learning presents several challenges, such as privacy protection, security issues, data availability, data distribution, communication overhead, and the heterogeneity of data and systems. These challenges need to be addressed to scale federated anomaly detection systems effectively across different hospital sizes.

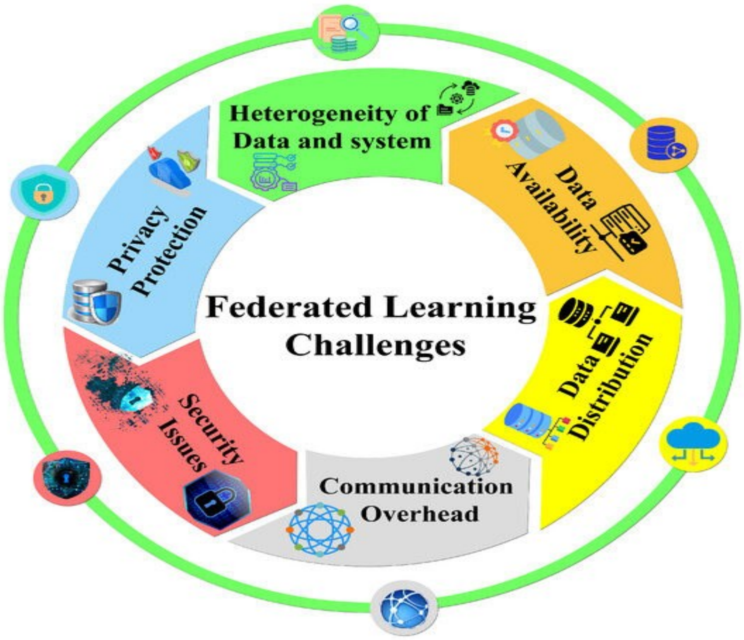

Figure 6: FL Challenges.

6.3 Limits

Accurate wearable sensors are essential to the system; low-quality data may lead to false alarms or other missed events (29). It is necessary to invest in validated devices. In these environments where models are resource-limited, reliable network infrastructure is also highly important for timely model updating. The other issue is data bias, where there is a limitation in diversity in training data, which makes models fail on underrepresented groups, causing disparities in care, e.g., through false positives or false negatives. Capturing diversity and representative datasets is central to fairness.

6.4 Ethical Considerations

Compliance with regulations such as HIPAA and GDPR is essential in healthcare AI systems. While federated learning supports compliance by retaining patient data on-site, institutions must still ensure full adherence to regulatory requirements when sharing model updates. Equally important is explainability—clinicians must understand how AI systems derive their conclusions in order to trust and act on their recommendations. The integration of explainable AI, along with transparent communication and proper training, enables healthcare providers to interpret alerts with confidence, especially in emergency situations (3).

7. Future Research Directions

As shown in Table 4 below, future research directions for enhancing AI in healthcare include improving model accuracy through deep learning, reinforcement learning, and personalized models for better anomaly detection. Expanding federated anomaly detection to other healthcare settings such as outpatient care, telemedicine, and home health monitoring is another key area.

Table 4: Future Research Directions for Enhancing AI in Healthcare

Research Area	Potential Improvements
Enhancing Model Accuracy	Deep learning techniques, reinforcement learning, and personalized models for better anomaly detection

Research Area	Potential Improvements
Expansion to Other Healthcare Settings	Applying federated anomaly detection to outpatient care, telemedicine, and home health monitoring
Long-Term Impact Studies	Assessing the sustained effect of AI on alarm fatigue and patient outcomes over time
Collaboration with Regulatory Bodies	Ensuring regulatory standards and AI transparency in healthcare environments

7.1 Enhancing Model Accuracy

With healthcare becoming increasingly significant in the use of real-time patient monitoring systems that rely on AI-based solutions, highly precise anomaly detection models are more essential than ever (26). Presently, there has been evidence in using federated anomaly detection systems to enhance alarm management and alleviate alarm fatigue. Nevertheless, the accuracy of these models could also be improved significantly, especially in identifying rare or subtle health events that may be overlooked using conventional methods. A major avenue of future research is looking into more complex AI methodologies, including deep learning and reinforcement learning, to improve model performance. This has been evidenced in the use of deep learning techniques, most recently on wearable data (derived ECG, or continuous heart rate data), which can pick up any nuances or complexities in patterns that a more simplistic model might miss. Deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are used to analyze wearable data to detect early symptoms of conditions such as arrhythmias, sepsis, or respiratory failure more reliably.

The other area that has the potential to enhance anomaly detection further is reinforcement learning (RL) (9). RL can also collect experience in a changing environment and learn to improve its decision-making over time. Situating ICU monitoring practices, RL may be utilized to perform automatic calibration of alarm thresholds in response to real-time feedback by medical professionals, establishing the system as more dynamic to the respective needs of each patient. As such methods advance, they will also facilitate the creation of more advanced, customizable monitoring systems that will offer an even greater degree of accuracy in real-time patient care.

As shown in the image below, AI-based healthcare systems integrate data from medical sensors and wearable devices, allowing for continuous monitoring of patient health. The AI models analyze this data in real time, sending alerts to healthcare professionals when anomalies are detected.

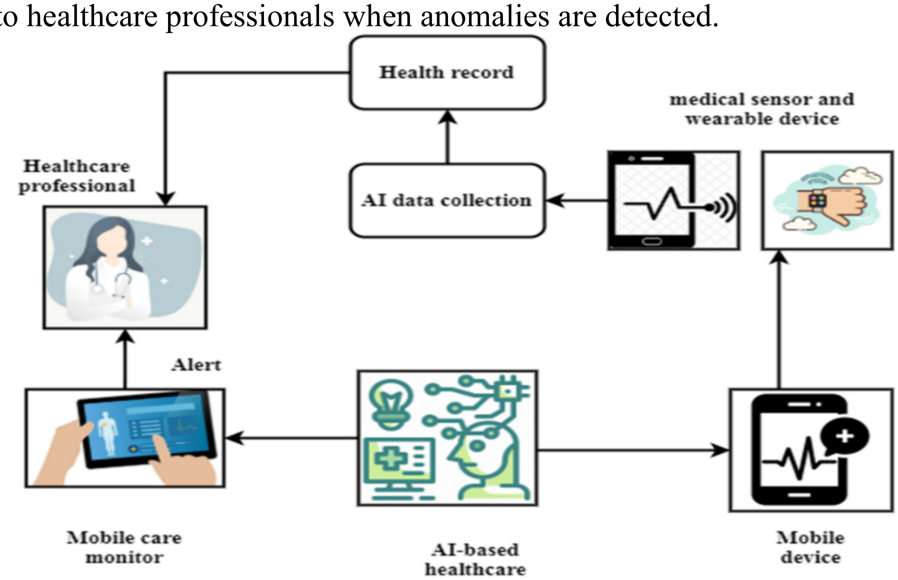

Figure 7: AI-based m-Health model on mobile phones

7.2 Scale-up to Other Healthcare Facilities

Although federated anomaly detection has demonstrated promising performance in the ICU, the opportunities for scaling it up to other medical areas are enormous. Researchers should discuss whether it is possible to apply federated learning models to the outpatient treatment, home monitoring, and telemedicine. The patient with chronic illnesses like diabetes, hypertension, or cardiovascular diseases may be monitored continuously in outpatient settings, such as clinics or during follow-up care after discharge. Vital signs and biometrics wearables may signal to healthcare provider's signs of early deterioration and allow early action before the problem becomes critical. The obscure form of the Federation's detecting systems could be applied to monitor patients at their homes, and more individualized care could be provided, while eliminating the need for frequent hospital visits (14).

Federated anomaly detection can also be applied to telemedicine. Healthcare providers can remotely supervise patients through a combination of wearable health data and telemedicine systems, advising them on when to use an intervention. Federated learning would facilitate decentralization of the data, thereby ensuring patient privacy, and the overall performance of virtual diagnoses and consultations would be increased in the sphere of remote diagnostics. The implementation of federated learning models outside the ICU comes with significant challenges of patient privacy, data integration, and regulatory compliance. Still, it is likely to be a game changer in the management of chronic diseases and remote care.

7.3 Long-Term Impact Studies

Though the short-term utility of Edge AI and the use of federated anomaly detection is established, long-term impact studies are necessary to determine the full implications they have on alarm fatigue and patient outcomes. These technologies could be tested in longitudinal studies that would assess their long-term efficiency, analyzing the influence of continuous real-time monitoring on the responsiveness of healthcare providers to critical events and patient recovery rates. The decrease in alarm fatigue in the long run is a significant area that should be researched. It is imperative to determine whether the deployment of smarter, AI-powered alarm systems has had long-lasting effects on staff efficiency, burnout, and job satisfaction. Moreover, researchers may evaluate whether decreasing the alarm fatigue results in a practical change in patient outcomes, including a lower number of adverse events, medical malpractices, and overall health recovery (30). The development of federated anomaly detection models over the long term (as they consume increasingly diverse patient data) could also be a topic of study. Studying a group of patients and how they navigate multiple healthcare environments, scholars could develop a more comprehensive picture of how these systems accommodate diverse demographics, health conditions, and treatment regimens, increasing their precision and effectiveness in diverse patients.

7.4 Cooperating with Regulatory Bodies

With the continued penetration of AI-based solutions into the healthcare industry, the cooperation between complete healthcare companies and the regulatory authorities is gaining even more significance as the relationships are intended to help AI-based solutions challenge their safety and ethical standards. Future studies should collaborate with regulatory bodies like the U.S. Food and Drug Administration (FDA), European Medicines Agency (EMA), and other global health systems to provide guidelines for AI and federated learning systems in medical settings. Such partnerships will be critical to develop common guidelines to deploy AI across healthcare, ensuring the safety and effectiveness of such systems. Moreover, working with regulators will help ensure that AI technologies are in line with privacy laws such as HIPAA in the U.S. and GDPR in the EU. Researchers can play a larger role in the ethical adoption of AI systems within healthcare by defining best practices around issues of model transparency, data security, and patient consent (27).

Dialogue with regulatory organizations on an ongoing basis can make the future of AI regulations significantly healthier, and regardless of whether different technologies will be able to make more progress, patients' rights will be upheld. Regulatory organizations might be instrumental in developing trust among healthcare practitioners and patients so that AI-based systems are regarded positively and are not perceived as a risk to privacy and safety.

As shown in the image below, the integration of AI in healthcare presents challenges such as data quality, data security and protection, algorithm validation, and ensuring ethics and equitable access. These challenges are connected to regulatory gaps, which can be addressed through collaboration with regulatory bodies like the FDA and EMA.

Figure 8: Regulatory gaps in AI for healthcare services.

8. Recommendations

Based on the results and conclusions of this work, several recommendations are made to integrate Edge AI and federated learning in the ICU environment. These recommendations aim to improve alarm management, reduce alarm fatigue, and enhance patient care. The recommendations revolve around the key action that needs to be undertaken to achieve successful implementation and maximize the potential of the technologies. Among the first and most crucial suggestions is that healthcare institutions need to invest in wearable technology of friction-free calibre, which can deliver high-quality, real-time data about the health of their patients. The success of Edge AI and federated anomaly detection models is centrally reliant on the trustworthiness and accuracy of the data worn by wearables. Hospitals must adopt a standardized strategy that would select and validate wearable devices to maintain high-quality and consistent data collection across all patients. Together with it, the modernization of the network infrastructure of healthcare institutions should also be practiced. The real-time informational data integrated on wearables needs to be seamlessly transferred to the local processing devices to reduce latency and provide timely alerts. These infra-proficiencies will help in the effective flow of data, minimizing the response lag in alarms, and finally enhance the overall system performance.

Since it is complicated to implement these advanced technologies in healthcare institutions, it is prudent to carry out small-scale pilot projects instead of broadly adopting them (5). All this should involve these pilots in ICU settings where they should be keen to establish the effects that technology has on alarm fatigue and alarm management, as well as the outcome of patients. The gradual approach through steps enables the identification and mitigation of possible challenges of integration before equipping it on a large scale. Pilot studies will also furnish useful information on the scalability of the system, which will be useful for healthcare institutions to revise their deployment strategies across different departments or facilities. Such a careful step provides the opportunity to work out any problems in the early stages of the process, and integration can occur across the healthcare system at the identified stage.

Another important recommendation will be the cooperation with technology providers and academic research organisations. The partnership will also assist in addressing the fact that Edge AI and federated learning systems deserve better optimisation when used in a real-life environment, and addressing ICU settings' needs. The AI developers must measure each aspect of healthcare delivery as healthcare providers seek to collaborate with them to ensure the models consider the wide spectrum of patients and medical issues encountered during critical care. Collaboration with research centres would also assist in basing the technology on evidence-based strategies, allowing iterative improvements on anomaly discovery algorithms and applying them in clinical settings.

Since these AI technologies are progressively entering the healthcare system, it is relevant to ensure ongoing training and education of care providers. The training should be on the process of decoding and responding to the AI-led cues, how to accept the system and how to leverage the AI tools to make better judgments. It is essential to develop trust toward AI systems when healthcare practices leveraging AI should be assured of the dependability and the clarity of the technology. Ethical implications of AI (such as data privacy and transparent decision-making in AI) should also be a part of the training programs.

The second consideration is the data privacy and meeting regulatory requirements related to healthcare in the U.S. (HIPAA) and the EU (GDPR). Healthcare organizations must collaborate with legal and regulatory agencies to certify that all the processes involved in data collection, processing, and storage comply with privacy guidelines. One of the main advantages of federated learning in this context is that there is no centralization of patient data, minimizing the risk of data security breaches and information privacy. Nonetheless, organizations must ensure that all AI solutions are aligned with the privacy laws and ethical principles during their implementation.

Long-term studies are needed that quantify the long-term effects of Edge AI and federated learning on alarm fatigue, staff performance, and patient outcomes. Longitudinal studies will provide useful information on the behaviour of such technologies over time, and researchers will be able to perfect algorithms to ensure accuracy and personalization. The information obtained in these studies can also be used to inform future applications of AI in other healthcare environments, such as in outpatient facilities, home health observation, and telemedicine. By investing in such research, future AI-based solutions will continue to evolve and support the needs of healthcare systems, patients, and healthcare providers (10).

9. Conclusion

An Edge AI and federated learning convergent technology, therefore, provides an innovative solution to a twenty-year-old curse of alarm fatigue in ICUs. Alarm fatigue became a significant problem in the domain of health care because of the large quantity of alarms that can be produced, thus distracting medical professionals, as alarm fatigue is linked to false positive alarms. Edge AI is therefore the answer to this problem since it will be converting data values on the fly, thus alerting only serious alarms in wearable devices. This will allow employees to focus on the basic needs of patients and provide faster responses to their inquiries, and therefore minimize their mental burden due to unnecessary distractions. In addition, federated learning allows training AI models using privacy-preserving, decentralized patient data, enhancing patient privacy, alarm system personalization, and accuracy.

The wearable devices further enhance the process of ICU by offering anomaly detection, which checks the information of the patient frequently and always, including heart rate, oxygen saturation, and respiratory rate. These devices examine the information locally and utilise AI algorithms to detect anomalies and notify medical experts in real-time. By predicting the onset of undesirable health conditions, e.g. arrhythmias, sepsis, or respiratory distress, it also supports prompt intervention for the patient and their condition. Rather, a healthcare system coupled with wearable health monitors, edge AI, and federated learning will produce a more efficient, safer, and personalised monitoring system that not only improves patient safety but also reduces the risk of missed medical events.

These technologies have a great impact on the ICU work. Edge AI, federated learning, and the possibility to mitigate unwarranted alarms can contribute to not only the well-being of staff but also to the care of patients. The healthcare professionals show a low rate of stress and distraction, as well as a heightened feeling of security provided by the alarm systems' redeeming capacity. On the patient end, this can be translated to a decrease in adverse incidents, quicker identification of serious health issues, and better overall recovery rates. Ultimately, these innovations can be applied to the development of a more efficient and sustainable healthcare environment, which will achieve better outcomes for both personnel and patients. Federated learning and edge AI offer a promising path forward as the healthcare sector expands under pressure to deliver quality care, limit expenses, and decrease burdens. Healthcare facilities should explore and experiment with these technologies to assist in the management of alarms used in ICUs. Using real-time anomaly detection systems, hospitals can both mitigate the alarm fatigue effect and enhance the performance of their operations and patient care environments. The scale of pilots or commercially sufficient implementations of whole systems may facilitate initial adoption of such technologies and allow easier perfection and scaling of the technologies.

The wearables and algorithm-augmented systems marketing is not only going to advance the monitoring. Still, it will also play a major role in promoting the culture of open and receptive healthcare. Moreover, it is also possible to apply such solutions safely, ethically, and in full compliance with privacy, which can be contributed by technology suppliers and regulatory organisations. It can provide such help to the healthcare systems. In addition, this trend needs more study and research to enhance and facilitate these technologies. Because of this, investigations of similar nature conducted over long periods are required to keep track of the relevance of Edge AI and federated learning in real-life situations of ICU operations. Researchers, doctors, and regulatory authorities must collaborate and ensure that the solutions associated with AI are scalable, accurate, and ethically embraced.

References;

[1] Abreha, H. G., Hayajneh, M., & Serhani, M. A. (2022). Federated learning in edge computing: a systematic survey. *Sensors*, *22*(2), 450. https://doi.org/10.3390/s22020450

[2] Chavan, A. (2021). Eventual consistency vs. strong consistency: Making the right choice in microservices. International Journal of Software and Applications, 14(3), 45-56. https://ijsra.net/content/eventual-consistency-vs-strong-consistency-making-right-choice-microservices

[3] Chavan, A. (2022). Importance of identifying and establishing context boundaries while migrating from monolith to microservices. Journal of Engineering and Applied Sciences Technology, 4, E168. http://doi.org/10.47363/JEAST/2022(4)E168

[4] Chui, K. T., Alhalabi, W., Pang, S. S. H., Pablos, P. O. D., Liu, R. W., & Zhao, M. (2017). Disease diagnosis in smart healthcare: Innovation, technologies and applications. *Sustainability*, *9*(12), 2309. https://doi.org/10.3390/su9122309

[5] Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., Hinder, S., ... & Shaw, S. (2017). Beyond adoption: a new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of medical Internet research*, *19*(11), e8775. https://doi.org/10.2196/jmir.8775

[6] Joshi, M., Pal, A., & Sankarasubbu, M. (2022). Federated learning for healthcare domain-pipeline, applications and challenges. *ACM Transactions on Computing for Healthcare*, *3*(4), 1-36. https://doi.org/10.1145/3533708

[7] Konneru, N. M. K. (2021). Integrating security into CI/CD pipelines: A DevSecOps approach with SAST, DAST, and SCA tools. *International Journal of Science and Research Archive*. Retrieved from https://ijsra.net/content/role-notification-scheduling-improving-patient

[8] Kumar, A. (2019). The convergence of predictive analytics in driving business intelligence and enhancing DevOps efficiency. International Journal of Computational Engineering and Management, 6(6), 118-142. Retrieved from https://ijcem.in/wp-content/uploads/THE-CONVERGENCE-OF-PREDICTIVE-ANALYTICS-IN-DRIVING-BUSINESS-INTELLIGENCE-AND-ENHANCING-DEVOPS-EFFICIENCY.pdf

[9] Kurt, M. N., Ogundijo, O., Li, C., & Wang, X. (2018). Online cyber-attack detection in smart grid: A reinforcement learning approach. *IEEE Transactions on Smart Grid*, *10*(5), 5174-5185. https://doi.org/10.1109/TSG.2018.2878570

[10] Latif, S., Qadir, J., Farooq, S., & Imran, M. A. (2017). How 5G wireless (and concomitant technologies) will revolutionize healthcare?. *Future Internet*, *9*(4), 93. https://doi.org/10.3390/fi9040093

[11] Lewandowska, K., Weisbrot, M., Cieloszyk, A., Mędrzycka-Dąbrowska, W., Krupa, S., & Ozga, D. (2020). Impact of alarm fatigue on the work of nurses in an intensive care environment—a systematic review. *International journal of environmental research and public health*, *17*(22), 8409. https://doi.org/10.3390/ijerph17228409

[12] Mamdiwar, S. D., R, A., Shakruwala, Z., Chadha, U., Srinivasan, K., & Chang, C. Y. (2021). Recent advances on IoT-assisted wearable sensor systems for healthcare monitoring. *Biosensors*, *11*(10), 372. https://doi.org/10.3390/bios11100372

[13] Mohr, M. A. (2016). *Quantitative Analysis of Periodic Breathing and Very Long Apnea in Preterm Infants*. The College of William and Mary. https://www.proquest.com/openview/33d3fca33f51320d834a2804b03e2de0/1?pq-origsite=gscholar&cbl=18750

[14] Munos, B., Baker, P. C., Bot, B. M., Crouthamel, M., de Vries, G., Ferguson, I., ... & Wang, P. (2016). Mobile health: the power of wearables, sensors, and apps to transform clinical trials. *Annals of the New York Academy of Sciences*, *1375*(1), 3-18. https://doi.org/10.1111/nyas.13117

[15] Nyati, S. (2018). Transforming telematics in fleet management: Innovations in asset tracking, efficiency, and communication. International Journal of Science and Research (IJSR), 7(10), 1804-1810. Retrieved from https://www.ijsr.net/getabstract.php?paperid=SR24203184230

[16] Oliveira, A. E. C. D., Machado, A. B., Santos, E. D. D., & Almeida, É. B. D. (2018). Alarm fatigue and the implications for patient safety. *Revista brasileira de enfermagem*, *71*(6), 3035-3040. https://doi.org/10.1590/0034-7167-2017-0481

[17] Qayyum, A., Ahmad, K., Ahsan, M. A., Al-Fuqaha, A., & Qadir, J. (2022). Collaborative federated learning for healthcare: Multi-modal covid-19 diagnosis at the edge. *IEEE Open Journal of the Computer Society*, *3*, 172-184. https://doi.org/10.1109/OJCS.2022.3206407

[18] Rahman, M. A., Hossain, M. S., Islam, M. S., Alrajeh, N. A., & Muhammad, G. (2020). Secure and provenance enhanced internet of health things framework: A blockchain managed federated learning approach. *Ieee Access*, *8*, 205071-205087. https://doi.org/10.1109/ACCESS.2020.3037474

[19] Raju, R. K. (2017). Dynamic memory inference network for natural language inference. International Journal of Science and Research (IJSR), 6(2). https://www.ijsr.net/archive/v6i2/SR24926091431.pdf

[20] Sardana, J. (2022). Scalable systems for healthcare communication: A design perspective. *International Journal of Science and Research Archive*. https://doi.org/10.30574/ijsra.2022.7.2.0253

[21] Sardana, J. (2022). The role of notification scheduling in improving patient outcomes. *International Journal of Science and Research Archive*. Retrieved from https://ijsra.net/content/role-notification-scheduling-improving-patient

[22] Sater, R. A., & Hamza, A. B. (2021). A federated learning approach to anomaly detection in smart buildings. *ACM Transactions on Internet of Things*, *2*(4), 1-23. https://doi.org/10.1145/3467981

[23] Shahid, J., Ahmad, R., Kiani, A. K., Ahmad, T., Saeed, S., & Almuhaideb, A. M. (2022). Data protection and privacy of the internet of healthcare things (IoHTs). *Applied Sciences*, *12*(4), 1927. https://doi.org/10.3390/app12041927

[24] Singh, B. (2017). Enhancing Real-Time Database Security Monitoring Capabilities Using Artificial Intelligence. *INTERNATIONAL JOURNAL OF CURRENT ENGINEERING AND SCIENTIFIC RESEARCH (IJCESR)*.

[25] Singh, V. (2022). Advanced generative models for 3D multi-object scene generation: Exploring the use of cutting-edge generative models like diffusion models to synthesize complex 3D environments. https://doi.org/10.47363/JAICC/2022(1)E224

[26] Singh, V., Oza, M., Vaghela, H., & Kanani, P. (2019, March). Auto-encoding progressive generative adversarial networks for 3D multi object scenes. In *2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT)* (pp. 481-485). IEEE. https://arxiv.org/pdf/1903.03477

[27] Spencer, K., Sanders, C., Whitley, E. A., Lund, D., Kaye, J., & Dixon, W. G. (2016). Patient perspectives on sharing anonymized personal health data using a digital system for dynamic consent and research feedback: a qualitative study. *Journal of medical Internet research*, *18*(4), e5011. https://doi.org/10.2196/jmir.5011

[28] Sukhadiya, J., Pandya, H., & Singh, V. (2018). Comparison of Image Captioning Methods. *INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH*, *6*(4), 43-48. https://rjwave.org/ijedr/papers/IJEDR1804011.pdf

[29] Tanantong, T., Nantajeewarawat, E., & Thiemjarus, S. (2015). False alarm reduction in BSN-based cardiac monitoring using signal quality and activity type information. *Sensors*, *15*(2), 3952-3974. https://doi.org/10.3390/s150203952

[30] Winters, B. D., Cvach, M. M., Bonafide, C. P., Hu, X., Konkani, A., O'Connor, M. F., ... & Kane-Gill, S. L. (2018). Technological distractions (part 2): a summary of approaches to manage clinical alarms with intent to reduce alarm fatigue. *Critical care medicine*, *46*(1), 130-137. https://journals.lww.com/ccmjournal/abstract/2018/01000/technological_distractions__part_2___a_summary_of.17.aspx

[31] Malik, G., & Prashasti, P. (2025). Shift Left Security. The Eastasouth Journal of Information System and Computer Science, 2(03), 219–245. https://doi.org/10.58812/esiscs.v2i03.528

[32] Malik, G.(2025). Implementing Zero Trust Architecture: Modern Approaches to Secure Enterprise Networks. International Journal of Networks and Security, 5(01), 22-45. https://doi.org/10.55640/