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DEEP LEARNING IN RADIOGRAPHIC TRIAGE: WORKFLOW OPTIMIZATION TO ADDRESS THE RADIOLOGIST WORKFORCE CRISIS

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ABSTRACT

Background: The global radiologist workforce faces a systemic crisis where imaging volume growth significantly outpaces specialist capacity, reducing per-image interpretation time from 16.0 to 2.9 seconds. This chronic overload contributes to burnout rates between 34% and 39% and increases the risk of diagnostic errors when daily productivity is exceeded by approximately 21%.

Methods: A comprehensive literature review examined peer-reviewed studies published between 2015 and 2025. The analysis focused on the efficacy and sociotechnical impact of deep learning (DL) models across four critical pathologies: intracranial hemorrhage (ICH), large vessel occlusion (LVO) stroke, pulmonary embolism (PE), and pneumothorax.

Results: DL models, primarily Convolutional Neural Networks and Vision Transformers, demonstrate high diagnostic accuracy, with pooled sensitivities and specificities frequently reaching 90%. "Active reprioritization" significantly reduces report turnaround times, yielding median savings of 12.3 minutes for PE and 20.5 minutes for stroke. For outpatient ICH, time-to-diagnosis dropped from 512 minutes to 19 minutes. In acute stroke care, AI facilitation resulted in a 30.2-minute reduction in door-to-treatment times and improved discharge NIHSS scores.

Conclusions: DL triage serves as a vital sociotechnical intervention to preserve patient safety amidst diagnostic overload. Its primary clinical value resides in workflow orchestration rather than standalone diagnosis. Successful implementation requires integrated "human-in-the-loop" systems to mitigate automation bias and the cognitive time penalty associated with false positives.

KEYWORDS

Deep Learning, Radiographic Triage, Worklist Prioritization, Radiologist Burnout, Clinical Workflow

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1. Introduction

The practice of diagnostic radiology is currently confronting a systemic crisis characterized by a widening disparity between the exponential growth in medical imaging volume and the limited capacity of the radiological workforce. Over the past three decades, the demand for cross-sectional imaging has surged; a foundational study by McDonald et al. (2015) established that while the number of radiologists increased modestly, the total number of CT and MRI images requiring interpretation increased significantly, driving a substantial rise in relative value units (RVUs) per professional. This trend has persisted and intensified; recent analyses indicate that the radiologist workload has now reached a state of chronic overload, with the quantity of procedures outpacing the availability of specialists (Markotić et al., 2023). This pressure is particularly acute during non-standard hours; Bruls and Kwee (2020) reported that the on-call workload for radiologists has quadrupled over a 15-year period, driven largely by the increasing complexity and frequency of emergency CT studies. Furthermore, census data from the National Health Service (NHS) in England highlights that the imaging support workforce remains insufficient to meet this escalating diagnostic demand (Nightingale et al., 2024).

The immediate consequence of this volume-capacity mismatch is a severe compression of the time available for image interpretation. A longitudinal analysis revealed that the average interpretation time available per image for radiologists plummeted from 16.0 seconds to just 2.9 seconds over a 16-year period (Peng et al., 2022). Such profound time pressures have contributed to a global prevalence of radiologist burnout estimated between 34% and 39%, a condition characterized by exhaustion and professional dissatisfaction (Thakore et al., 2024). Crucially, this state of cognitive saturation poses a direct threat to patient safety. Retrospective data indicates a significant association between relative work overload and perceptual errors; specifically, radiologists are more likely to commit diagnostic errors on days when their workload exceeds their average daily productivity by approximately 21% (Kasalak et al., 2023).

In response to these operational and safety challenges, Deep Learning (DL) applications have emerged as a necessary technological intervention to augment human capability. Rather than serving solely as diagnostic aids, these tools are increasingly utilized for workflow orchestration and triage. A systematic review by Momin et al. (2025) demonstrated that DL-driven worklist prioritization significantly improves clinical efficiency, reducing median report turnaround times by 12.3 minutes for pulmonary embolism and 20.5 minutes for stroke. However, the successful adoption of these technologies requires moving beyond isolated algorithms toward a holistic implementation strategy that integrates seamlessly with existing radiological workflows (Kim et al., 2024). This review examines the efficacy of deep learning models in prioritizing acute radiographic findings, evaluating their potential to mitigate workforce strain and improve timely access to critical care.

2. Methods and Literature Search Strategy

To evaluate the efficacy of deep learning models in radiographic triage and their sociotechnical impact on the radiological workforce, a comprehensive literature review was conducted. The search strategy was designed to identify high-quality evidence at the intersection of medical imaging technology, clinical workflow optimization, and healthcare workforce management.

2.1. Data Sources and Search Criteria

Primary electronic databases including PubMed/MEDLINE and Google Scholar were queried for peer-reviewed studies published between January 1, 2015, and November 2025, a timeframe selected to capture the emergence and maturation of modern Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) in medical imaging. Additionally, workforce data from the National Health Service (NHS) and foundational studies regarding radiologist utilization trends were included to establish the clinical context for AI implementation.

2.2. Keywords and Taxonomy

The search utilized boolean logic combining three primary domains:

1. **Technology:** "Deep learning," "Artificial Intelligence," "Convolutional Neural Networks," "Computer-Aided Triage," "Automated Detection."
2. **Clinical Application:** "Radiology," "Intracranial Hemorrhage," "Pulmonary Embolism," "Large Vessel Occlusion," "Pneumothorax," "Emergency Department."
3. **Socio-Technical Impact:** "Worklist prioritization," "Turnaround time (TAT)," "Radiologist burnout," "Cognitive load," "Automation bias"

2.3. Inclusion and Exclusion Criteria

Articles were included if they provided quantitative data on diagnostic accuracy (Sensitivity/Specificity/AUC) or operational metrics (Time-to-Notification, Report Turnaround Time) in a clinical or simulated clinical environment. Priority was given to studies reporting "real-world" validation over purely internal technical pilots. Articles were excluded if they focused solely on model architecture without addressing clinical workflow integration, or if they predated the widespread adoption of deep learning in radiology (pre-2015).

2.4. Data Synthesis

Extracted data were synthesized narratively and organized by pathological entities (Intracranial Hemorrhage, Stroke, Pulmonary Embolism, Pneumothorax). Operational outcomes were categorized into "Diagnostic Accuracy," "Workflow Efficiency," and "Clinical Outcomes" to facilitate a structured comparison of algorithmic efficacy across different clinical environments.

3. Technological Foundations

The efficacy of radiographic triage relies on the synergy between advanced Deep Learning (DL) architectures and their seamless integration into hospital information systems. This section outlines the core computational models used for pathology detection and the technical mechanisms enabling automated worklist reprioritization.

3.1. Deep Learning Architectures: CNNs and Transformers

The majority of FDA-cleared triage algorithms currently utilize Convolutional Neural Networks (CNNs). CNNs are designed to process pixel data by applying learnable filters (kernels) that slide across the image to extract local spatial features, such as edges, textures, and shapes (Huang et al., 2020). These architectures, including variations like ResNet and DenseNet, are highly effective at identifying specific anomalies within a localized region, such as a pulmonary embolus within a contrast-filled vessel or a fracture line in bone (Huang et al., 2020; Huhtanen et al., 2022).

More recently, Vision Transformers (ViTs) have emerged as a powerful alternative. Unlike CNNs, which process images via local receptive fields, ViTs utilize a self-attention mechanism to analyze the entire image context simultaneously. This capability allows the model to capture long-range dependencies and global relationships between anatomical structures, which is particularly advantageous for complex tasks such as differentiating between similar pathologies or analyzing volumetric 3D datasets (Alhasan et al., 2025).

3.2. Worklist Reprioritization and Systems Integration

For a triage algorithm to influence clinical workflow, it must move beyond image analysis to system orchestration. The technical standard for this process involves the integration of the AI server with the Picture Archiving and Communication System (PACS) and the Radiology Information System (RIS).

The workflow typically follows a standardized "push" model:

1. **Image Routing:** Upon image acquisition, a DICOM (Digital Imaging and Communications in Medicine) router automatically forwards the study to an AI inference server based on protocol tags (e.g., "CT Head Non-Contrast") (O'Neill et al., 2021).
2. **Inference and Alerting:** The DL model processes the images. If a target pathology (e.g., Intracranial Hemorrhage) is detected, the system generates a structured alert.
3. **Active Reprioritization:** The AI server transmits this result back to the RIS using HL7 (Health Level Seven) messaging or DICOM Structured Reports (SR). The RIS then utilizes this signal to dynamically update the radiologists' worklist, physically moving the flagged study to the top of the reading queue and assigning it a "STAT" or "Critical" priority status (Baltruschat et al., 2020; O'Neill et al., 2021).

This "active reprioritization" is distinct from "passive notification" (such as a separate widget or email), as it forces the critical case into the radiologist's immediate line of sight without requiring voluntary user interaction (Savage et al., 2024).

4. Efficacy by Pathology

4.1. Intracranial Hemorrhage (ICH)

Intracranial hemorrhage (ICH) is a time-critical emergency where rapid diagnosis is essential to optimize patient outcomes. Deep learning (DL) models have been extensively evaluated for their ability to detect ICH and prioritize these studies within the radiologist's worklist. The efficacy of these tools is generally measured across three dimensions: diagnostic accuracy, impact on report turnaround time (TAT), and operational efficiency in diverse clinical settings.

4.1.1 Diagnostic Accuracy and Subtype Performance

Deep learning algorithms have demonstrated high diagnostic performance in detecting ICH on non-contrast computed tomography (NCCT). A systematic review and meta-analysis of machine learning algorithms found acceptable performance levels for diagnosing ICH, with DL models frequently utilized for this purpose (Maghami et al., 2023). In a large-scale meta-analysis, commercial AI systems demonstrated a pooled sensitivity of 0.899 (95% CI: 0.858–0.940) and a specificity of 0.951 (95% CI: 0.928–0.974) (Alhasan et al., 2025).

However, performance varies significantly by hemorrhage subtype. In a retrospective assessment of the Canon AUTOStroke solution, the algorithm achieved high overall accuracy but showed disparate sensitivities for specific bleed types; it achieved a sensitivity of 98.1% for intraparenchymal hemorrhage (IPH) and 100% for intraventricular hemorrhage (IVH), but significantly lower sensitivities for subdural (75.0%) and subarachnoid (81.3%) hemorrhages (Rava et al., 2021). Similarly, Alhasan et al. (2025) noted that while AI systems excel at detecting IPH (pooled sensitivity 0.948), detecting epidural hemorrhage remains more challenging (pooled sensitivity 0.845).

4.1.2 Impact on Workflow Prioritization and Turnaround Time

The primary clinical utility of these algorithms is their ability to reprioritize positive cases to the top of a reporting queue. Arbabshirani et al. (2018) demonstrated that re-prioritizing "routine" outpatient head CTs based on AI detection reduced the median time to diagnosis from 512 minutes to 19 minutes ($p < 0.0001$), effectively identifying critical pathology in patients who would otherwise have waited hours for a report.

The method of notification is a critical determinant of efficacy. O'Neill et al. (2021) found that "active reprioritization", where the AI system physically moves the study to the top of the worklist, significantly reduced the wait time for ICH-positive examinations (12.01 minutes vs. 15.75 minutes at baseline; $p < 0.0001$). In contrast, a "passive" notification system (e.g., a widget or flag without reordering) had no significant impact on examination wait times (O'Neill et al., 2021). This finding is supported by Kim et al. (2025), who observed that while AI assistance did not significantly improve the diagnostic accuracy of board-certified radiologists, it drastically improved the median reading order of ICH cases from 7.25 to 1.5 ($p < 0.001$), thereby increasing the early diagnosis rate from 50.0% to 100.0%.

However, not all prospective studies have shown a benefit. Savage et al. (2024) reported that in a tertiary academic medical center with 24-hour attending coverage, the implementation of a commercial AI triage system did not result in a significant difference in mean report turnaround times for ICH-positive examinations (147.1 minutes without AI vs. 149.9 minutes with AI; $p = 0.11$) or improve radiologists' diagnostic accuracy.

4.1.3 Operational Challenges and False Positives

The deployment of AI tools also introduces new operational dynamics regarding false positives (FP). In a prospective analysis of 2,011 scans, Ginat (2019) found that the AI software flagged 18.5% of cases, with 72.4% of those flags being true positives. The impact of false positives is particularly pronounced in low-prevalence settings. Del Gaizo et al. (2024) evaluated AI in a national teleradiology program with a low ICH prevalence of 2.70%. They found that the AI tool had a positive predictive value (PPV) of only 21.1%. Consequently, examinations falsely flagged as positive took radiologists significantly longer to interpret (median 8 minutes 7 seconds) compared to true negatives (median 6 minutes 53 seconds), suggesting that disproving a false AI alert imposes a "time penalty" on the radiologist (Del Gaizo et al., 2024).

Furthermore, the seamless integration of these tools is essential for viability. Villringer et al. (2024) demonstrated that a cloud-based AI solution could process and return results with a median turnaround time of approximately 9 to 12 minutes, confirming that technical latency is sufficiently low to support acute clinical workflows. Despite these technical capabilities, the variability in clinical impact underscores that AI efficacy is highly dependent on the baseline efficiency of the radiology department and the specific prevalence of disease in the patient population (Savage et al., 2024; Del Gaizo et al., 2024

4.2. Large Vessel Occlusion (LVO) & Ischemic Stroke

The management of acute ischemic stroke, specifically that caused by Large Vessel Occlusion (LVO), is governed by the principle that "time is brain." Deep learning (DL) algorithms have emerged as critical tools for automating the detection of LVOs on Computed Tomography Angiography (CTA) and, increasingly, Non-Contrast CT (NCCT), serving to streamline communication within complex hospital networks.

4.2.1. Diagnostic Accuracy

Commercial DL algorithms have demonstrated robust diagnostic performance, functioning effectively as screening tools to expedite radiologist review. A 2025 systematic review and meta-analysis comparing two leading software platforms found that *Viz.ai* achieved a pooled sensitivity of 84% (95% CI: 81–87%) and specificity of 95% (95% CI: 95–96%), while *RAPID* software demonstrated a sensitivity of 88% (95% CI: 85–90%) and specificity of 84% (95% CI: 82–85%) (Sarhan et al., 2025). Earlier single-center validation studies corroborated this high performance; Amukotuwa et al. (2019) reported that an automated LVO-detection tool achieved a sensitivity of 94% and a negative predictive value of 98% with a median processing time of only 158 seconds.

Recent advancements have expanded these capabilities to NCCT, allowing for earlier triage before advanced angiography is performed. A study utilizing a DL-based software (Heuron ELVO) on NCCT scans demonstrated a sensitivity of 86% and specificity of 97% for detecting LVOs, suggesting that AI can facilitate rapid decision-making even in resource-limited settings where CTA may not be immediately interpreted (Lim et al., 2025). Furthermore, DL applications are evolving beyond simple detection to include the quantification of infarct volume and the automated calculation of the Alberta Stroke Program Early CT Score (ASPECTS), further aiding in patient selection for endovascular therapy (Soun et al., 2020).

4.2.2. Workflow Optimization and Transfer Metrics

The most significant impact of AI in stroke care is observed in "Hub-and-Spoke" networks, where patients presenting at peripheral centers (spokes) must be rapidly transferred to comprehensive stroke centers (hubs) for thrombectomy. AI algorithms facilitate "parallel workflows" by triggering automated alerts to the entire stroke team simultaneously.

Reduction in Notification and Transfer Times:

In a retrospective cohort study, Matsoukas et al. (2023) demonstrated that AI implementation significantly decreased the time from CTA acquisition at the peripheral hospital to interventional neuroradiology team notification from a median of 58 minutes to 12 minutes ($p < .001$). Consequently, the total time from arrival at the peripheral hospital to arrival at the central hub was reduced by approximately one hour (145 minutes vs. 207 minutes; $p < .001$) (Matsoukas et al., 2023). Similarly, Hassan et al. (2020) found that the utilization of AI software reduced the median transfer time (CTA at primary center to arrival at comprehensive center) by 66 minutes ($p = .0163$).

Systematic Efficiency:

A meta-analysis of AI impact on stroke management confirmed these findings on a broader scale, reporting significant reductions in "Door-to-Intervention Notification" time (Odds Ratio [OR] 0.30) and "Door-to-Arterial Puncture" time (OR 0.50) (Zebrowitz et al., 2024).

4.2.3. Clinical Outcomes and Resource Utilization

The acceleration of triage and transfer processes has translated into measurable improvements in patient outcomes and resource utilization. Lim et al. (2025) observed that the implementation of AI triage was associated with a significant reduction in the National Institutes of Health Stroke Scale (NIHSS) score at discharge (mean reduction of 4.3 points) compared to the pre-AI period. Furthermore, faster processing times have economic implications; Hassan et al. (2020) reported that AI implementation correlated with a significant reduction in the length of stay in the neurological intensive care unit (2.9 days vs. 6.4 days; $p = .0039$). Collectively, these data suggest that DL algorithms do not merely augment diagnostic accuracy but fundamentally restructure the logistical delivery of acute stroke care (Shlobin et al., 2022).

4.3. Pulmonary Embolism (PE)

Pulmonary embolism (PE) is a high-acuity condition where clinical outcomes are closely linked to the speed of diagnosis and initiation of anticoagulation (Shapiro et al., 2024). Deep learning (DL) models have been developed to automate PE detection on computed tomography pulmonary angiography (CTPA) and incidental contrast-enhanced CT scans, aiming to mitigate the risks associated with diagnostic delays and perceptual errors.

4.3.1. Diagnostic Performance and Accuracy

Deep learning algorithms demonstrate robust diagnostic accuracy for PE detection across varied technical architectures. Huhtanen et al. (2022) developed a DL model utilizing an InceptionResNet V2 architecture that achieved a stack-based sensitivity of 86.6% and a specificity of 93.5%. Similarly, the scalable 3D convolutional neural network PENet achieved an Area Under the Curve (AUC) of 0.84 on external validation sets, demonstrating strong generalizability (Huang et al., 2020). Performance typically remains highest for central and lobar emboli, while sensitivity may decrease for smaller, subsegmental clots located in the peripheral vasculature (Abed et al., 2025).

4.3.2. Impact on Worklist Triage and Turnaround Time (TAT)

The clinical value of PE triage AI is primarily assessed through its impact on the time interval between scan completion and radiologist reporting.

Reported Time Savings:

Multiple studies indicate that active worklist reprioritization - physically moving positive cases to the top of the reporting queue, yields significant operational gains. Batra et al. (2023) observed that AI integration reduced the mean report turnaround time (TAT) for PE-positive examinations by 12.3 minutes (from 59.9 minutes to 47.6 minutes; $p < .05$). On a larger scale, an analysis of over 11,000 CTPA exams reported real-world time-savings of 22.2 minutes during standard work hours when AI triage was utilized (Thompson et al., 2025).

Neutral Workflow Findings:

In contrast, some implementations have failed to show a significant operational impact. Schmuelling et al. (2021) found that nine months after the technical implementation of an AI triage tool, there were no statistically significant changes in report communication times or patient turnaround in the emergency department. These findings suggest that technical accuracy is a prerequisite, but the ultimate efficiency of AI is modulated by existing hospital standard operating procedures and the baseline efficiency of the human reporting team (Schmuelling et al., 2021).

4.3.3. Detection of Incidental Pulmonary Embolism (iPE)

A critical "safety net" application of DL is the detection of incidental PE (iPE) on scans performed for non-vascular indications, such as oncologic staging or cardiac assessment. In oncology populations, where iPE prevalence is high but frequently overlooked by human readers, AI has demonstrated the ability to reduce the radiologist miss rate from 44.8% to 2.6% (Topff et al., 2023). This intervention shortened the median time to detection and notification from several days to just 87 minutes (Topff et al., 2023). High diagnostic accuracy has also been reported for iPE in oncology cohorts, with sensitivities reaching 97.3% (Ammari et al., 2024). Furthermore, the application of DL to cardiac CT angiography (CCTA) scans has proven feasible, identifying incidental emboli in approximately 1% of scans that might otherwise go undetected due to the limited field of view and focus on coronary anatomy (Brin et al., 2025).

4.3.4. Sociotechnical Challenges: False Positives and Acceptance

The operational utility of PE AI is occasionally hindered by false positives (FP), which typically arise from flow artifacts, respiratory motion, or enlarged lymph nodes misinterpreted as vascular occlusions (Abed et al., 2025). Despite these technical pitfalls, radiologist acceptance of these tools is generally high, as they are perceived as valuable adjuncts for improving diagnostic confidence and safety during high-volume shifts (Abed et al., 2025). Shapiro et al. (2024) further highlighted that the integration of AI-triggered alerts into mobile communication platforms can facilitate the rapid activation of Pulmonary Embolism Response Teams (PERT), potentially translating algorithmic detection into faster bedside clinical interventions.

4.4. Pneumothorax

Pneumothorax is a critical clinical condition characterized by the presence of air in the pleural space, which can lead to lung collapse and life-threatening tension physiology if not promptly identified (Hillis et al., 2022). Deep learning (DL) models have been developed to automate the detection of pneumothorax on chest radiographs (CXRs) and prioritize these critical findings to reduce reporting delays in emergency and acute care settings.

4.4.1. Diagnostic Accuracy and Performance

DL algorithms demonstrate high diagnostic proficiency for pneumothorax detection, often achieving performance levels comparable to experienced clinicians. A systematic review and meta-analysis found that AI models achieved a pooled sensitivity of 87% and specificity of 93% for pneumothorax on CXRs (Sugibayashi et al., 2023). In a large-scale evaluation of 1,000 radiographs, an AI model demonstrated an Area Under the Curve (AUC) of 0.978 for detecting any pneumothorax and 0.987 specifically for tension pneumothorax (Hillis et al., 2022). Furthermore, specialized models have achieved accuracies as high as 98.34% in controlled datasets (Dal & Kaya, 2025).

The performance of these models remains robust across varying clinical conditions. In a study comparing AI against human readers, the AI model achieved a sensitivity of 76.5%, significantly higher than the 56.4% achieved by junior clinicians working unaided (Novak et al., 2024). However, model performance can be influenced by the type of training labels and clinical settings. For instance, Mosquera et al. (2021) noted that while detection is generally reliable, some architectures may produce false positives due to subpleural bullae or technical artifacts such as patient rotation.

4.4.2. Impact on Workflow and Turnaround Time (TAT)

The operational value of AI for pneumothorax lies in its ability to reorder the diagnostic queue, moving critical "perceptual misses" to the top of the worklist.

Reduction in Reporting Delays:

In a clinical simulation using over 470,000 radiographs, the implementation of AI-based triaging reduced the mean reporting delay for critical findings, including pneumothorax, from 11.2 days to 2.7 days (Annarumma et al., 2019). Similarly, Baltruschat et al. (2020) demonstrated that smart worklist prioritization could reduce the mean report turnaround time (RTAT) for urgent cases by approximately 16%, minimizing the risk of "hidden" critical findings languishing in high-volume queues.

Support for Junior Clinicians:

AI acts as a vital "safety net" for less experienced readers. The use of AI-assisted image interpretation was found to improve the sensitivity of junior clinicians in identifying pneumothoraces from 56.4% to 77.9% (Novak et al., 2024). This diagnostic augmentation is particularly beneficial in emergency departments where non-radiologists may be the first to interpret imaging (Ho et al., 2025).

4.4.3. Localization and Visualization

To facilitate human verification, many triage tools provide visual aids such as heatmaps or bounding boxes. High-resolution networks have demonstrated improved localization capabilities, with some achieving a mean intersection-over-union (IoU) of 0.825 for segmenting pneumothorax regions (Dal & Kaya, 2025). However, clinicians must remain vigilant, as some algorithms, such as CheXNet, have shown lower localization accuracy despite high classification scores, occasionally flagging incorrect regions of the lung (Mosquera et al., 2021).

4.4.4. Comparative Efficacy and Implementation

While many commercial AI tools are available, their standalone performance varies. A study comparing four commercially available AI tools for pneumothorax detection found sensitivities ranging from 75% to 88% and specificities from 85% to 95% in an emergency department cohort (Plesner et al., 2023). These results underscore that while AI is a reliable tool for reducing diagnostic imaging delays for time-sensitive chest diseases, its effectiveness is optimized when used as a triage tool to prioritize studies for expert radiologist review (Kolossváry et al., 2023).

5. Impact on Workflow & Society

The deployment of deep learning (DL) models for radiographic triage extends beyond diagnostic accuracy, fundamentally altering the operational efficiency of healthcare systems and the cognitive patterns of clinical practitioners. This section evaluates the quantitative impact on report delivery, the clinical implications for hyper-acute care, and the sociotechnical risks associated with human-AI interaction.

5.1. Reduction in Turnaround Time (TAT)

The primary metric of success for triage algorithms is the reduction of Report Turnaround Time (TAT), defined as the interval between the completion of image acquisition and the finalization of the radiologist’s report. Meta-analytic data indicate that DL-driven worklist prioritization significantly alleviates reporting delays. Momin et al. (2025) reported median TAT reductions of 12.3 minutes for pulmonary embolism (PE) and 20.5 minutes for stroke across diverse clinical settings.

The magnitude of these savings is often contingent upon the patient's initial priority status. Arbabshirani et al. (2018) demonstrated that for outpatient intracranial hemorrhage (ICH) cases, which are traditionally queued as "routine", AI intervention reduced the median time to diagnosis from 512 minutes to 19 minutes. Similarly, for chest radiographs, AI-based triaging has been shown to reduce mean reporting delays for critical findings from 11.2 days to 2.7 days (Annarumma et al., 2019). However, these gains are not universal; in environments where human reporting is already highly optimized (e.g., 24/7 academic attending coverage), the introduction of AI triage may yield no significant difference in TAT (Savage et al., 2024).

5.2. Impact on the "Golden Hour" of Patient Care

In hyper-acute conditions such as large vessel occlusion (LVO) stroke and tension pneumothorax, the "Golden Hour" refers to the critical window where immediate intervention can prevent irreversible tissue loss or death. DL models act as "force multipliers" in these scenarios by enabling parallel processing.

In stroke care, AI platforms facilitate a "Door-to-Needle" and "Door-to-Puncture" compression by alerting interventional teams before a formal radiologist report is even initiated. Implementation of these tools has been associated with a 30.2-minute reduction in "Door-to-Endovascular Thrombectomy" (EVT) times (Lim et al., 2025). Furthermore, in "hub-and-spoke" networks, AI-driven synchronization has halved the time required for transfer activation, reducing the delay from 64 minutes to 32 minutes (Matsoukas et al., 2023). This clinical acceleration translates into measurable patient benefits, including a mean reduction of 4.3 points in National Institutes of Health Stroke Scale (NIHSS) scores at discharge (Lim et al., 2025). Similarly, in PE management, AI-triggered mobile alerts allow for the rapid mobilization of Pulmonary Embolism Response Teams (PERT), ensuring that high-risk patients receive anticoagulation or intervention within shorter clinical windows (Shapiro et al., 2024).

5.3. Automation Bias: Do Radiologists Become Complacent?

The integration of AI into clinical practice introduces the risk of "automation bias," a sociotechnical phenomenon where clinicians may over-rely on algorithmic outputs, leading to a potential decline in independent human vigilance.

Human-AI Symbiosis vs. Over-reliance:

Research indicates that while AI serves as an effective "safety net" for junior clinicians, improving their sensitivity for pneumothorax from 56.4% to 77.9%, there is a risk that users may become "blind" to findings the AI fails to flag (Novak et al., 2024). This is particularly critical given that AI sensitivity is often lower for distal or subtle pathologies, such as subsegmental PE or small subdural hematomas (Abed et al., 2025; Alhasan et al., 2025).

The "Penalty of Disconfirmation":

Complacency is further challenged by the cognitive burden of false positives. Del Gaizo et al. (2024) observed that in low-prevalence settings, radiologists spend significantly more time interpreting scans falsely flagged by AI (8 minutes 7 seconds) than true negative scans (6 minutes 53 seconds). This "time penalty" required to disprove an AI error suggests that rather than becoming complacent, radiologists may face increased cognitive fatigue as they navigate high-volume alerts. To mitigate these risks, researchers advocate for "human-in-the-loop" systems where AI-generated heatmaps and explainable confidence scores are used to guide, rather than replace, human interpretation (Wu et al., 2024; Kim et al., 2024)

6. Discussion

The synthesis of recent literature reveals a complex landscape where the theoretical efficacy of deep learning (DL) models often diverges from their operational reality. While DL algorithms demonstrate high standalone diagnostic performance, with sensitivities for intracranial hemorrhage (ICH) and large vessel occlusion (LVO) frequently exceeding 90% (Alhasan et al., 2025; Sarhan et al., 2025), their ability to translate this potential into tangible workflow improvements is not guaranteed.

6.1. The "Implementation Gap" between Accuracy and Efficiency

A recurring theme across pathologies is the discrepancy between algorithmic accuracy and clinical time savings. In high-volume or resource-constrained environments, the impact of AI is profound; for example, Arbabshirani et al. (2018) reported a reduction in time-to-diagnosis for outpatient ICH from 512 minutes to 19 minutes. Similarly, in "hub-and-spoke" stroke networks, AI-driven synchronization reduced transfer times by over an hour (Matsoukas et al., 2023). However, in optimized tertiary centers with 24/7 attending coverage, the addition of AI triage has shown negligible improvements in turnaround times (Savage et al., 2024). This suggests that AI triage yields diminishing returns in systems where human efficiency is already maximized, acting most effectively as a "force multiplier" in settings plagued by backlog or staffing shortages (Schmuelling et al., 2021).

6.2. The Influence of Disease Prevalence on Workflow

The operational utility of triage tools is heavily modulated by the prevalence of the target condition. In low-prevalence settings, the "penalty of disconfirmation" becomes a significant burden. Del Gaizo et al. (2024) demonstrated that in a population with only 2.7% ICH prevalence, the time required for radiologists to verify and dismiss false positive alerts (median 8 minutes 7 seconds) exceeded the time to read true negatives. This finding highlights a critical sociotechnical challenge: as disease prevalence drops, the positive predictive value (PPV) of the algorithm declines, potentially increasing the cognitive load on radiologists rather than alleviating it (Del Gaizo et al., 2024).

6.3. Integration Modalities: Active vs. Passive Triage

The mechanism of alert delivery is a decisive factor in system efficacy. "Active reprioritization", where positive cases are physically moved to the top of the worklist, has consistently proven superior to "passive" notifications (e.g., flags or widgets). O’Neill et al. (2021) found that while passive alerts had no significant impact, active reordering significantly reduced wait times for critical ICH studies ($p < .0001$). This validates the hypothesis that for AI to effectively function as a triage tool, it must be integrated directly into the Radiology Information System (RIS) workflow rather than existing as a parallel notification stream requiring voluntary clinician engagement (Momin et al., 2025).

6.4. The Human-AI "Safety Net"

Despite the risks of automation bias, the role of AI as a diagnostic safety net remains robust, particularly for less experienced clinicians. Novak et al. (2024) observed that AI assistance improved the sensitivity of junior clinicians for detecting pneumothorax from 56.4% to 77.9%. Similarly, in oncology workflows, AI triage reduced the miss rate for incidental pulmonary emboli from 44.8% to 2.6% (Topff et al., 2023). These findings support a "human-in-the-loop" model where AI serves not to replace radiologist judgment, but to augment vigilance against perceptual errors driven by fatigue and volume overload (Kasalak et al., 2023; Wu et al., 2024)

7. Conclusions

The integration of deep learning (DL) models into radiographic triage marks a definitive shift in addressing the systemic crisis within diagnostic radiology. As imaging demand continues to outpace workforce capacity, resulting in interpretation times as low as 2.9 seconds per image and significantly increased error rates during periods of work overload (Peng et al., 2022; Kasalak et al., 2023), these technologies provide a vital mechanism for clinical prioritization.

Evidence across multiple pathologies, including intracranial hemorrhage, large vessel occlusion stroke, pulmonary embolism, and pneumothorax, demonstrates that DL algorithms achieve high diagnostic accuracy, often reaching pooled sensitivities and specificities near 90% (Alhasan et al., 2025; Sarhan et al., 2025; Sugibayashi et al., 2023). However, the primary clinical value of these tools is not derived from standalone diagnosis but from their operational role as workflow orchestrators. When implemented through "active reprioritization," these systems successfully compress the "Golden Hour" of care, reducing report turnaround times by significant margins and facilitating faster transfers in "hub-and-spoke" networks (Matsoukas et al., 2023; Batra et al., 2023). In stroke care specifically, this acceleration has been linked to measurable improvements in patient outcomes, such as reduced NIHSS scores at discharge (Lim et al., 2025).

Despite these advancements, the efficacy of DL triage is not universal and is heavily dependent on the clinical environment. In low-prevalence settings, the "penalty of disconfirmation" associated with false positives can impose an additional cognitive and temporal burden on radiologists (Del Gaizo et al., 2024). Furthermore, the risk of automation bias necessitates a "human-in-the-loop" approach where AI serves as a "safety net" to augment, rather than replace, clinical vigilance (Novak et al., 2024; Wu et al., 2024). Ultimately, deep learning triage functions as a critical sociotechnical intervention that ensures life-threatening findings are prioritized, thereby mitigating the safety risks inherent in the current era of chronic diagnostic overload.

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