SAR Journal of Medicine

Abbreviated Key Title: *SAR J Med*
Home page: https://sarpublication.com/journal/sarjm/home
DOI: https://doi.org/10.36346/sarjm.2026.v07i02.002

OPEN ACCESS

ISSN 2707-773X (P)
ISSN 2709-6920 (O)

Review Article

Artificial Intelligence for Predicting Radiologist Burnout and Cognitive Fatigue: A New Frontier in Workflow Optimization

Dr. Aneeqa Qureshi[1*], Dr. Muzammil Shakeel[2], Dr. Azka Noor[3], Ayesha Nazeef[4], Sheeza Yousaf[5], Syed Ibraheem Ul Hassan Ramzi[6], Dr. Ayesha Khan[7], Ayesha Atta[8], Syed Hameed-Ul-Hassan Shah[9], Hammad Khalid Malik[10], Dr Huzafa Ali[11]

[1]Assistant Professor, Radiology, Dow University Health Sciences
[2]Fellow VIR [Vascular Interventional Radiology], Aga Khan University
[3]Radiology Department, Shifa International Hospital, Islamabad,
[4]Quaid e Azam Medical College, Bahawalpur
[5]King Edward Medical University, Lahore, Pakistan, MBBS,
[6]Final Year MBBS, Multan Medical and Dental College
[7]PGY3 Internal Medicine, CMH Multan
[8]CMH Institute of Medical Sciences CIMS, Multan, 3rd Year MBBS
[9]Multan Medical and Dental College, Multan
[10]CMH Multan Institute of Medical Sciences
[11]CMH Multan Institute of Medical Sciences

***Corresponding Author:** Dr. Aneeqa Qureshi
Assistant Professor, Radiology, Dow University Health Sciences

Article History: | Received: 30.01.2026 | Accepted: 24.03.2026 | Published: 27.03.2026 |

Abstract: Radiologist burnout has become a significant global concern due to the rapid increase in imaging volumes, administrative responsibilities, and continuous diagnostic workload. Studies report that a large proportion of radiologists experience symptoms such as emotional exhaustion, depersonalization, and reduced professional satisfaction. Increasing case complexity, time pressure, and repetitive cognitive tasks contribute to mental fatigue and reduced diagnostic performance, making burnout a critical workforce and patient-safety issue. Artificial intelligence [AI] tools are increasingly being integrated into radiology workflows and can prioritize imaging worklists, generate draft reports, and analyze operational data to detect patterns associated with workload stress and cognitive fatigue. Evidence suggests that AI-assisted reporting systems can reduce interpretation time and improve workflow efficiency without compromising diagnostic accuracy. Additionally, predictive models using electronic health record activity logs have been proposed to detect early signals of clinician burnout through behavioral analytics and digital workflow metrics. This review aims to explore the emerging role of artificial intelligence in predicting radiologist burnout and cognitive fatigue through workflow analytics. It seeks to synthesize current literature on AI-based monitoring of radiologist workload, predictive modeling of burnout risk, and the potential of intelligent systems to support sustainable radiology practice and improve diagnostic performance.

Keywords: Radiology, Artificial Intelligence, Burnout, Machine Learning, Workload.

INTRODUCTION

In a fast-paced, high-volume reading environment, the persistent, gradual drain on a radiologist's cognitive abilities is not simply a peril associated with their professional responsibilities; rather, it has recently escalated into a significant threat to the overall health outcomes of patients. The workload-resource mismatch that has intensified the landscape of diagnostic radiology has brought the profession to a critical juncture.

Radiologists have a high burnout rate of 54%, comparable to rates in general surgery [51%] and anesthesia [55%]. Across studies utilizing the MBI, reported prevalence rates vary widely from 5% to 85% [1]. A substantial proportion [76.7%] of participating radiologists were classified as experiencing a high prevalence of burnout, which aligns with data reported in international studies and stresses the global nature of the issue[2]. An analysis of variance [ANOVA] and Dunnett's test indicated a significant difference in imaging volumes. 2019 data showed a substantial deficit compared to 2022, driven by a rapid spread of COVID-19 due to a surge in fatality, transforming the patient admission model[3,4]. Outpatient imaging volumes increased markedly during the third wave, reaching 115.7% of the pre-COVID-19 volume while CT volumes dropped by 53% during the pandemic nadir, and have surpassed their pre-pandemic performance, that indicate a backlog of outpatient examinations that were deferred during the first wave of the pandemic[5]. The top quartile of most productive radiologists now reads 30.6% more examinations per day than they did in 2018, not just more cases, but thinner slices, meaning thousands more images to scroll through per shift[6].

Current trends suggest that the ongoing pressures of contemporary reading environments, exacerbated by the COVID-19 pandemic, have escalated from manageable stressors to significant contributors to workforce attrition and clinical fatigue[7]. Specifically, demonstrated perceptual errors on CT scan correlate with workloads reaching 121% of average daily capacity. Due to a lack of recovery time, the primary catalyst for moral injury and chronic fatigue in contemporary reading environments[8]. An Error-Prone-State[EPS] observed in radiologists increases the risk of perceptual error in radiologists, potentially due to perceptual decoupling, and recognizes fatigue as a crucial variable[9]. Physicians exceeding 55 hours of work weekly exhibited a high risk of serious adverse events, indicating that surpassing a critical workload threshold correlates with an increased threat to patient safety[10]. Cognitive fatigue erodes diagnostic accuracy, which can lead to subsequent legal action. The predominant cause of medical malpractice litigation against radiologists is diagnostic errors. The errors in radiological practice are prevalent, approximately 4% of radiologic interpretations that can result in medical malpractice lawsuits when they affect patients safety[11].

Recent studies indicate a subjectivity gap between clinicians' perceived competence and their actual diagnostic performance. The Physicians Foundation 2025 Wellbeing Survey, that reported burnout rates have eased, yet actual levels of clinical stress and anxiety have surged to near-pandemic peaks[12]. It implies that self-report tools measure resilience rather than fatigability. So, unlike surveys, AI can monitor shift volume in real-time.

A novel AI-based metric was discovered, integrating speed, time, and depth of anatomical coverage [13]. Using this metric, anticipate changes in fatigue-related image patterns. It addresses the limitations of subjective fatigue assessments and provides real-time monitoring. This review delves deeper into burnout among radiologists and how AI models are playing their part in it.

3. Understanding Burnout in Radiology

3.1 Concept and Unique Stressors in Radiology

According to the Maslach Burnout Inventory [MBI], a work-related syndrome involving emotional exhaustion, depersonalization, and a feeling of reduced personal accomplishment, which is prevalent internationally, is defined as Physician burnout, representing a negative impact on individual physicians, patients, and healthcare organizations and systems, showing it to be a public health crisis. Recent studies show that over 50% of physicians, including both trainees and practicing doctors, are affected by burnout.

Research also suggests that despite work hours, physicians experience higher burnout rates than many other professions, with higher rates of burnout reported in female and younger physicians. Burnout among physicians is most commonly due to longer work hours, frequent night/weekend duties, work done at home, and work–home conflicts [14]. And rapid changes in healthcare, including technological advancements and high service demand, have created stressful working conditions for radiology technicians.

Other factors like excessive workload, job insecurity, and lack of recognition, high workload, staff shortages, shift work, role ambiguity, workplace bullying, limited professional recognition, and insufficient managerial support, and the quality of patient care also contribute to increased burnout among health care professionals[14–16]. Support strategies such as professional recognition, psychological support, physical activity, and healthier workplace policies may help to improve their well-being. Protective factors like self-compassion, effective coping strategies, and workplace physical activity were identified as promising approaches to reducing stress and burnout and enhancing well-being[16]. It is different from depression, fatigue, or job dissatisfaction, although it can be related to them.

3.2 Measurable Digital Workflow Markers

The rapid advancement of artificial intelligence [AI] technology has significantly impacted various sectors, including healthcare, through various AI-based techniques.

Turnaround Time [TAT] in radiology measures the time from imaging order to report completion, and it is used to evaluate the efficiency of work, patient care quality and performance of any institution. Excessive focus on meeting TAT targets may also negatively impact resident education, diagnostic accuracy, and contribute to radiologist burnout due to increased workflow burden[17].

Some studies suggested that increased workload has deteriorated the efficacy of a radiologist's reading time, gaze distance, image coverage, and information gain over lung X-rays, indicating fatigue-related changes in visual search behavior[13].

Some studies found that radiologists made more diagnostic errors on days when their workload was about 21% higher than their normal productivity, which suggests that excessive caseloads may increase the risk of mistakes affecting the efficacy of work. The findings highlight the need for balanced staffing, manageable workloads, and further research to better understand and prevent diagnostic errors in radiology[7].

Hence, increased workload directly affects the efficacy of diagnostic measures, potentially harming the well-being of both patients and healthcare workers. In order to address these challenges, strategies such as improved staffing models, optimized PACS worklists, subspecialty reporting, AI-based prioritization systems, and better workflow management are being implemented to balance reporting speed with quality of care.

4. AI Techniques for Burnout Prediction

4.1 Machine Learning Models in Workflow Analytics

Machine learning [ML] and deep learning [DL] are increasingly important in modern healthcare, helping improve diagnosis, medical image analysis, drug discovery, and smart health monitoring. By integrating real-time patient data from various healthcare systems, ML-DL technologies can enhance treatment effectiveness and support better decision-making. As these technologies expand, they are expected to significantly improve patient care and healthcare system efficiency[18,19]

In research by Chao Liu, multiple machine-learning models were evaluated to determine the most effective approach for the prediction of burnout. Four algorithms—Logistic Regression [LR], K-Nearest Neighbors [KNN], Decision Tree [DT], and Random Forest [RF]—were compared based on their prediction accuracy and F1-scores. Among the tested models, the Random Forest algorithm demonstrated the best overall performance, indicating its strong capability to capture complex relationships within the data. The Decision Tree model also showed good predictive performance, outperforming Logistic Regression and KNN. Overall, the study analyzes the factors affecting medical burnout in hospitals[20]. Another scoping review highlights the potential of natural language processing [NLP] and text mining techniques to automatically detect work-related stress among healthcare professionals[21]. By integrating NLP-based insights with workflow analytics, AI systems may provide a more comprehensive assessment of radiologist performance and mental workload.

4.2 Computer Vision and Behavioral Analytics

A pilot study investigated the use of deep learning and eye-tracking data to predict radiologist fatigue during chest X-ray interpretation. The results showed that AI-derived gaze features, particularly lung-coverage patterns on x-rays, strongly correlated with fatigue levels, outperforming traditional metrics such as reading time or gaze distance. The findings suggest that AI-based gaze analysis could enable real-time fatigue monitoring and improve diagnostic performance in radiology using different techniques, like U-Net to segment lung regions on chest X-rays and ResNeXt-50 to analyze gaze-based features[22].

4.3 Deep Learning for Pattern Drift Detection

Another study proposes MMC+, an AI-based framework designed to detect model drift in medical imaging systems and ensure the long-term reliability of AI diagnostics. The framework uses multi-modal data monitoring and deep learning foundation models like Med Image Insight to analyze changes in imaging data and identify shifts that may affect model performance. By detecting these data drifts early and correlating them with performance changes, MMC+ acts as an early warning system that enables timely intervention to maintain the accuracy and safety of AI systems in clinical practice[23]. This study introduces CheXStray, an AI-based framework designed to detect model drift in deployed medical imaging systems without requiring ground-truth labels. The framework uses multi-modal inputs including DICOM metadata, image features extracted using a Variational Autoencoder [VAE], and model prediction probabilities to monitor changes in data and model behavior. The results demonstrate that this approach can effectively track drift and provide a reliable proxy for model performance, enabling real-time monitoring and improving the reliability of clinical AI systems[24].

5. Existing Evidence and Early Studies

A large cross-sectional study of 6,726 radiologists from 1,143 hospitals found that frequent AI use was associated with a higher risk of burnout, especially among radiologists with heavy workloads or low acceptance of AI compared with the non-AI group. A survey at 68 hospitals found that radiologists often experience burnout due to long working hours and increasing imaging workload. Although artificial intelligence [AI] may improve workflow efficiency, current evidence is mostly observational, and larger validation studies are still needed[25]. A recent study evaluated an AI algorithm for identifying normal chest radiographs. It showed high diagnostic accuracy, enabling the reliable exclusion of normal cases. This may reduce radiologists' workload, improve workflow efficiency, and potentially decrease fatigue and burnout[26]. Another study investigated a deep learning detection algorithm for triaging chest radiographs in outpatient settings. Simulation results showed that AI-based triaging could reduce the radiologist's worklist by up to 50% without reducing diagnostic sensitivity. The study highlights the potential of AI to improve workflow efficiency and reduce workload-related stress in radiology departments[27]. This experimental study used AI-based eye-tracking analysis to evaluate fatigue during radiological image interpretation. Researchers found that increasing workload significantly altered gaze patterns, reading time, and lung coverage, suggesting that AI may help detect cognitive fatigue through behavioral markers[13]. Another study used an AI system to identify normal chest X-rays. The algorithm achieved high diagnostic accuracy and could exclude many normal studies, which potentially reduces radiologists' reporting workload by approximately 15 %[26].

A systematic review evaluated the role of artificial intelligence in addressing radiologist shortages and increasing imaging demand. The authors concluded that AI may support workflow optimization and automated image analysis, but large-scale validated models and long-term clinical evidence are still limited[28]. The use of AI-generated draft radiology reports to help radiologists finish imaging reports was investigated in this study. Researchers measured reporting time and diagnosis accuracy by comparing AI-assisted workflows with conventional reporting. The study assessed whether AI help may reduce workload pressure by accelerating report generation without sacrificing clinical accuracy.

In order to assess the opinions of academic radiology department chairs from the Society of Chairs of Academic Radiology Departments regarding the use of AI in radiology practice, this study administered a web-based survey to them in October 2023. The study evaluated anticipated clinical uses, optimism toward AI, and expected impacts on the radiology workforce and departmental productivity. Additionally, researchers looked at the particular phases of imaging practice, such as image capture, post-processing, and interpretation workflows, where AI may be used[29]

6. Ethical, Legal, and Professional Concerns

6.1 Privacy of Performance Data

The integration of artificial intelligence [AI] systems capable of monitoring radiologist workflow raises serious concerns regarding the privacy and governance of physician performance data. Modern radiology procedures generate extensive digital traces, including reporting time, diagnostic accuracy, eye-tracking metrics, and interaction logs, which can be analyzed using machine learning algorithms to infer cognitive fatigue or burnout risk. While these systems offer potential improvements in workflow optimization, the collection and storage of individual clinician performance data raises critical ethical and legal issues.

According to research, healthcare workers are frequently skeptic of how institutions manage sensitive digital data, with many reporting concerns about privacy and data protection in electronically managed record systems [30]. Similarly, the expanding use of AI-based monitoring tools has heightened fears related to data misuse, unauthorized access, and limited transparency in governance. These concerns underscore the need for explicit institutional policies on data ownership, security, and anonymization to protect clinicians from potential misuse of performance metrics[31].

6.2 Risk of Administrative Surveillance

However, with the increasing implementation of artificial intelligence for monitoring clinical workflow, concerns about its potential use as a tool for administrative surveillance have also surfaced. Performance analytics based on metrics such as reporting speed, case volume, and workflow efficiency may extend beyond quality improvement to influence managerial oversight. Persistent digital monitoring can also affect perceptions of professional autonomy and heighten performance-related scrutiny, especially when evaluation processes lack transparency. Research on AI-driven workplace systems reveal that insufficient governance clarity and limited clinician engagement may undermine trust and amplify concerns regarding surveillance

6.3 Bias and Fairness in Performance Metrics

Another critical ethical issue relates to the potential bias and unfairness embedded within algorithm-derived performance metrics. Models trained on historical workflow data may unintentionally reinforce institutional disparities or misinterpret legitimate variations in practice as indicators of suboptimal performance. Consequently, clinicians working with more complex case mixes or in resource-constrained environments may be disproportionately affected by automated assessments. Research shows that biased training data can result in unequal outcomes, underlining the importance of thorough dataset evaluation, clear validation processes, and constant monitoring to assure fairness in clinical applications[34,35].

6.4 Psychological Impact of AI Monitoring

The psychological impact of AI monitoring in healthcare is increasingly being studied as institutions adopt algorithm-enabled tools to assist clinicians and evaluate workflow patterns. A randomized trial showed that AI reduced work exhaustion and interpersonal disengagement, suggesting relief when the administrative burden is lowered[36]. On the other hand, research on AI “technostress” indicates that perceived complexity, workload overload, and threats to professional esteem can increase stress and job insecurity among physicians[37]. Studies further show that the impact of AI on satisfaction depends on factors like autonomy, competence, and the complexity of the job, highlighting that those effects vary across contexts[38]. These findings emphasize that AI monitoring does not have uniform psychological outcomes; instead, its impact depends on how the technology is implemented and supported in practice.

7. Proposed Conceptual Framework

To explore how AI could predict radiologist burnout and cognitive fatigue, a conceptual framework can be proposed that integrates diverse workflow and behavioral data from routine practice. Radiology systems like Picture Archiving and Communication Systems [PACS], Radiology Information Systems [RIS], and reporting platforms generate extensive interaction logs that reflect workload, reading behavior, and cognitive load. These measurable indicators allow analysis of fatigue risk. The framework combines operational workflow metrics with optional physiological data to enable predictive modeling of burnout and cognitive strain[39,40].

Inputs and Data Sources

The initial layer of the proposed framework collects diverse data reflecting both behavioral and physiological aspects of radiologist work. Key behavioral inputs include PACS interaction logs, which track image viewing times, case navigation, and study switching patterns metrics, increasingly utilized in radiology research to quantify workload and reading behavior. Reporting system timestamps, such as report start times, dicta on dura on, and turnaround me, provide temporal indicators of cognitive efficiency, with studies showing significant varia on based on location and case priority[41]. Patterns of error correction, like report amendments, can signal diagnostic uncertainty or fatigue, with studies showing mistakes increase when workloads are high[7]. Likewise, long hours and heavy workload are linked to increased diagnostic errors and are recognized contributors to physician fatigue and burnout, underscoring the value of including scheduling and cumulative workload data in predictive models[42]. Physiological inputs from wearable devices such as heart rate variability, sleep duration, and activity metrics offer objective measures of stress and fatigue, and integrating this with workflow metrics improves the accuracy of fatigue predictions[43]. Together, these data sources provide a comprehensive basis for assessing cognitive strain and anticipating burnout risk.

AI Layer: Modeling and Features

The AI layer forms the central component of the proposed framework, where machine learning algorithms combine workflow and physiological data to model cognitive fatigue and identify performance declines. Supervised learning models can be trained on labeled clinical or workflow data to estimate the probability of fatigue or burnout, using patterns such as prolonged reporting times, cumulative workload, and temporal behavior changes. Evidence from research demonstrates that models trained on electronic health records and clinical notes can detect fatigue signals and align with objective work patterns, confirming the feasibility of predictive fatigue modeling with large datasets[44]. Beyond supervised approaches, anomaly detection and unsupervised learning techniques can identify deviations from an individual clinician's baseline workflow, serving as early indicators of cognitive overload or performance deterioration. Exploratory studies using biosignal data further show that longitudinal machine learning can accurately detect fatigue-related physiological patterns, supporting the integration of anomaly detection and change-point analysis into predictive frameworks for assessing cognitive strain[45].

Outputs: Risk Scores and Scheduling Optimization

The final layer of the framework converts predictive analytics into practical outputs that can enhance radiology workflow and reduce fatigue-related risks. Central to this is a quantitative fatigue risk score generated by machine learning models, offering an interpretable measure of cognitive load or burnout probability for individual radiologists based on combined workflow and physiological data. Similar methods using clinical audit logs have successfully predicted burnout, showing that algorithmic scores can reflect real-world cognitive stress and guide targeted interventions[46]. In other clinical settings, real-me alerts from predictive models have improved workflow and patient safety, such as early warning systems in critical care that trigger action when risk thresholds are exceeded[47]. Applying this approach in radiology could enable notifications for high fatigue risk, supporting timely breaks or task redistribution. Additionally, AI-derived risk scores can inform adaptive scheduling, balancing case complexity and workload to reduce cognitive strain, with evidence from other healthcare domains confirming the effectiveness of predictive staffing and workload management[48].

8. Integration into Clinical Practice

Artificial intelligence [AI] systems that predict radiologist burnout and cognitive fatigue can be integrated into the current clinical processes in such a way that radiologists would gain considerable advantages with the increased automation of a variety of image-related tasks made by AI, and radiology feedback is employed to improve the AI usage further[49]. Researchers have suggested a framework according to which clinical integration can take three levels of maturity: research, production, and feedback. In the research level, the results of AI can be visualized and examined by radiologists to evaluate without interfering with patient records. During the production phase, validated AI models are incorporated, and systems, including picture archiving and communication systems [PACS], and their output are integrated into the clinical process. The feedback phase allows radiologists to view and amend AI-generated outputs and proceed with the process of constant model enhancement through retraining and clinical feedback[50]

In addition to the established digital systems, including picture archiving and communication systems [PACS], radiology information systems [RIS], and electronic health records [EHR], some of the new AI techniques including convolutional neural networks [CNNs] can be proposed to optimize the clinical workflow and decrease report turnaround times [RTATs] in critical findings in the chest radiograph[51]. These data can help to gain important insights into the work pattern of radiologists, and AI algorithms can supervise the dynamics of workflow and identify the signs of cognitive fatigue or workload imbalance in the early stages, enhancing diagnostic efficiency and decreasing delays in patient care.

8.1 Adaptive Workload Redistribution

Real-time analysis of parameters like volumes of imaging, reporting periods, and case complexity can enable the AI systems to prioritize critical research and dynamically manipulate the radiology worklist, enabling radiologists to work on the high-priority cases at the expense of routine check-ups divided among the available personnel. Several clinical studies have identified that AI-based triage and prioritization tools, which are incorporated in radiology workflows, can substantially decrease report turnaround times and increase efficiency[52,53]. As an illustration, AI-based worklist prioritization in chest radiography has been shown to identify critical findings faster and provide a higher-quality reporting order in high workload situations. In the same way, the results of other studies investigating the use of AI triage systems in CT imaging have reported that it reduces the time to diagnosis of urgent conditions like pulmonary embolism[54]. The findings indicate that the redistribution of workloads with the help of AI can improve the balance of the workflow, diagnostic efficiency, and potentially reduce the decline of performance related to fatigue in radiologists.

8.2 AI-Guided Break Scheduling

Around 60-80% of radiological errors are attributed to overlooked abnormalities, the rate of which increases at the end of work shifts. Monitoring systems based on artificial intelligence can be used to analyze workflow indicators like the time spent reading, gazes, and reports to identify the initial symptoms of fatigue and reduced productivity. As an example, radiologists' patterns have been analyzed using AI models to determine changes related to workload caused by fatigue when interpreting images[13]. Another study assesses the performance of readers during digital breast tomosynthesis screening, showing that the modern eye tracking technology enables non-invasive monitoring of the eye movements and other visual search parameters. According to it, the more time a person blinks, the more advanced levels of mental workload and fatigue are linked with it[55]. The implementation of such fatigue-detection measures in clinical workflows may enable AI systems to suggest micro-breaks or the most effective rest times on radiology shifts, which would facilitate the promotion of cognitive recovery, maintenance of diagnostic accuracy, and the overall health of radiologists.

8.3 Fatigue-Aware Diagnostic Assistance

Fatigue-aware decision support systems are also another noteworthy attribute of clinical integration. Diagnostic assistance tools can be used to offer further support to radiologists when AI models identify possible symptoms of cognitive overload. Such systems may indicate suspicious imaging results, prioritize the cases, or give automated second-reader analysis. As an illustration, the radiologists and the Deep learning-based automated detection algorithm had similar diagnostic measures in the detection of active pulmonary tuberculosis on the chest radiographs[56,57].

8.4 Institutional Policy Implications

The introduction of AI-powered burnout prediction tools can also affect the institutional policies in the area of workforce management and physician wellness. Aggregated workflow data can be used by healthcare organizations to streamline staffing approaches, create fatigue-reduction initiatives, and enhance scheduling approaches[58]. Nevertheless, there should be transparent governance frameworks to allow the responsible use of performance data

9 FUTURE DIRECTIONS

The use of AI as an imaging identification aid is gaining traction as a solution to the workload issues in radiology, but longitudinal studies are needed to help better understand this association, and the role of AI in decreasing radiologist burnout must be weighed. The development of a deep learning model of electronic health record [EHR] activity logs that, unlike other approaches that solely used questionnaires to measure the severity of burnout, directly learns deep representations of physician behaviours based on large clinical activity logs in predicting burnout. This is a show of how more comprehensive and sophisticated methods are expected to be researched in the future[59]

The advantages of AI embedded into clinical decision-making can be enumerated as a number of them, particularly in terms of enhancement of the precision of diagnosis, acceleration of clinical processes, and reduction of healthcare expenses due to resource optimisation. Such advantages may make it more widely adopted by health care systems. Consistent with previous studies that show that AI decreases manual labour and the potential of human error, AI systems can be used to reduce idle time and automate healthcare processes to eventually contribute to greater operational efficiency and cost reduction [60].

Multimodal AI [workflow + physiologic sensors]

The idea of multimodal artificial intelligence systems, which integrate workflow analytics with data gathered by physiological sensors, is increasingly becoming significant in future studies touching upon the detectability of radiologist burnout and cognitive fatigue. As the continuous observation of heart rate variability [HRV] can become an effective predictor of human health, inexpensive, wearable photoplethysmography [PPG] sensors are currently easily available in the market that can be used to predict fatigue in daily life conditions by combining these physiological measurements with electronic workflow data [61,62]. AI programs have the potential to improve fatigue forecasting and allow real-time measurement of the well-being of physicians by combining these physiological signals with computerized workflow information [63]. To maintain diagnostic performance and accuracy, these combined systems could benefit from timely treatments and identify early signs of cognitive stress [64].

Federated Burnout Prediction across Institutions

Addressing the privacy concerns of decentralised medical data, a distinctive adaptive aggregation method has maximised the model convergence in the federated learning environment and retained high classification rates, also enabling healthcare organisations to create extremely accurate models without compromising patient privacy. A study suggests that transfer learning combined with federated learning is a scalable, reliable, and secure method that can be used to make practical medical diagnoses. One of the significant concerns is to ensure that the AI models are accurate and reliable. Moreover, the reliability problems of multi-access edge computing can be addressed with federated learning [65].

Federated learning can solve healthcare AI ethical challenges such as privacy, governance, transparency and explainability, fairness and reduction of bias, and equitable access to AI models that allow hospitals of any size to develop models explicitly and collaboratively, and increase their generalisability across different hospital settings, imaging volumes, and workload patterns [66].

Explainable AI for Transparency

Explainable AI [XAI] can influence the trust and dependence of the user, who should be the key to the successful implementation of such systems. The high levels of confidence contributed greatly to amplifying the trust, yet it led to overreliance and reduced diagnostic accuracy, as per research. Conversely, low scores on the confidence scale were a sign of more conservative behaviour and reduced trust and agreement to the process of lengthening the diagnosis.

To address this, the black box character of most machine learning models and associated mistrust and acceptance of results could be overcome with a hybrid machine learning framework utilizing XAI skills to increase interpretability, transparency, and clinician trust, besides enhancing the prediction performance. This strategy will encourage the ethical and successful implementation of AI in healthcare applications by ensuring that AI outputs are reliable and actionable [67].

Prospective Interventional Trials

Future interventional studies are vital to determine the true world performance of AI-based burnout prediction systems since most of the existing studies are retrospective and are only predictive. In radiology, the use of the AI tool and its effect on patient outcomes in the long run can be evaluated in terms of the workload of clinicians, diagnostic quality, and workflow rates. This form of prospective evidence is vital in the process of validating AI interventions and greater clinical implementation [68–70].

CONCLUSION

Radiologist burnout is increasing due to rising imaging volumes, administrative workload, and cognitive demands, affecting physician well-being and diagnostic performance. Artificial intelligence can analyze workflow patterns, reporting time, and electronic health record activity logs to detect early signs of fatigue and burnout risk. This review explores the role of AI-based workflow analytics in predicting radiologist burnout and cognitive fatigue. Major themes include burnout drivers, machine-learning prediction models, AI-assisted workflow optimization, and the impact of AI on clinician well-being. AI integration with radiology systems may enable proactive workload management and sustainable radiology practice.

REFERENCES

1. Thakore NL, Lan M, Winkel AF, Vieira DL, Kang SK. Best Practices: Burnout Is More Than Binary. AJR Am J Roentgenol. 2024 Oct;223[4]:e2431111. doi:10.2214/AJR.24.31111 PubMed PMID: 39016454.
2. Bastian MB, Fröhlich L, Wessendorf J, Scheschenja M, König AM, Jedelska J, *et al.,* Prevalence of burnout among German radiologists: a call to action. Eur Radiol. 2024 Sep;34[9]:5588–94. doi:10.1007/s00330-024-10627-5 PubMed PMID: 38345608; PubMed Central PMCID: PMC11364704.
3. Alhazmi FH, Alrehily FA, Alsharif W, Gameraddin M, Alsultan KD, Alsaedi HI, *et al.,* The extended impact of the COVID-19 pandemic on medical imaging case volumes: a retrospective study. PeerJ. 2025;13:e18987. doi:10.7717/peerj.18987 PubMed PMID: 40061237; PubMed Central PMCID: PMC11890034.
4. Rennert-May E, Leal J, Thanh NX, Lang E, Dowling S, Manns B, *et al.,* The impact of COVID-19 on hospital admissions and emergency department visits: A population-based study. PloS One. 2021;16[6]:e0252441. doi: 10.1371/journal.pone.0252441 PubMed PMID: 34061888; PubMed Central PMCID: PMC8168854.
5. Schwertner A, McMenamy J, Naeger DM. Radiology Imaging Volume Changes During Discrete COVID-19 Pandemic Waves: Implications for the Delta Variant of Coronavirus and Future Pandemics. J Am Coll Radiol JACR. 2022

Mar;19[3]:415–22. doi:10.1016/j.jacr.2021.09.045 PubMed PMID: 34883068; PubMed Central PMCID: PMC8608677.

6. Zamani H, Fruscello T, Burleson J, Bhargavan-Chatfield M, Davenport MS. US Radiology Imaging and Workforce Volumes 2017-2024: An Analysis of 46.4 Million Imaging Examinations From 167 Radiology Facilities. J Am Coll Radiol JACR. 2025 Dec 26;S1546-1440[25]00744-6. doi:10.1016/j.jacr.2025.12.026 PubMed PMID: 41456840.
7. Kasalak Ö, Alnahwi H, Toxopeus R, Pennings JP, Yakar D, Kwee TC. Work overload and diagnostic errors in radiology. Eur J Radiol. 2023 Oct;167:111032. doi:10.1016/j.ejrad.2023.111032 PubMed PMID: 37579563.
8. Furlan A, Sumkin JH. Navigating Moral Injury in Radiology: Adapting to the Winds of Change. J Am Coll Radiol JACR. 2025 Aug;22[8]:860. doi:10.1016/j.jacr.2025.05.014 PubMed PMID: 40404035.
9. Bruno MA, Krupinski EA, Bunce SC, Baird GL, Mills C, Karunanayaka PR, *et al.,* Neurocognitive Mechanism of Radiologists' Perceptual Errors: Results of Preliminary Studies [Internet]. bioRxiv; 2025 [cited 2026 Mar 16]. p. 2024.04.29.591746. Available from: https://www.biorxiv.org/content/10.1101/2024.04.29.591746v4 doi:10.1101/2024.04.29.591746
10. Arai Y, Kachi Y, Hikichi H, Watanabe K, Inoue R, Iwata N, *et al.,* Association between long working hours of doctors and the seriousness of adverse events: a cross-sectional study using national adverse event reporting system data in Japan. Ind Health. 2025 Apr 1;63[2]:156–63. doi:10.2486/indhealth.2023-0125 PubMed PMID: 39135231; PubMed Central PMCID: PMC11995148.
11. Cannavale A, Santoni M, Mancarella P, Passariello R, Arbarello P. Malpractice in Radiology: What Should You Worry About? Radiol Res Pract. 2013;2013:219259. doi:10.1155/2013/219259 PubMed PMID: 23691316; PubMed Central PMCID: PMC3649698.
12. Physicians A. The Physicians Foundation [Internet]. 2025 [cited 2026 Mar 16]. The Physicians Foundation Releases 2025 Wellbeing Survey: Stress and Anxiety Surge During a Tumultuous Year in Medicine. Available from: https://physiciansfoundation.org/the-physicians-foundation-releases-2025-wellbeing-survey-stress-and-anxiety-surge-during-a-tumultuous-year-in-medicine/
13. Pershin I, Kholiavchenko M, Maksudov B, Mustafaev T, Ibragimova D, Ibragimov B. Artificial intelligence for the analysis of workload-related changes in radiologists' gaze patterns. IEEE J Biomed Health Inform. 2022;26[9]:4541–50.
14. West CP, Dyrbye LN, Shanafelt TD. Physician burnout: contributors, consequences and solutions. J Intern Med. 2018;283[6]:516–29.
15. Mahecha-Naranjo G, Álvarez-Alucema L, Campo-Torregroza Y, López-Sepúlveda R, García-Martínez D, Tuirán-Tinoco M. Burnout and work stress in radiology technicians: A narrative review. Duazary. 2025 Apr 25;22:e6465. doi:10.21676/2389783X.6465
16. Ramalho P, Nunes A, Silva F, Ramalho A, Flores G, Santos B, *et al.,* Occupational Stress, Burnout, and Quality of Life in Radiographers: A Scoping Review of Workforce Well-Being. Healthcare. 2026 Feb 22;14:538. doi:10.3390/healthcare14040538
17. Ritchie B, Summerville L, Sheng M, Choi M, Tirumani S, Ramaiya N. Impact of turnaround time in radiology: The good, the bad, and the ugly. Curr Probl Diagn Radiol. 2026;55[2]:268–72. doi:10.1067/j.cpradiol.2025.04.018 PubMed PMID: 40268614.
18. A Review of Deep Learning Algorithms and Their Applications in Healthcare [Internet]. [cited 2026 Mar 16]. Available from: https://www.mdpi.com/1999-4893/15/2/71
19. Rahman A, Debnath T, Kundu D, Khan MdSI, Aishi AA, Sazzad S, *et al.,* Machine learning and deep learning-based approach in smart healthcare: Recent advances, applications, challenges and opportunities. AIMS Public Health. 2024 Jan 5;11[1]:58–109. doi:10.3934/publichealth.2024004 PubMed PMID: 38617415; PubMed Central PMCID: PMC11007421.
20. Liu C, Chuang YC, Qin L, Ren L, Chien CW, Tung TH. Machine-learning-based model for analysing and accurately predicting factors related to burnout in healthcare workers. BMJ Public Health. 2025 Sep 4;3[2]:e000777. doi:10.1136/bmjph-2023-000777 PubMed PMID: 40922936; PubMed Central PMCID: PMC12414203.
21. Bieri JS, Ikae C, Souissi SB, Müller TJ, Schlunegger MC, Golz C. Natural Language Processing for Work-Related Stress Detection Among Health Professionals: Protocol for a Scoping Review. JMIR Res Protoc. 2024 May 15;13:e56267. doi:10.2196/56267 PubMed PMID: 38749026; PubMed Central PMCID: PMC11137421.
22. Pershin I, Kholiavchenko M, Maksudov B, Mustafaev T, Ibragimov B. AI-based analysis of radiologist's eye movements for fatigue estimation: a pilot study on chest X-rays. In. 2022. p. 39. doi:10.1117/12.2612760
23. Merkow J, Dorfner FJ, Yang X, Ersoy A, Dasegowda G, Kalra M, *et al.,* Scalable Drift Monitoring in Medical Imaging AI. 2024. doi:10.48550/arXiv.2410.13174
24. Merkow J, Soin A, Long J, Cohen JP, Saligrama S, Bridge C, *et al.,* CheXstray: A Real-Time Multi-Modal Monitoring Workflow for Medical Imaging AI. In: Greenspan H, Madabhushi A, Mousavi P, Salcudean S, Duncan J, Syeda-Mahmood T, *et al.,*,

editors. Medical Image Computing and Computer Assisted Intervention – MICCAI 2023. Cham: Springer Nature Switzerland; 2023. p. 326–36. doi:10.1007/978-3-031-43898-1_32

25. Fang X, Ma C, Liu X, Deng X, Liao J, Zhang T. Burnout crisis in Chinese radiology: will artificial intelligence help? Eur Radiol. 2025 Mar;35[3]:1215–24. doi:10.1007/s00330-024-11206-4 PubMed PMID: 39567429.
26. Schalekamp S, van Leeuwen K, Calli E, Murphy K, Rutten M, Geurts B, *et al.,* Performance of AI to exclude normal chest radiographs to reduce radiologists' workload. Eur Radiol. 2024 Nov;34[11]:7255–63. doi:10.1007/s00330-024-10794-5 PubMed PMID: 38758252; PubMed Central PMCID: PMC11519193.
27. Yoon SH, Park S, Jang S, Kim J, Lee KW, Lee W, *et al.,* Use of artificial intelligence in triaging of chest radiographs to reduce radiologists' workload. Eur Radiol. 2024 Feb;34[2]:1094–103. doi:10.1007/s00330-023-10124-1 PubMed PMID: 37615766.
28. Achour N, Zapata T, Saleh Y, Pierscionek B, Azzopardi-Muscat N, Novillo-Ortiz D, *et al.,* The role of AI in mitigating the impact of radiologist shortages: a systematised review. Health Technol. 2025;15[3]:489–501. doi:10.1007/s12553-025-00970-y PubMed PMID: 40390867; PubMed Central PMCID: PMC12085355.
29. Burnside ES, Grist TM, Lasarev MR, Garrett JW, Morris EA. Artificial Intelligence in Radiology: A Leadership Survey. J Am Coll Radiol JACR. 2025 May;22[5]:577–85. doi:10.1016/j.jacr.2025.01.006 PubMed PMID: 39800091; PubMed Central PMCID: PMC12048273.
30. Qashqari AA, Almutairi DS, Ennaceur SA, Farhah NS, Almohaithef MA. Healthcare professionals' perceptions of electronic medical record privacy and its impact on work quality in Riyadh hospitals. Saudi Med J. 2025 Mar;46[3]:299–306. doi:10.15537/smj.2025.46.3.20240928 PubMed PMID: 40096979; PubMed Central PMCID: PMC11918673.
31. Yang Y, Wang H, Du K, Wang X, Zhao J, Han D, *et al.,* Factors associated with patient privacy concerns in AI-based health monitoring devices among nursing students: a cross-sectional study. BMC Nurs. 2025 Jul 1;24:726. doi:10.1186/s12912-025-03453-7 PubMed PMID: 40598528; PubMed Central PMCID: PMC12210904.
32. Tawfik D, Shanafelt TD, Bayati M, Profit J. Electronic Health Record Use Patterns Among Well-Being Survey Responders and Nonresponders: Longitudinal Observational Study. JMIR Med Inform. 2025 Feb 4;13:e64722. doi:10.2196/64722 PubMed PMID: 39903913; PubMed Central PMCID: PMC11813195.
33. Kellogg K, Valentine M, Christin A. Algorithms at Work: The New Contested Terrain of Control. Acad Manag Ann. 2019 Nov 21;14. doi:10.5465/annals.2018.0174
34. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019 Oct 25;366[6464]:447–53. doi:10.1126/science.aax2342 PubMed PMID: 31649194.
35. Rajkomar A, Hardt M, Howell MD, Corrado G, Chin MH. Ensuring Fairness in Machine Learning to Advance Health Equity. Ann Intern Med. 2018 Dec 18;169[12]:866–72. doi:10.7326/M18-1990 PubMed PMID: 30508424; PubMed Central PMCID: PMC6594166.
36. Afshar M, Baumann MR, Resnik F, Hintzke J, Sullivan AG, Wills G, *et al.,* A Pragmatic Randomized Controlled Trial of Ambient Artificial Intelligence to Improve Health Practitioner Well-Being. Nejm Ai. 2025 Dec;2[12]. doi:10.1056/aioa2500945 PubMed PMID: 41625485; PubMed Central PMCID: PMC12858090.
37. Liu CF, Lin TC, Ko YL. Exploring the impact of AI technostress on physicians' job insecurity and performance from an empirical multi-hospital study. iScience. 2025 Dec 9;29[1]:114394. doi:10.1016/j.isci.2025.114394 PubMed PMID: 41550736; PubMed Central PMCID: PMC12811485.
38. Huo W, Li Q, Liang B, Wang Y, Li X. When Healthcare Professionals Use AI: Exploring Work Well-Being Through Psychological Needs Satisfaction and Job Complexity. Behav Sci. 2025 Jan 18;15[1]:88. doi:10.3390/bs15010088 PubMed PMID: 39851892; PubMed Central PMCID: PMC11761562.
39. Forsberg D, Rosipko B, Sunshine JL. Analyzing PACS Usage Patterns by Means of Process Mining: Steps Toward a More Detailed Workflow Analysis in Radiology. J Digit Imaging. 2016 Feb;29[1]:47–58. doi:10.1007/s10278-015-9824-2 PubMed PMID: 26353749; PubMed Central PMCID: PMC4722035.
40. Bruls RJM, Kwee RM. Workload for radiologists during on-call hours: dramatic increase in the past 15 years. Insights Imaging. 2020 Nov 23;11[1]:121. doi:10.1186/s13244-020-00925-z PubMed PMID: 33226490; PubMed Central PMCID: PMC7683675.
41. Udare A, Agarwal M, Dhindsa K, Alaref A, Patlas M, Alabousi A, *et al.,* Radiologist Productivity Analytics: Factors Impacting Abdominal Pelvic CT Exam Reporting Times. J Digit Imaging. 2022 Apr;35[2]:87–97. doi:10.1007/s10278-021-00548-w PubMed PMID: 35013824; PubMed Central PMCID: PMC8921423.
42. Tee QX, Nambiar M, Stuckey S. Error and cognitive bias in diagnostic radiology. J Med Imaging Radiat Oncol. 2022 Mar;66[2]:202–7. doi:10.1111/1754-9485.13320 PubMed PMID: 34467643.
43. Harrell M, Dayal D, Rahaman C, Dekle J, Lister R, Skelton A, *et al.,* Using Wearable Technology to

Evaluate Sleep and Stress for Physicians. South Med J. 2025 Apr;118[4]:213–20. doi:10.14423/SMJ.0000000000001816 PubMed PMID: 40153857.
44. Hsu CC, Obermeyer Z, Tan C. A machine learning model using clinical notes to identify physician fatigue. Nat Commun. 2025 Jul 1;16[1]:5791. doi:10.1038/s41467-025-60865-4 PubMed PMID: 40592818; PubMed Central PMCID: PMC12217598.
45. [PDF] An exploratory analysis of longitudinal artificial intelligence for cognitive fatigue detection using neurophysiological based biosignal data [Internet]. [cited 2026 Mar 16]. Available from: https://www.researchgate.net/publication/391487418_An_exploratory_analysis_of_longitudinal_artificial_intelligence_for_cognitive_fatigue_detection_using_neurophysiological_based_biosignal_data
46. Lou SS, Liu H, Warner BC, Harford D, Lu C, Kannampallil T. Predicting Physician Burnout using Clinical Activity Logs: Model Performance and Lessons Learned. J Biomed Inform. 2022 Mar;127:104015. doi: 10.1016/j.jbi.2022.104015 PubMed PMID: 35134568; PubMed Central PMCID: PMC8901565.
47. Levin MA, Kia A, Timsina P, Cheng FY, Nguyen KAN, Kohli-Seth R, *et al.,* Real-Time Machine Learning Alerts to Prevent Escalation of Care: A Nonrandomized Clustered Pragmatic Clinical Trial. Crit Care Med. 2024 Jul 1;52[7]:1007–20. doi:10.1097/CCM.0000000000006243 PubMed PMID: 38380992.
48. Hunstein D, Fiebig M. Staff Management with AI: Predicting the Nursing Workload. Stud Health Technol Inform. 2024 Jul 24; 315:231–5. doi:10.3233/SHTI240142 PubMed PMID: 39049259.
49. Automated medical image segmentation techniques - PMC [Internet]. [cited 2026 Mar 16]. Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC2825001/
50. Dikici E, Bigelow M, Prevedello LM, White RD, Erdal BS. Integrating AI into radiology workflow: levels of research, production, and feedback maturity. J Med Imaging. 2020 Jan;7[1]:016502. doi:10.1117/1.JMI.7.1.016502 PubMed PMID: 32064302; PubMed Central PMCID: PMC7012173.
51. Baltruschat I, Steinmeister L, Nickisch H, Saalbach A, Grass M, Adam G, *et al.,* Smart chest X-ray worklist prioritization using artificial intelligence: a clinical workflow simulation. Eur Radiol. 2021 Jun;31[6]:3837–45. doi:10.1007/s00330-020-07480-7 PubMed PMID: 33219850; PubMed Central PMCID: PMC8128725.
52. Thompson YLE, Fergus J, Chung J, Delfino JG, Chen W, Levine GM, *et al.,* Impact of Artificial Intelligence Triage on Radiologist Report Turnaround Time: Real-World Time Savings and Insights From Model Predictions. J Am Coll Radiol JACR. 2026 Jan;23[1]:63–73. doi: 10.1016/j.jacr.2025.07.033 PubMed PMID: 41026071.
53. Annarumma M, Withey SJ, Bakewell RJ, Pesce E, Goh V, Montana G. Automated Triaging of Adult Chest Radiographs with Deep Artificial Neural Networks. Radiology. 2019 Apr;291[1]:196–202. doi:10.1148/radiol.2018180921 PubMed PMID: 30667333; PubMed Central PMCID: PMC6438359.
54. Topff L, Ranschaert ER, Bartels-Rutten A, Negoita A, Menezes R, Beets-Tan RGH, *et al.,* Artificial Intelligence Tool for Detection and Worklist Prioritization Reduces Time to Diagnosis of Incidental Pulmonary Embolism at CT. Radiol Cardiothorac Imaging. 2023 Apr;5[2]:e220163. doi:10.1148/ryct.220163 PubMed PMID: 37124638; PubMed Central PMCID: PMC10141443.
55. Chen Y, Sudin ES, Partridge GJ, Taib AG, Darker IT, Phillips P, *et al.,* Measuring reader fatigue in the interpretation of screening digital breast tomosynthesis [DBT]. Br J Radiol. 2023 Mar;96[1143]:20220629. doi:10.1259/bjr.20220629 PubMed PMID: 36633316; PubMed Central PMCID: PMC9975365.
56. Lee JH, Park S, Hwang EJ, Goo JM, Lee WY, Lee S, *et al.,* Deep learning-based automated detection algorithm for active pulmonary tuberculosis on chest radiographs: diagnostic performance in systematic screening of asymptomatic individuals. Eur Radiol. 2021 Feb;31[2]:1069–80. doi:10.1007/s00330-020-07219-4 PubMed PMID: 32857202.
57. Hwang EJ, Park S, Jin KN, Kim JI, Choi SY, Lee JH, *et al.,* Development and Validation of a Deep Learning-Based Automated Detection Algorithm for Major Thoracic Diseases on Chest Radiographs. JAMA Netw Open. 2019 Mar 1;2[3]:e191095. doi:10.1001/jamanetworkopen.2019.1095 PubMed PMID: 30901052; PubMed Central PMCID: PMC6583308.
58. Jansen C, Lindequist B, Strohmenger K, Romberg D, Küster T, Weiss N, *et al.,* The vendor-agnostic EMPAIA platform for integrating AI applications into digital pathology infrastructures. Future Gener Comput Syst. 2023 Mar 1;140:209–24. doi: 10.1016/j.future.2022.10.025
59. Liu H, Lou SS, Warner BC, Harford DR, Kannampallil T, Lu C. HiPAL: A Deep Framework for Physician Burnout Prediction Using Activity Logs in Electronic Health Records. In: Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining [Internet]. New York, NY, USA: Association for Computing Machinery; 2022 [cited 2026 Mar 16]. p. 3377–87. [KDD '22]. Available from: https://dl.acm.org/doi/10.1145/3534678.3539056 doi:10.1145/3534678.3539056
60. [PDF] Evaluating accountability, transparency, and bias in AI-assisted healthcare decision- making: a

qualitative study of healthcare professionals' perspectives in the UK [Internet]. [cited 2026 Mar 16]. Available from: https://www.researchgate.net/publication/393511253_Evaluating_accountability_transparency_and_bias_in_AI-assisted_healthcare_decision-_making_a_qualitative_study_of_healthcare_professionals'_perspectives_in_the_UK

61. Tazarv A, Labbaf S, Reich SM, Dutt N, Rahmani AM, Levorato M. Personalized Stress Monitoring using Wearable Sensors in Everyday Settings. Annu Int Conf IEEE Eng Med Biol Soc IEEE Eng Med Biol Soc Annu Int Conf. 2021 Nov; 2021:7332–5. doi:10.1109/EMBC46164.2021.9630224 PubMed PMID: 34892791.
62. Baigutanova A, Park S, Constantinides M, Lee SW, Quercia D, Cha M. A continuous real-world dataset comprising wearable-based heart rate variability alongside sleep diaries. Sci Data. 2025 Aug 23;12[1]:1474. doi:10.1038/s41597-025-05801-3 PubMed PMID: 40849317; PubMed Central PMCID: PMC12375003.
63. AlArnaout Z, Zaki C, Kotb Y, AlAkkoumi M, Mostafa N. Exploiting heart rate variability for driver drowsiness detection using wearable sensors and machine learning. Sci Rep. 2025 Jul 10;15[1]:24898. doi:10.1038/s41598-025-08582-2 PubMed PMID: 40640285; PubMed Central PMCID: PMC12246425.
64. Haripriya R, Khare N, Pandey M. Privacy-preserving federated learning for collaborative medical data mining in multi-institutional settings. Sci Rep. 2025 Apr 11;15[1]:12482. doi:10.1038/s41598-025-97565-4 PubMed PMID: 40217112; PubMed Central PMCID: PMC11992079.
65. Eshwarappa NM, Baghban H, Hsu CH, Hsu PY, Hwang RH, Chen MY. Communication-efficient and privacy-preserving federated learning for medical image classification in multi-institutional edge computing. J Cloud Comput. 2025 Aug 15;14[1]:44. doi:10.1186/s13677-025-00734-z
66. Mir BA, Abbas SR, Lee SW. Federated Learning in Healthcare Ethics: A Systematic Review of Privacy-Preserving and Equitable Medical AI. Healthcare. 2026 Jan 26;14[3]:306. doi:10.3390/healthcare14030306 PubMed PMID: 41682156; PubMed Central PMCID: PMC12896918.
67. [PDF] Explainability and AI Confidence in Clinical Decision Support Systems: Effects on Trust, Diagnostic Performance, and Cognitive Load in Breast Cancer Care [Internet]. [cited 2026 Mar 16]. Available from: https://www.researchgate.net/publication/388459675_Explainability_and_AI_Confidence_in_Clinical_Decision_Support_Systems_Effects_on_Trust_Diagnostic_Performance_and_Cognitive_Load_in_Breast_Cancer_Care
68. Agrawal R, Gupta T, Gupta S, Chauhan S, Patel P, Hamdare S. Fostering trust and interpretability: integrating explainable AI [XAI] with machine learning for enhanced disease prediction and decision transparency. Diagn Pathol. 2025 Sep 25; 20:105. doi:10.1186/s13000-025-01686-3 PubMed PMID: 40999511; PubMed Central PMCID: PMC12465982.
69. Huang X, Zhou S, Ma X, Jiang S, Xu Y, You Y, *et al.,* Effectiveness of an artificial intelligence clinical assistant decision support system to improve the incidence of hospital-associated venous thromboembolism: a prospective, randomised controlled study. BMJ Open Qual. 2023 Oct;12[4]:e002267. doi:10.1136/bmjoq-2023-002267 PubMed PMID: 37832969; PubMed Central PMCID: PMC10582876.
70. Dean G, Montañà E, Kyriazi S, Shelmerdine SC, Buckens CF, Agrell H, *et al.,* Real-World Monitoring of Artificial Intelligence in Radiology: Challenges and Best Practices. Korean J Radiol. 2025 Nov;26[11]:1010–21. doi:10.3348/kjr.2025.0962 PubMed PMID: 41078022; PubMed Central PMCID: PMC12568762.