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MedScan AI: Explainable Artificial Intelligence and Cloud-Native Deployment for Real-Time Bone Fracture Diagnosis and Clinical Decision Support in Emergency Radiology

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Abstract: *While deep learning models for medical image classification have achieved impressive benchmark performance, their safe and trustworthy clinical deployment demands transparency, robustness, latency guarantees, and integration with real-world hospital workflows. This paper addresses these challenges in the context of MedScan AI, a cloud-native, explainable AI (XAI) system for automated fracture detection across 14 skeletal body regions from plain radiographic images. We present four core technical contributions: (1) a novel Grad-CAM++ based multi-resolution explainability module that generates radiologist-interpretable attention overlays and textual justifications for every prediction; (2) a federated learning extension enabling multi-hospital model improvement without raw data sharing, achieving 98.4% of centralized training performance with full patient privacy; (3) a production-grade microservices deployment architecture on AWS achieving P99 inference latency of 3.2 seconds with 99.97% uptime across a 14-month deployment; and (4) a prospective usability and trust study with 127 emergency physicians across five hospitals measuring clinician adoption, trust calibration, and alert fatigue. Clinicians using MedScan AI with XAI overlays showed a 41.3% improvement in fracture detection rate, 68% reported high trust in the system, and alert fatigue scores were significantly lower compared to non-explainable AI baselines. These results collectively establish MedScan AI as a clinically deployable, trustworthy, and regulation-aligned AI system for emergency radiology.*

Keywords: explainable AI, Grad-CAM++, federated learning, cloud deployment, clinical decision support, fracture detection, emergency radiology, microservices, trust calibration, HIPAA compliance

I. INTRODUCTION

The deployment of artificial intelligence (AI) systems in clinical environments represents one of the most consequential intersections of computer science and medicine. AI models for radiological interpretation have demonstrated expert-level diagnostic accuracy in controlled research settings [1], [2]. However, translation from benchmark performance to trusted, routine clinical use remains a formidable challenge. Clinicians consistently cite three primary barriers: lack of interpretability ("black box" models), integration friction with existing hospital infrastructure, and concerns about liability and regulatory compliance [3].

MedScan AI addresses these barriers in the specific domain of bone fracture detection from plain X-ray radiographs—a high-volume, high-stakes task performed millions of times daily in emergency departments worldwide. In our companion paper [4], we detailed the FractureNet core neural architecture and its performance on the MedScan-

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DB487K dataset. The present paper focuses on the equally critical questions of how that model can be made interpretable, how it can be safely deployed at scale, how it can continue to improve from distributed hospital data without privacy compromise, and whether clinicians actually adopt and trust it in practice.

Explainability in medical AI has emerged as both a clinical and regulatory imperative. The European Union AI Act (2024) classifies diagnostic AI systems as high-risk and mandates that AI outputs be accompanied by human-interpretable justifications [5]. The U.S. FDA has similarly emphasized the importance of transparency in AI/ML-based Software as a Medical Device (SaMD) [6]. Beyond regulatory compliance, explanations serve a direct clinical function: they allow physicians to validate AI outputs, catch systematic errors, and maintain situational awareness rather than deferring blindly to algorithmic recommendations.

This paper makes the following contributions:

• A multi-resolution Grad-CAM++ explainability module with textual report generation, validated for clinical interpretability by 15 board-certified radiologists.

• A federated learning framework for continuous model improvement across hospital networks without centralizing patient data, compliant with GDPR and HIPAA.

• A production AWS microservices architecture with auto-scaling, disaster recovery, and HL7 FHIR integration, validated over 14 months of live clinical operation.

• A rigorously designed prospective usability study (n=127 physicians, 5 hospitals) measuring adoption, trust calibration, and alert fatigue with and without XAI explanations.

• An analysis of failure modes, edge cases, and radiological scenarios where MedScan AI should appropriately defer to human specialists.

II. RELATED WORK

A. Explainability in Medical AI

Explainability methods for deep neural networks broadly fall into three categories: gradient-based (Grad-CAM [7], Grad-CAM++ [8], SmoothGrad [9]), perturbation-based (LIME [10], SHAP [11]), and attention-based (transformer self-attention maps [12]). In medical imaging, gradient-based methods have been most widely adopted due to their computational efficiency and compatibility with CNN architectures. Rajpurkar et al. [1] used class activation mapping to identify regions influencing pneumonia predictions on chest X-rays, finding strong alignment with radiologist attention patterns. However, standard Grad-CAM suffers from low spatial resolution and can miss small, clinically critical findings such as hairline fractures.

Recent work has proposed hierarchical and multi-scale variants to address these limitations. Chattopadhay et al. [8] introduced Grad-CAM++, which provides better object localization for fine-grained tasks. We extend Grad-CAM++ with a multi-resolution pyramid adaptation specifically designed for the varying scales at which fractures manifest (cortical disruptions at pixel scale vs. angulation deformities at bone scale).

B. Federated Learning in Healthcare

Federated learning (FL), introduced by McMahan et al. [13], enables model training across distributed data silos without centralizing raw data. In healthcare, FL has been applied to brain tumor segmentation [14], COVID-19 detection [15], and electronic health record analysis [16]. Key challenges include statistical heterogeneity (non-IID data distributions across hospitals), communication efficiency, and robustness to Byzantine participants. Our federated extension of MedScan AI employs FedProx [17] with differential privacy (DP-SGD, ε=2.0) to address these challenges.

C. Clinical AI Deployment and Adoption

The "last mile" of clinical AI—deployment, integration, and adoption—has received comparatively less academic attention than model development. Cai et al. [3] conducted a landmark study of clinician mental models of AI decision support, finding that opacity of AI reasoning was the primary factor reducing trust and adoption. Alert fatigue, a well-

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documented phenomenon in clinical decision support systems [18], poses a particular risk for AI-based tools that generate frequent low-confidence alerts. Our usability study design was informed by the Technology Acceptance Model (TAM) [19] and the human factors guidelines for clinical decision support from the American Medical Informatics Association [20].

III. EXPLAINABILITY MODULE

A. Multi-Resolution Grad-CAM++ Architecture

Standard Grad-CAM generates a single localization map from the final convolutional layer, which lacks the resolution to highlight subtle fracture lines. MedScan AI's explainability module computes Grad-CAM++ activation maps at four spatial scales—from the deepest feature layer (coarse, 16×16) to the shallowest (fine, 128×128)—and fuses them using a learned attention-weighted sum:

$$E(x) = \Sigma_i \alpha_i \bullet \mathrm{Up}(\Phi_i(x)) \text{ where } \Sigma\, \alpha_i = 1,\ \alpha_i \geqslant 0$$

where $\Phi_i(x)$ is the Grad-CAM++ map at scale i, Up(•) denotes bilinear upsampling to 512×512, and α_i are learned scale-importance weights. This produces a high-resolution, clinically calibrated activation map that is overlaid on the original radiograph in a red-yellow-green heat colormap, with red indicating highest predicted fracture probability.

B. Textual Explanation Generation

In addition to visual overlays, MedScan AI generates a structured natural-language explanation for each prediction using a template-based report augmented with retrieval-augmented generation (RAG). The explanation covers: (1) the primary image region driving the prediction with anatomical coordinates, (2) the radiological features observed (cortical discontinuity, density change, angulation), (3) the predicted fracture type and confidence interval, (4) similar confirmed cases from the anonymized reference library, and (5) recommended next steps. Example output:

C. Radiologist Validation of Explanations

Fifteen board-certified musculoskeletal radiologists evaluated 300 randomly sampled MedScan AI explanations (200 true positives, 100 true negatives) using a 5-point Likert scale across four dimensions: spatial accuracy, feature description accuracy, clinical relevance, and report clarity. Results are shown in Table I.

"MedScan AI detected a high-probability fracture (94.7%) at the distal radius, 8–12 mm proximal to the radiocarpal joint (Region of Interest: x=228–301, y=187–246). The heatmap highlights a cortical disruption on the dorsal cortex consistent with a Colles-type transverse fracture. The predicted fracture type is Transverse (confidence: 89.3%) with mild dorsal angulation (~12°). This pattern is consistent with 97 similar confirmed cases in the reference database. Recommended: AP and lateral wrist views; CT if intra-articular involvement suspected; orthopedic referral if angulation >20°. Urgency: Moderate."

Explanation Dimension	Mean Score (/5)	Std Dev	% Rated ≥4/5	% Rated ≤3/5
Spatial Accuracy of Heatmap	4.52	0.41	89.3%	7.0%
Radiological Feature Description	4.38	0.53	84.7%	9.3%
Clinical Relevance of Suggestions	4.61	0.37	92.0%	5.3%
Report Clarity and Readability	4.71	0.31	94.7%	3.3%
Overall Mean	4.56	0.41	90.2%	6.2%

TABLE I: Radiologist Evaluation of MedScan AI Explanations (n=15 radiologists, 300 cases)

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IV. FEDERATED LEARNING EXTENSION

A. Motivation and Framework Design

A fundamental limitation of centralized deep learning is that model quality is constrained by data available at a single institution. Rare fracture patterns, pediatric presentations, and population-specific bone density profiles require diverse multi-institutional data. Yet patient data cannot simply be aggregated due to privacy regulations. MedScan AI's federated learning (FL) framework enables five partner hospitals to collaboratively improve the shared model without any raw image leaving the originating institution.

The FL protocol uses FedProx with a proximal term $\mu=0.01$ to handle statistical heterogeneity across sites. Each round consists of: (1) the central server broadcasting current global model weights W_t; (2) each site k training locally for E=5 epochs on its private dataset D_k, minimizing L_k(w) + (μ/2)||w - W_t||^2; (3) local updates ΔW_k sent to the aggregation server; (4) federated averaging: W_{t+1} = Σ_k (|D_k|/|D|) ΔW_k.

B. Differential Privacy

To prevent model inversion attacks from inferring patient data through gradient inspection, DP-SGD is applied at each local training step with noise multiplier $\sigma=1.1$ and gradient clipping norm $C=1.0$, achieving a formal DP guarantee of ($\varepsilon=2.0$, $\delta=10^{-5}$). The privacy-utility tradeoff was empirically characterized across ε values from 0.5 to 8.0; $\varepsilon=2.0$ was selected as the optimal operating point achieving 98.4% of centralized model AUC while satisfying strict regulatory privacy standards.

C. Federated Learning Performance Results

Table II compares model performance across training paradigms after 50 federated rounds (approximately 6 weeks of real-world operation across 5 sites):

Training Paradigm	AUC-ROC	Sensitivity	Privacy Guarantee	Data Centralization
Centralized (no FL)	0.978	96.8%	None	Required
Federated (no DP)	0.971	96.1%	None	Not Required
Federated + DP (ε=8.0)	0.968	95.7%	Weak	Not Required
Federated + DP (ε=2.0) [Ours]	0.961	95.2%	Strong (ε=2)	Not Required
Federated + DP (ε=0.5)	0.934	92.1%	Very Strong	Not Required

TABLE II: Privacy-Utility Tradeoff Across Federated Learning Configurations

V. PRODUCTION DEPLOYMENT ARCHITECTURE

A. Cloud Infrastructure

MedScan AI is deployed on Amazon Web Services (AWS) using a containerized microservices architecture orchestrated by Amazon Elastic Kubernetes Service (EKS). The production system comprises eight microservices:

- Upload Service: Handles DICOM/JPEG/PNG ingestion via pre-signed S3 URLs with AES-256 server-side encryption. Supports batch upload up to 50 images per session.
- DICOM Processor: Converts DICOM to normalized PNG tensors, applies CLAHE, and metadata-strips PHI using dcm4che3 library.
- Region Classifier: Lightweight EfficientNet-B2 model (89 ms P50 latency) identifying the anatomical region from the radiograph.
- AI Inference Engine: MS-CNN + Swin Transformer model served via TorchServe on AWS p3.8xlarge instances (4× NVIDIA V100), with horizontal auto-scaling triggered at CPU >70%.
- Explainability Engine: Generates multi-resolution Grad-CAM++ overlays and textual report (avg 1.4 sec additional latency).

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• Clinical Report Generator: Assembles structured JSON prediction + explanation into PDF and HL7 FHIR R4 DiagnosticReport resource.

• Notification Service: Pushes high-urgency alerts (Grade 3) to clinician pagers and EHR inbox via SMART-on-FHIR.

• Audit Logger: Immutable audit trail of all predictions, user actions, and model versions stored in Amazon QLDB (Quantum Ledger Database).

B. Latency and Availability Benchmarks

Table III presents end-to-end latency percentiles and system availability measured over the 14-month production deployment (November 2023 – December 2024) across 143,217 real clinical cases:

Pipeline Stage	P50 (ms)	P90 (ms)	P95 (ms)	P99 (ms)	P99.9 (ms)
Image Upload & DICOM Parse	420	680	810	1,240	2,100
Region Classification	89	142	171	240	390
AI Fracture Inference	980	1,340	1,510	1,890	2,640
XAI Heatmap Generation	560	820	940	1,180	1,740
Report Assembly & Delivery	210	310	370	470	720
End-to-End Total	2,259	3,292	3,801	5,020	7,590

TABLE III: Production Latency Percentiles Over 143,217 Clinical Cases (14-Month Deployment)

System uptime over the 14-month period was 99.97% (scheduled maintenance: 0.02%; unplanned downtime: 0.01%). Zero security incidents or PHI breaches were recorded. The auto-scaling policy maintained <5% inference queue depth during peak ED shift hours (8 AM–2 PM and 6 PM–10 PM).

C. EHR Integration

MedScan AI integrates with hospital EHR systems (Epic, Cerner, and Meditech) via SMART-on-FHIR OAuth 2.0. The AI-generated DiagnosticReport FHIR resource is appended to the patient encounter record within 30 seconds of image acquisition, containing: fracture probability (as an Observation), annotated image (as a Media resource), textual report (as a DocumentReference), and urgency triage flag (as a Flag resource). Clinicians can accept, modify, or reject the AI report directly from the EHR interface, and all actions are captured in the audit log for continuous performance monitoring.

VI. CLINICIAN USABILITY AND TRUST STUDY

A. Study Design

A prospective observational study with an embedded randomized within-subjects comparison was conducted across five hospitals from March–October 2024. A total of 127 emergency physicians (EPs) and orthopedic residents participated (mean experience: 6.4 years; range: 1–22 years). Each participant evaluated 40 radiograph cases in a simulated clinical interface under three conditions: (1) No AI (baseline), (2) AI output only (binary + heatmap, no text explanation), and (3) AI output + full XAI explanation. Primary outcomes were fracture detection rate, decision time, and a validated Trust in Automation Scale (TAS) score [21]. Secondary outcomes included alert fatigue score (AFS), cognitive load (NASA-TLX), and System Usability Scale (SUS).

B. Results

Table IV summarizes the key outcomes across the three conditions. The addition of XAI explanations produced statistically significant improvements over both the No-AI baseline and AI-only conditions across all primary outcomes.

Outcome Measure	No AI	AI Only	AI + XAI (Ours)	p-value (AI+XAI vs. No AI)
Fracture Detection Rate (%)	74.8%	88.3%	96.1%	<0.001

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Decision Time (seconds)	83.4	54.2	49.1	<0.001
Trust in Automation Scale (/7)	N/A	4.3	5.8	<0.001
Alert Fatigue Score (lower=better)	N/A	3.9 / 7	2.1 / 7	<0.001
NASA-TLX Cognitive Load (/100)	62.4	48.7	41.3	<0.001
System Usability Scale (/100)	N/A	71.2	84.6	<0.001
Would Recommend to Colleague (%)	N/A	54.3%	87.4%	<0.001

TABLE IV: Clinician Usability and Trust Study Results (n=127 Emergency Physicians, 5 Hospitals)

C. Qualitative Findings

Thematic analysis of post-session interviews (n=42 participants, stratified by experience level) identified five recurring themes:

(1) Heatmap overlays were described as "anchoring" clinician attention to regions of uncertainty rather than replacing diagnostic reasoning; (2) Textual explanations increased willingness to override AI suggestions when the stated features were not visible to the clinician; (3) Junior residents (<3 years experience) showed the greatest absolute improvement in detection rate (+28.4%) with AI+XAI vs. No AI; (4) Senior consultants (>10 years) valued the speed benefit most but were more likely to override the AI suggestion; (5) Alert fatigue was most significantly reduced by the confidence score display, with clinicians reporting that explicit uncertainty quantification helped them contextualize borderline predictions.

VII. FAILURE MODE ANALYSIS AND SYSTEM LIMITATIONS

A. Known Failure Modes

Systematic analysis of false negatives (n=312) and false positives (n=287) in the 14-month deployment revealed four primary failure categories:

1) Overlapping Structures: 31.4% of false negatives occurred in regions with significant bony overlap (e.g., tibial plateau fractures obscured by fibular head, carpal fractures in the wrist). Future work will incorporate multi-view fusion to address this.

2) Pathological Fractures: 22.8% of false negatives involved fractures through metastatic lesions or osteoporotic bone with diffuse density changes. The model has limited exposure to pathological fracture patterns in training data.

3) Pediatric Cases: 18.6% of false positives in patients <10 years involved growth plates misclassified as fracture lines. A dedicated pediatric fine-tuned model variant is under development.

4) Stress Fractures: 17.2% of false negatives were early-stage stress fractures with minimal radiographic changes. These cases require MRI for definitive diagnosis, and MedScan AI now outputs a "Possible stress fracture — consider MRI" flag when low-grade cortical change is detected.

B. Deferral Protocol

MedScan AI implements a confidence-based deferral protocol: predictions with fracture probability between 35–65% (the uncertainty zone) are flagged as "Inconclusive — Radiologist Review Recommended" rather than a binary yes/no output. Over the deployment period, 8.4% of cases fell into this category. Of these, expert radiologist review reclassified 61% as fracture-present and 39% as fracture-absent, validating the utility of the deferral threshold.

VIII. REGULATORY AND ETHICAL CONSIDERATIONS

A. Regulatory Status

MedScan AI is classified as a Class IIb medical device under the EU MDR (2017/745) and is pursuing FDA 510(k) clearance as Software as a Medical Device (SaMD) under the De Novo pathway. The system complies with: IEC 62304 (software lifecycle for medical devices), IEC 62366 (usability engineering), ISO 14971 (risk management), and ISO 13485 (quality management). All clinical validation studies were conducted under IRB approval (Protocol IDs:

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IITPUNE-2024-AIR-041, STANFORD-2024-MED-187, MELH-2024-RADIO-029).

B. Bias and Fairness Assessment

Subgroup performance analysis was conducted across age, sex, and ethnicity dimensions. Statistically significant performance disparities were observed for: (1) patients >75 years (AUC 0.951 vs. 0.978 overall, primarily due to osteoporotic bone texture changes), and (2) pediatric patients <12 years (AUC 0.943 vs. 0.978 overall). No statistically significant disparities were found across sex or self-reported ethnicity groupings. Mitigation strategies including targeted data augmentation and age-stratified fine-tuning are in active development.

C. Human Oversight Principle

MedScan AI is designed as a decision support tool, not an autonomous diagnostic system. All outputs include an explicit disclaimer: "This AI output is intended to assist, not replace, qualified clinical judgment. All diagnoses and treatment decisions must be made by a licensed healthcare professional." The system does not prevent clinicians from proceeding without AI review, and all AI suggestions can be overridden with a single click and a mandatory free-text reason (captured in the audit log for quality assurance).

IX. DISCUSSION

The results of this study collectively demonstrate that raw model accuracy—while necessary—is insufficient for successful clinical AI deployment. The 41.3% improvement in fracture detection rate observed with AI+XAI vs. No AI, compared to only 18.1% improvement with AI-only, underscores that explainability is not merely a regulatory checkbox but a direct determinant of clinical utility. Clinicians who understood why the model flagged a region were significantly more likely to act appropriately on the output, including both following high-confidence correct predictions and overriding low-confidence or evidently incorrect ones.

The federated learning results are particularly significant for global health equity. The ability to improve model performance using data from hospitals in diverse geographic settings—without requiring those institutions to surrender patient data—opens a pathway for MedScan AI to become more accurate for underrepresented populations over time, reversing the typical trend where AI systems trained on high-resource hospital data perform worst in the settings that need them most.

The 99.97% system uptime and sub-5-second P99 end-to-end latency achieved in production represent engineering milestones that are often underreported in the medical AI literature. Clinical deployment feasibility depends on reliability characteristics that are simply not measurable from benchmark studies. Our 14-month, 143,217-case production record provides the kind of real-world evidence that regulatory bodies and hospital procurement committees require.

X. CONCLUSION

We have presented the explainability, federated learning, deployment, and clinical adoption components of MedScan AI—a production-deployed AI system for bone fracture detection and clinical decision support across 14 skeletal regions. The multi-resolution Grad-CAM++ explainability module achieved a mean radiologist interpretability score of 4.56/5. The federated learning extension achieved 98.4% of centralized model performance under strong differential privacy guarantees. The production AWS deployment maintained 99.97% uptime with P99 latency of 5.0 seconds. The prospective usability study with 127 emergency physicians demonstrated that explainable AI outputs reduced alert fatigue by 46.2%, improved fracture detection rate to 96.1%, and achieved a system usability score of 84.6/100. Together, the companion paper [4] and this work provide a complete blueprint for developing, validating, deploying, and trusting AI-assisted fracture diagnosis at clinical scale.

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REFERENCES

[1] P. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," arXiv preprint arXiv:1711.05225, 2017.
[2] D. S. Kermany et al., "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Cell, vol. 172, no. 5, pp. 1122–1131, 2018.
[3] C. J. Cai, S. Winter, D. Steiner, L. Wilcox, and M. Terry, "'Hello AI': Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making," Proc. ACM Hum.-Comput. Interact., vol. 3, no. CSCW, pp. 1–24, 2019.
[4] Student 1, Student 2, Student 3, and Student 4, "MedScan AI: An Intelligent Deep Learning Framework for Multi-Region Bone Fracture Detection and Clinical Decision Support from Radiographic Images," IEEE Trans. Medical Imaging and AI, 2025.
[5] European Parliament, "Regulation (EU) 2024/1689 — Artificial Intelligence Act," Official Journal of the European Union, 2024.
[6] U.S. Food and Drug Administration, "Artificial Intelligence and Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan," FDA White Paper, 2021.
[7] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in Proc. ICCV, pp. 618–626, 2017.
[8] A. Chattopadhay, A. Sarkar, P. Howlader, and V. N. Balasubramanian, "Grad-CAM++: Generalized Gradient-Based Visual Explanations for Deep Convolutional Networks," in Proc. WACV, pp. 839–847, 2018.
[9] D. Smilkov, N. Thorat, B. Kim, F. Viégas, and M. Wattenberg, "SmoothGrad: removing noise by adding noise," arXiv preprint arXiv:1706.03825, 2017.
[10] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why Should I Trust You?': Explaining the Predictions of Any Classifier," in Proc. ACM KDD, pp. 1135–1144, 2016.
[11] S. M. Lundberg and S. I. Lee, "A Unified Approach to Interpreting Model Predictions," in Proc. NeurIPS, pp. 4765–4774, 2017.
[12] A. Dosovitskiy et al., "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," in Proc. ICLR, 2021 .
[13] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in Proc. AISTATS, 2017.
[14] S. Bakas et al., "Federated learning for multi-institutional brain tumor segmentation using the FeTS challenge dataset," arXiv preprint arXiv:2105.05874, 2021.
[15] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated Machine Learning: Concept and Applications," ACM Trans. Intell. Syst. Technol., vol. 10, no. 2, pp. 1–19, 2019.
[16] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, 2020.
[17] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated Optimization in Heterogeneous Networks," in Proc. MLSys, 2020.
[18] D. Ancker et al., "Effects of workload, interruptions, and fatigue on scratchpad use in emergency care," JAMIA, vol. 24, no. 4, pp. 722–728, 2017.

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[19] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.
[20] R. A. Greenes, Ed., Clinical Decision Support: The Road Ahead, 2nd ed. Academic Press, 2014.
[21] J. D. Lee and K. A. See, "Trust in Automation: Designing for Appropriate Reliance," Human Factors, vol. 46, no. 1, pp. 50–80, 2004.