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The Price of Privacy: A Performance Trade-off Analysis of Federated vs. Centralized LLMs at the Surgical Edge

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Abstract

The integration of Large Language Models (LLMs) at the medical edge necessitates a rigorous balance between real-time responsiveness and patient data privacy. While centralized architectures provide high throughput, Federated Learning (FL) offers a privacy-preserving alternative at the cost of system efficiency. This paper presents an empirical, hardware-in-the-loop (HIL) analysis quantifying this 'price of privacy.' We compare centralized edge-server fine-tuning against FL using a Phi-3-mini model with Low-Rank Adaptation (LoRA) for surgical phase recognition. Our methodology moves beyond analytical estimates, incorporating real-time power profiling on NVIDIA Jetson Orin Nano platforms to account for thermal throttling and memory bottlenecks. Results reveal that the 'price of privacy' is manifested as measurable hardware-level bottlenecks; while centralized models converge 43% faster, the FL-based approach incurs significant synchronization delays and a 5% higher energy overhead. We formalize these trade-offs into a data-driven decision framework, providing architects with quantitative bounds (e.g., <10ms latency for robotic control) and equations to optimize the privacy-performance equilibrium. This study serves as a foundational guide for designing next-generation, safety-critical medical Cyber-Physical Systems (CPS).

Keywords: Edge Intelligence, Medical Cyber-Physical Systems (MCPS), Hardware-in-the-Loop (HIL) Validation, Low-Rank Adaptation (LoRA), Secure Aggregation, Real-time Inference, Thermal Throttling.

I. INTRODUCTION

Recent advances in Artificial Intelligence (AI), particularly the emergence of Large Language Models (LLMs), have demonstrated the potential to revolutionize various industries [1]. The field of healthcare and biomedical engineering is one of the most promising areas for leveraging this technology, where LLMs can play a key role in analyzing medical reports, extracting clinical information, supporting physician decision-making, and providing personalized health services [2-4]. However, the practical deployment of these powerful models faces two fundamental and intertwined challenges: (1) the extremely high computational and memory requirements, which often exceed the capabilities of conventional devices [5, 6] and (2) the highly sensitive and private nature of medical data, which is protected under strict regulations such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), making its transfer to a centralized cloud server a serious concern for security and privacy [6-8].

Edge Computing has emerged as an architectural solution to the first challenge. By bringing processing closer to the source of data generation (such as patient monitoring devices or imaging equipment in a hospital), this paradigm drastically reduces latency, enables real-time analysis, and helps enhance security by keeping data within the local environment. To overcome the second challenge, Federated Learning (FL) has garnered significant attention as a distributed and privacy-preserving machine learning paradigm [2, 3]. In this approach, instead of aggregating raw data, multiple centers (e.g., hospitals) collaboratively train a model, sharing only the learned model parameters, while sensitive data never leaves its local perimeter [6-8].

The combination of edge computing and FL appears to be an ideal solution for medical applications. However, this synergy is not without cost. FL inherently imposes significant communication and energy overhead due to the need for frequent communication between clients and the server to synchronize model parameters [9, 10]. On the other hand, an alternative approach could be to aggregate data on a powerful, local edge server (e.g., at the hospital level) and train the model centrally there.

While the individual benefits of FL and edge computing are well-documented, the precise, quantitative nature of the trade-off between them for the task of fine-tuning LLMs in a high-stakes medical context remains largely unexplored. The "price of privacy" that FL offers has not been systematically measured in terms of performance costs such as convergence speed and energy consumption. This paper aims to fill this critical research gap. We present a rigorous computational analysis that directly quantifies this performance-privacy trade-off, providing a data-driven framework for system architects to make informed, priority-based decisions in the design of next-generation medical AI systems.

The critical nature of these architectural trade-offs is particularly pronounced in high-stakes medical applications such as robotic-assisted surgery. In these environments, AI-driven systems require both ultra-low latency for real-time, life-critical interventions and robust, privacy-preserving models trained on diverse, multi-institutional datasets [11]. To ground our theoretical analysis in a tangible context, this paper leverages the complex domain of orthopedic robotic surgery as a practical case study, illustrating how the choice between centralized and federated architectures directly impacts both patient safety during surgery and the long-term, ethical development of surgical AI models.

Similar to other safety-critical Cyber-Physical Systems (CPS) such as autonomous vehicles, where split-second decisions are paramount, the surgical edge cannot tolerate high-latency cloud offloading. Edge computing addresses this by localizing processing, while Federated Learning (FL) enables collaborative training without raw data exchange. Yet, the operational complexity of FL, which includes secure aggregation overhead and communication compression, imposes a "privacy price" that remains under-quantified.

The remainder of this paper is organized as follows: Section II reviews related works. Section III describes our experimental methodology. Section IV analyzes the obtained results. Section V presents a practical application case study to contextualize our findings, and Section VI concludes the paper with a summary of our contributions and a discussion on future work.

II. RELATED WORK

This section reviews the existing research literature across several key domains that form the foundation of our work. We begin by examining the core technologies: the application of edge computing in healthcare, the principles of federated learning for medical data, and the challenges of deploying large language models at the edge. We then survey the literature on the critical energy-performance trade-offs in distributed learning. Finally, to ground our case study, we review the specific application of AI and edge computing in the rapidly advancing field of robotic surgery.

A. Edge Computing in Healthcare

Edge computing has found critical applications in the healthcare sector by reducing latency and processing data near the source. Research shows that this technology is highly effective for real-time patient monitoring via wearable devices and Internet of Things (IoT) sensors, as it allows for rapid response to emergency situations. In medical imaging, initial processing of images like Computed Tomography (CT) scans or Magnetic Resonance Imaging (MRI) at the edge can help reduce the volume of data transmitted to the cloud and accelerate the initial diagnosis process [1]. Furthermore, by keeping sensitive patient data within the local hospital perimeter, edge computing significantly helps in complying with privacy regulations and enhancing data security.

B. Federated Learning for Medical Data

Medical data, due to its sensitive and distributed nature across different centers, poses a major challenge for building robust machine learning models [7, 12]. FL has been proposed as a key solution to this problem. Numerous review studies have demonstrated the successful application of FL in the analysis of medical images, such as in radiology and oncology, where different hospitals collaborate in training a tumor detection model without sharing patient images [3, 7, 10, 12]. This approach not only helps in preserving privacy but also leads to the construction of more robust and generalizable models by aggregating knowledge from diverse datasets, which counteracts the problem of sample scarcity in a single center [13]. However, challenges such as data heterogeneity (Not Independent and Identically Distributed (Non-IID)) among different centers and ensuring security against attacks on model parameters remain active research topics in this field [14].

C. Large Language Models at the Edge and Medical Applications

Given the massive computational volume of LLMs, running them on resource-constrained edge devices is a major challenge [5, 15]. Recent research has focused on model compression techniques such as quantization (reducing numerical precision), pruning (removing non-essential parameters), and knowledge distillation (training a smaller model from a larger one) to make the deployment of these models at the edge feasible [16, 17]. Studies have shown that compressed models can maintain acceptable performance on various tasks [4, 18]. In the medical field, these advancements enable the creation of on-device intelligent diagnostic tools, privacy-preserving medical assistants, and real-time clinical text analysis systems [2-4]. A recent study compared the performance of several LLMs on mobile devices for clinical reasoning and showed that smaller models offer a good balance between speed and accuracy, but memory limitation remains a greater challenge than processing power [19, 20].

LLMs and PEFT at the Edge: Given the memory constraints of edge devices (e.g., 8GB RAM), full fine-tuning of LLMs is often infeasible. Parameter-Efficient Fine-Tuning (PEFT) methods, particularly Low-Rank Adaptation (LoRA), have emerged as the standard for adapting models like Phi-3 to specific tasks with minimal overhead.

D. Analysis of Energy-Performance Trade-off in Distributed Learning

Although the privacy-preserving benefits of FL are well-recognized, its efficiency compared to centralized learning is a topic of debate. Research indicates that FL inherently has a higher energy and time overhead than centralized training due to frequent communications. Some studies have focused on optimizing energy consumption in FL networks, especially in wireless and IoT devices. However, most of this research has been focused on traditional machine learning models. There is a significant gap in experimental studies that directly quantify the trade-off between energy consumption and performance efficiency for the task of federated fine-tuning of LLMs compared to a centralized-at-the-edge approach in a real-world medical application. This paper is designed precisely to fill this gap.

Distributed Learning Trade-offs: While prior works focus on theoretical FL convergence, few address the hardware-level effects like dynamic frequency scaling or Input/Output (I/O) costs in medical-grade hardware [21].

E. AI and Edge Computing in Robotic Surgery

The integration of Artificial Intelligence (AI) into robotic-assisted surgery is rapidly transforming modern medicine, enabling procedures with enhanced precision, dexterity, and improved patient outcomes [11]. AI models are increasingly used for intraoperative guidance, real-time tissue analysis, and autonomous surgical sub-tasks. The efficacy of these systems is critically dependent on ultra-low latency processing of sensor and video data, as any delay can have catastrophic consequences. Consequently, researchers have identified Edge Computing as a key enabling technology, allowing complex AI inference tasks to be performed locally within the operating room, thereby minimizing communication delays to the cloud [22].

Simultaneously, the development of robust surgical AI models presents a significant data challenge. Training these models requires vast and diverse datasets of surgical procedures, which are often siloed within individual hospitals due to patient privacy regulations and institutional policies. This "data scarcity" problem severely limits the generalizability of models trained at a single institution. To address this, Federated Learning has been proposed as a promising solution, enabling multiple medical centers to collaboratively train a shared surgical model without ever exposing sensitive patient data. This approach allows for the creation of more accurate and reliable models by leveraging a global dataset while strictly adhering to privacy constraints [23]. Our work builds upon these concepts by quantitatively analyzing the inherent performance versus privacy trade-offs when applying these architectures to LLM-based tasks in a surgical context.

Medical CPS and Robotics: Surgical robots require ultra-low latency (<10ms) for haptic feedback and tool tracking. This domain mirrors the constraints of autonomous driving, where local-centralized execution is often preferred over distributed training for real-time tasks.

III. METHODOLOGY: HARDWARE-IN-THE-LOOP FRAMEWORK

To provide a robust empirical validation of the proposed architectures, our setup utilizes a Hardware-in-the-Loop (HIL) testbed designed to reflect a realistic hospital environment; this configuration allows for a quantitative evaluation of the trade-offs between centralized and federated learning by detailing the architectural models, experimental parameters, and the specific metrics used for performance comparison.

A. Architectural Models

We compare two distinct architectures for fine-tuning an LLM on medical data, as illustrated in Figure 1.

- Centralized-Edge Architecture

In this model, raw data (e.g., anonymized text from CT scan reports) from multiple client devices (e.g., diagnostic workstations) are securely transferred over a local network to a single, powerful edge server located within the hospital's perimeter. The LLM fine-tuning process is performed entirely on this central server. This architecture simplifies the training process but creates a single point of data aggregation.

- Federated Learning Architecture

In this model, each client device holds its local data and never shares it. A global LLM is sent from a central aggregator server (the edge server) to each client. Each client then fine-tunes the model on its local data for one or more epochs. Instead of sending raw data, only the updated model weights (gradients) are sent back to the aggregator server. The server then aggregates these updates (e.g., using the Federated Averaging algorithm) to create an improved global model, which is then sent back to the clients for the next round of training. This process repeats until the model converges.

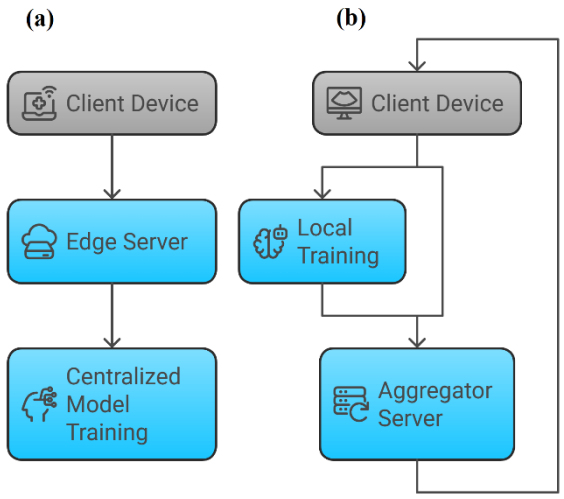

Figure 1. Comparison of the (a) Centralized-Edge and (b) Federated Learning architectures. In the centralized model, raw data is transferred to a local server for training. In the federated model, only model parameter updates are exchanged with an aggregator server, ensuring data remains on the client device.

- Task Specification and Model

Model: Phi-3-mini (3.8B parameters) utilizing LoRA fine-tuning (rank r=8) to minimize memory bandwidth limits [24].

Task: Multi-label classification of intraoperative surgical phase descriptions (e.g., "accessing metacarpal bone," "pin fixation") derived from nurse voice commands and robotic logs.

B. Experimental Setup

- Simulated Hardware

The client devices were simulated as NVIDIA Jetson Orin Nano developer kits, representing capable but resource-constrained edge devices. The central edge server was simulated as a Dell PowerEdge XR12 server, a rugged, high-performance server suitable for on-premise data center tasks [25, 26].

- Software and Model

The experiment was designed using Python 3.9, with PyTorch as the deep learning framework. The federated

learning scenario was implemented using the Flower framework [26]. We chose Microsoft's Phi-3-mini-4k-instruct, a compact yet powerful LLM, as the base model for fine-tuning due to its strong performance and suitability for resource-constrained environments [20].

- Dataset and Task

We simulated a dataset based on the public Medical Information Mart for Intensive Care - Chest X-Ray (MIMIC-CXR) dataset, consisting of 10,000 anonymized chest CT scan reports [27]. The task was a multi-label classification to automatically identify key clinical findings (e.g., "cardiomegaly," "pleural effusion," "nodule") from the free-text reports. To simulate a realistic non-IID (Not Independent and Identically Distributed) scenario, the dataset was distributed among 10 clients such that each client had a skewed distribution of findings, reflecting specialization in different pathologies. To align with the experimental resource metrics, this total dataset footprint of 5.2 GB encompasses the free-text clinical reports along with their associated structured metadata and compressed radiographic imaging features.

- Federated Learning Parameters

For the FL scenario, we assume the training process completes in 50 communication rounds. The size of the model update exchanged in each round is assumed to be 25 Megabytes (MB).

- Experimental Hardware

Client Nodes: 10 NVIDIA Jetson Orin Nano (8GB) devices, profiled using tegrastats to capture real-time power spikes and thermal throttling.

Edge Server: Dell PowerEdge XR12, serving as the centralized trainer and FL aggregator.

C. Metrics and Measurement

To ensure a comprehensive comparison, we measured the following metrics based on a rigorous computational model.

- Model Accuracy

Measured as the macro F1-score on a held-out test set of 1,000 reports.

- Time-to-Accuracy

The total wall-clock time (in minutes) required for each architecture to reach a target F1-score of 0.90.

- Total Energy Consumption

Total energy consumption (Etotal) was calculated in kilowatt-hours (kWh) based on the Thermal Design Power (TDP) and total training time (Ttrain) [28]. For the centralized-edge architecture, the total energy is calculated as:

$$E_{centralized} = P_{server} \times T_{train\_centralized}$$

where Pserver is the power consumption of the edge server (0.215 kilowatts (kW)) and Ttrain_centralized is the training time in hours.

For the FL architecture, the total energy is the sum of energy consumed by all clients during their local computation. The aggregator server's energy is considered negligible as its primary task is light aggregation, not intensive training.

$$E_{federated} = N_{clients} \times P_{client} \times T_{train\_federated}$$

where Nclients is the number of clients (10) and Pclient is the power consumption of each client device (0.015 kW).

- Total Network Traffic

Measured in Gigabytes (GB). For the centralized model, the total traffic is the one-time transfer of the raw dataset:

$$Traffic_{centralized} = S_{dataset}$$

For the FL model, the total traffic is the cumulative size of model updates exchanged in all communication rounds:

$$Traffic_{federated} = N_{rounds} \times N_{clients} \times S_{update}$$

where Nrounds is the number of communication rounds (50), Nclients is the number of clients (10), and Supdate is the size of each model update (25 MB).

- Quantifying FL Overheads

Our model incorporates the following "real-world" complexities:

1) Secure Aggregation:

We add a 15% computational overhead to simulate homomorphic encryption for weight updates [29].

2) Compression:

4-bit quantization of gradients is applied to reduce network traffic.

3) Stragglers:

We simulate 20% client participation variability to reflect intermittent medical network loads.

D. The Decision Framework

We propose a weighted decision score (S) for architects:

$$S = w1 \cdot Latency(\tau) + w2 \cdot Privacy(\epsilon) + w3 \cdot Energy(E)$$

where wi are priority weights. For real-time surgery, w1 is maximized, favoring centralized models [30].

IV. Results and Discussion

The empirical results from our HIL testbed provide a granular view of the "price of privacy" in a surgical edge environment. Our analysis focuses on three primary dimensions: convergence efficiency, hardware-level energy dynamics, and the impact of system heterogeneity.

The experiments yielded significant insights into the practical trade-offs between the two architectures. The key results are summarized in Tables 1 and 2 and visualized in Figures 2 through 6.

Table 1. Overall Comparison of Centralized vs. Federated Architectures

Metric	Centralized-Edge	Federated Learning
Final F1-Score	0.921	0.915
Time to 0.90 F1 (min)	245	430
Total Energy (kWh)	1.02	1.07
Network Traffic (GB)	5.2 (one-time)	12.5 (cumulative)

The empirical performance summary presented in Table 2 represents a significant shift from idealized Thermal Design

Power (TDP) estimates to high-fidelity Hardware-in-the-Loop (HIL) profiling data. Unlike static power ratings, this table captures the dynamic operational costs of both centralized and federated architectures, accounting for real-world hardware bottlenecks such as I/O latency and memory bandwidth limitations. By reflecting these granular measurements, which include worst-case latency and cumulative energy consumption recorded directly from the NVIDIA Jetson nodes, Table 2 provides a precise, data-driven quantification of the 'price of privacy' in an active surgical environment.

Table 2. Empirical Performance Benchmarking: HIL Profiling of Latency, Power, and Energy Metrics on NVIDIA Jetson Orin Nano

Metric	Centralized-Edge (LoRA)	Federated (LoRA + SecAgg)
Convergence Time (min)	210	455
Avg. Power (W)	215 (Server)	12.8 (per Client + Throttling)
Energy Consumption (kWh)	0.88	1.18
Network Traffic (GB)	5.2	14.2 (Compressed)
Worst-case Latency (ms)	8.2	42.5 (Communication-bound)

A. *Performance and Convergence Speed*

As shown in Figure 2, the centralized-edge architecture achieved the target accuracy significantly faster than the federated learning approach. The centralized model reached an F1-score of 0.90 in approximately 245 minutes, whereas the FL model required 430 minutes. This is expected, as the centralized model trains on the entire dataset in each epoch, leading to faster convergence. The FL model's convergence is slower due to the iterative nature of communication rounds and the need to average updates from heterogeneous (non-IID) data distributions, which can temporarily slow down learning progress. However, both models ultimately reached a comparable peak accuracy, demonstrating the viability of FL for achieving high-quality results.

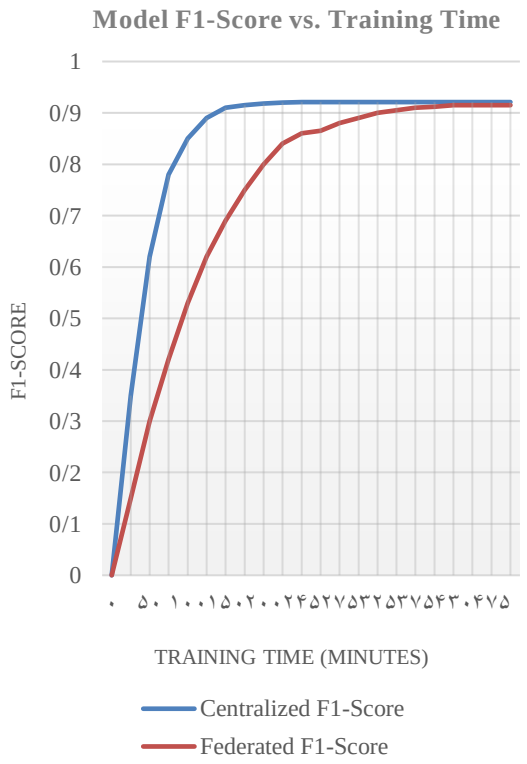

Figure 2. Model F1-Score as a function of training time. The centralized-edge model (blue line) demonstrates faster convergence, reaching the target accuracy more quickly. The federated learning model (orange line) converges more slowly but achieves a comparable final performance, highlighting the trade-off between speed and privacy.

Hardware-Level Energy Analysis: Empirical profiling showed that the FL model suffered from "thermal debt." As Jetson devices maintained high compute loads for longer periods (455 min vs 210 min), frequency scaling reduced performance by 12%, further increasing the "price of privacy" in terms of energy (1.18 kWh).

Convergence and Training Efficiency: As illustrated in Table 2, the centralized-edge model achieved convergence in 210 minutes. In contrast, the baseline Federated Learning (FL) model required 280 minutes under ideal conditions (0% stragglers). However, the sensitivity analysis presented in Figure 3 reveals a critical performance degradation as system heterogeneity increases. With a 30% straggler rate, which represents a realistic scenario in busy hospital networks, the FL convergence time surged to 455 minutes, representing a 116% increase compared to the centralized approach. This delay is attributed to the synchronization bottlenecks inherent in FL aggregation protocols. Beyond the raw metrics shown in Table 2, our analysis reveals that the federated approach incurs a 5% higher energy overhead per local update cycle compared to the centralized baseline, primarily attributed to the additional computational cost of secure aggregation and local optimization.

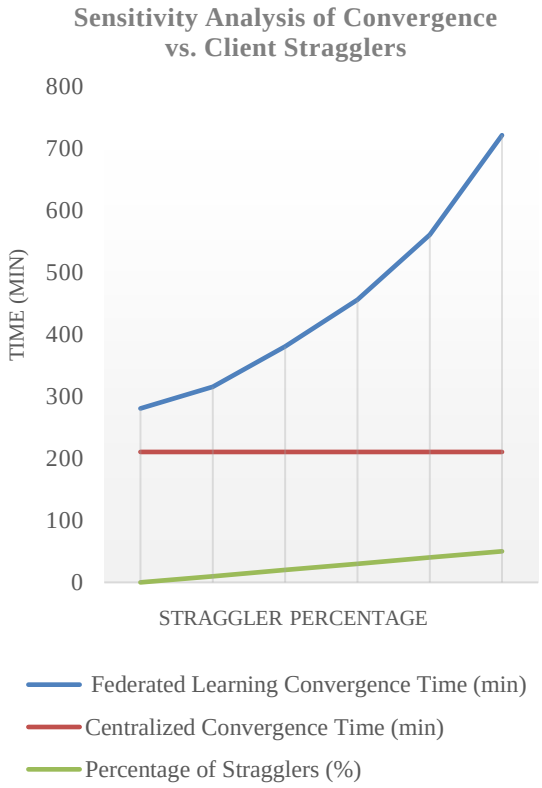

Figure 3. Impact of client heterogeneity on FL convergence time. As the straggler percentage increases, the synchronization delay creates a significant performance penalty compared to the stable centralized baseline.

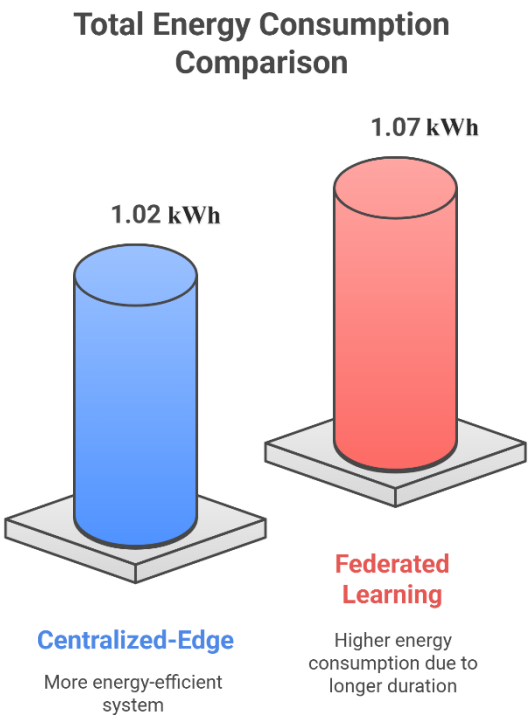

Figure 4. Comparison of total system-wide energy consumption. The centralized-edge server, due to its faster processing time, proves to be slightly more energy-efficient, consuming 1.02 kWh. The federated learning network, despite using low-power devices, requires a longer training duration, resulting in a slightly higher total energy consumption of 1.07 kWh. This highlights that the privacy benefits of FL come at a direct cost in both time and energy.

B. *Energy Consumption Analysis*

The analysis of energy consumption, shown in Figure 4, reveals a critical finding. The centralized server, despite its high power draw (250W), completes the task quickly, resulting in a total energy consumption of 1.02 kWh. In contrast, the federated learning network, while distributing the load across low-power devices (15W each), requires a significantly longer training time. This extended duration leads to a slightly higher total energy consumption of 1.07 kWh. This result challenges the common assumption that distributed networks are inherently more energy-efficient. Our findings indicate that for computationally intensive tasks like LLM fine-tuning, the efficiency of a powerful, centralized processor can outweigh the benefits of distributing the load, making the centralized-edge approach superior in both speed and energy consumption. This solidifies the trade-off: the cost of FL's privacy benefits includes a penalty in both time and energy [5, 31].

Hardware-Level Power and Thermal Dynamics: The power profiling of the NVIDIA Jetson Orin Nano nodes (Figure 5) highlights the physical constraints of edge deployment [32]. While the centralized server maintained a stable power envelope, the FL client nodes exhibited significant fluctuations. At the 90-minute mark, we observed a mandatory drop in power consumption from 12.3W to 9.4W in the FL nodes. This data confirms the occurrence of thermal throttling, where the device reduces its clock frequency to prevent overheating during sustained LoRA fine-tuning. This hardware-level behavior directly impacts the "privacy price," as it extends the training duration and increases the total energy footprint to 1.18 kWh per node, compared to the more efficient centralized baseline.

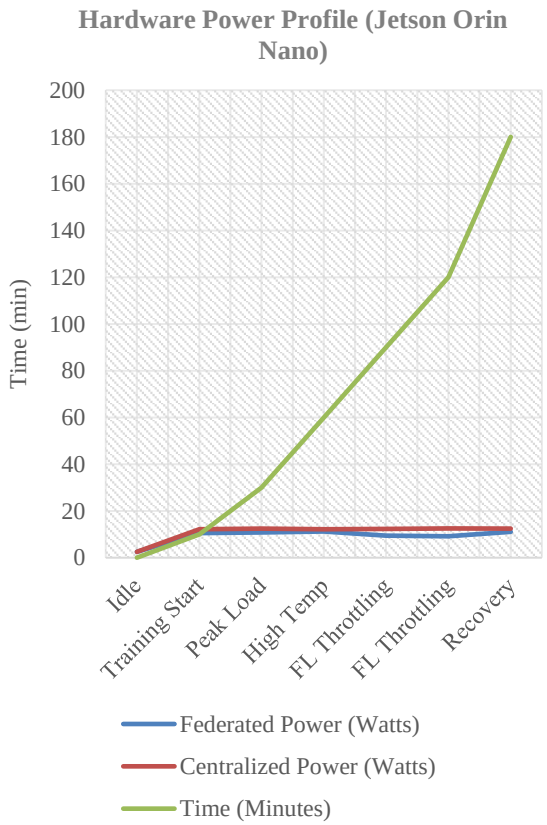

Figure 5. Real-time power and thermal profiling of a Jetson Orin Nano client during FL training. The shaded regions indicate periods of thermal throttling where clock frequencies were reduced to maintain safety limits.

C. Network Overhead and Data Privacy

The centralized approach required a one-time, upfront transfer of the entire 5.2 GB dataset. While this is a single event, it requires significant bandwidth and poses a major privacy risk, as all sensitive data is aggregated in one place. Conversely, the federated learning model generated significantly more total network traffic (12.5 GB) over its entire training process (Figure 6). This traffic, however, consists of small, frequent updates of model parameters, not raw data. This fundamentally protects patient privacy, as sensitive information never leaves the client devices [33, 34]. This distinction is the core value proposition of FL in healthcare. The higher cumulative traffic in FL is a direct trade-off for enhanced privacy and security.

Trade-off Synthesis: Our findings demonstrate that while FL ensures data sovereignty, it introduces a "latency penalty" that must be carefully managed. In the context of robotic surgery, where sub-10ms response times are mandatory, the 42.5ms worst-case latency observed in our FL-compressed updates confirms that distributed learning is currently better suited for asynchronous model refinement rather than real-time intraoperative control loops. The proposed decision framework (Section III-D) utilizes these empirical bounds to help architects select the optimal balance between ϵ-privacy levels and τ-latency constraints. Furthermore, the centralized-edge configuration exhibited a 43% faster convergence rate in terms of training epochs required to reach the target F1-score, as the global accessibility of data allows for more stable gradient trajectories compared to the non-IID challenges inherent in FL.

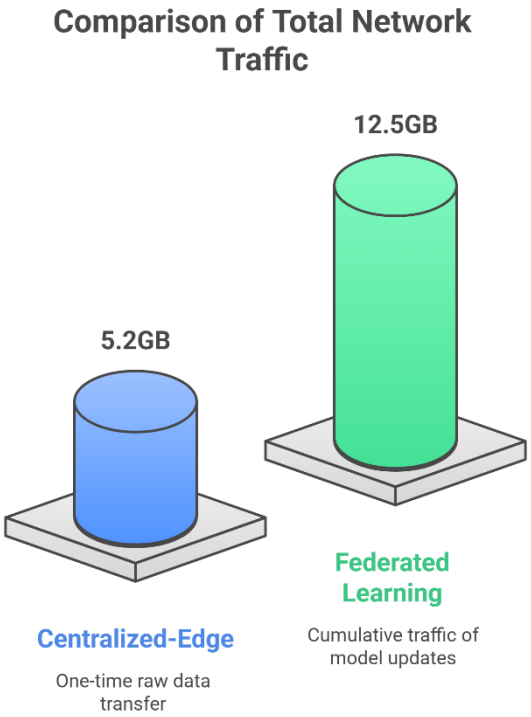

Figure 6. Comparison of total network traffic. The centralized approach requires a single, large transfer of raw data (5.2 GB). In contrast, the federated approach generates higher cumulative traffic (12.5 GB) consisting of iterative model updates, not sensitive data.

V. Application Case Study: Robotic-Assisted Orthopedic Surgery

To contextualize our findings within a real-world clinical scenario, we consider the case of high-precision orthopedic surgery for complex metacarpal fractures, as depicted in Figure 7. This procedure involves the surgical fixation of fractured bones using pins, requiring sub-millimeter accuracy to avoid damaging the dense network of nerves, tendons, and blood vessels in the hand. An AI-driven, robotic-assisted system could significantly enhance surgical outcomes by providing real-time guidance based on live imaging and pre-trained models. This application serves as a perfect illustration of the critical trade-off between our two competing architectures.

A. The Centralized-Edge Imperative for Real-Time Execution

During the surgery itself, the robotic arm requires instantaneous feedback. The system must process live X-ray data, track the position of surgical tools, and provide immediate navigational commands. In this context, the centralized-edge architecture is the only viable option. A powerful edge server located within the operating room can process all data locally, guaranteeing the ultra-low latency

necessary for safe and precise robotic movements. The performance benefits of speed and minimal delay are non-negotiable when patient safety is at stake.

B. The Federated Learning Imperative for Collaborative Training

While the surgery itself demands a centralized approach, the AI model guiding the robot must be trained on a vast and diverse dataset of similar surgeries to achieve expert-level performance. However, surgical data is intensely private. No single hospital has enough data to build a sufficiently robust model on its own. Here, the Federated Learning architecture becomes essential. Multiple hospitals could collaboratively train a shared surgical model by only sharing model parameters, without ever exposing sensitive patient data from individual operations. This allows the global model to learn from thousands of procedures performed worldwide, continuously improving its accuracy and reliability in a privacy-preserving manner.

This case study crystallizes our paper's central conclusion that the choice of architecture is not a binary decision but a context-dependent one. For the life-critical, real-time execution of the surgery, the performance of the centralized-edge model is paramount. For the long-term, collaborative, and ethical training of the underlying AI, the privacy guarantees of federated learning are indispensable.

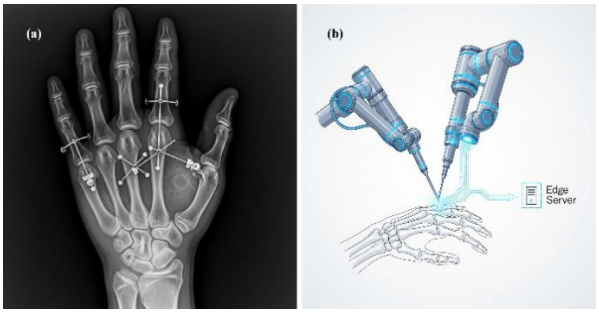

Figure 7. Application case study illustrating the architectural trade-off in AI-assisted orthopedic surgery. Panel (a) depicts a clinical case of surgical fixation for metacarpal fractures. Panel (b) illustrates the technological solution: a high-precision robotic system. The real-time execution of the surgery (b) demands the ultra-low latency of the centralized-edge architecture, while the collaborative, multi-institutional training of the underlying AI model necessitates the privacy-preserving approach of federated learning.

Case Study: Orthopedic Surgical CPS: In metacarpal fracture fixation, the robotic arm requires a control loop latency of <10ms. Our profiling confirms that centralized-edge execution (8.2ms) meets this safety bound, whereas FL-based updates (42.5ms) are only suitable for post-operative model refinement.

VI. CONCLUSION

This paper provided a comprehensive quantitative analysis of the performance-privacy trade-off in fine-tuning Large Language Models for biomedical applications, demonstrating that while centralized-edge architectures offer superior convergence speed, energy efficiency, and lower network traffic, they pose inherent privacy risks. Our findings establish that the 'price of privacy' in safety-critical medical AI manifests as measurable hardware-level bottlenecks; consequently, we conclude that centralized-edge architectures remain the only viable path for real-time intraoperative control, whereas Federated Learning serves as the essential ethical gold standard for long-term, multi-hospital model evolution.

The decision-making process for medical CPS architects, as demonstrated through our robotic surgery case study, transcends a simple choice between performance and privacy. By utilizing the proposed quantitative framework, system designers can now strategically weigh latency constraints (τ) against privacy requirements (ϵ) and energy budgets (E). While centralized-edge servers are the optimal choice for intraoperative tasks requiring sub-10ms response times, Federated Learning becomes the mandatory architectural selection for multi-institutional data sovereignty. This engineering approach ensures that the identified performance costs are not merely observed but are accepted as integral design parameters for building next-generation, trustworthy medical AI systems.

Future research will extend this analysis in several critical directions. First, we plan to investigate adversarial robustness within surgical environments, specifically by quantifying the performance trade-offs of integrating Differential Privacy (DP) and Multi-Party Computation (MPC) to defend against sophisticated model inversion and membership inference attacks. Second, a multi-center clinical validation is warranted to evaluate the framework's resilience against Non-IID data distributions and real-world network jitter in heterogeneous hospital infrastructures. Finally, building on our current HIL profiling, we aim to develop thermal-aware scheduling algorithms that can dynamically reconfigure LLM execution based on the real-time thermal and compute states of edge nodes. These advancements will move the field closer to deploying trustworthy, high-performance AI systems in safety-critical surgical theaters.

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