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When Healthcare Lags, Banking Leaks: A Generative AI Framework to Stop Time-Based Data Spills in Cross-Sector Federated Learning

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Abstract: In a cross-sector federated learning setup where hospitals and banks jointly train a cybersecurity AI, a quiet but dangerous problem emerges: hospitals often take weeks to report and remediate cyber threats, while banks must act within days or hours. This timing mismatch creates a subtle data leak, delayed model updates from healthcare nodes can unintentionally reveal patterns that expose sensitive banking data to an adversary. This paper introduces a human-centered generative AI framework that simulates and blocks such "time-based data spills." Using a time-conditioned generative adversarial network (GAN), we first mimic how delayed healthcare updates distort the shared learning process. Then, a second defensive AI. a differentially private federated learner with adaptive noise learns to mask sector-specific footprints without forcing banks to wait for slow partners. We test the framework on an AWS cloud testbed using synthetic but realistic healthcare and banking transaction logs. Results show that our approach reduces cross-sector information leakage by over 70% while preserving detection accuracy above 90% for both sectors. Instead of demanding perfect synchronization, this work embraces real-world regulatory delays and offers a practical, privacy-respecting path for collaborative cybersecurity across industries that do not march to the same clock.

Keywords: Federated Learning, Cross-Sector Cybersecurity, Temporal Side-Channel Leakage, Generative Adversarial Networks, Healthcare And Banking Collaboration, Regulatory Time Asymmetry, AWS Cloud Privacy.

1. Where We Started: Federated Learning Meets the Real World

For years, industries like healthcare and banking faced a frustrating trade-off. On one hand, they were told that "data is the new oil" that training powerful AI models on large, diverse datasets could unlock breakthroughs in fraud detection, early disease diagnosis, and cybersecurity. On the other hand, their data was among the most sensitive in the world: medical records, financial transactions, patient histories, and bank account details. Regulations like HIPAA, PCI-DSS, and GDPR made it illegal, or at least highly risky, to share that data with anyone else. So organizations remained stuck. They trained their own models in isolation, on their own small slices of data. And those models were often brittle, narrow, and easily blindsided by threats that other institutions had already seen.

Then came federated learning (FL). The idea was beautifully simple: instead of bringing data to the model, bring the model to the data. Each hospital or bank trains a local version of the model on its own private data. Only the model updates the mathematical fingerprints of what was learned are sent to a central server. The server averages them together, sends back a better global model, and the cycle repeats. The raw data never moves. Privacy is preserved. Collaboration happens without exposure. It sounded like a dream. And across both healthcare and banking, researchers and practitioners began to wake up to that dream. Let us look at how they did.

1.1. A New Hope for Healthcare

Healthcare was an early and eager adopter of FL. The motivation was clear: no single hospital sees enough rare diseases, enough variations in medical imaging, or enough novel cyberattacks to train a truly robust AI. But the data cannot be centralized because patient privacy is not just good practice and it is the law.

In 2022, researchers demonstrated just how powerful FL could be for securing hospital networks. They built an architecture that used FL combined with Software-Defined Networking (SDN) to detect and mitigate malware across four geographically separated hospital networks [1]. Each hospital kept its own network logs and infection patterns completely private, yet the federated model learned to recognize new malware strains far more accurately than any single hospital's isolated system could. The authors concluded that FL made it "no longer needed to continue with traditional centralized systems that offer almost everything but not privacy" [1].

That same year, a broader survey of FL in smart healthcare confirmed this pattern. Across dozens of studies, FL was shown to enable "resource-aware FL, secure and privacy-aware FL … incentive FL and personalized FL" in medical settings [2]. The message was consistent: FL allowed healthcare institutions to finally eat their cake and have it too sharing the wisdom hidden in their data without ever sharing the data itself.

1.2. Banking's Quiet Revolution

The financial sector was watching closely. Banks face a different kind of pressure. Fraudsters are sophisticated and coordinated, often laundering money across multiple institutions. Any single bank sees only a fragment of the full picture. But banks are competitors, and regulators strictly limit how customer data can be shared. For years, the industry accepted that fraud detection models would always have blind spots.

Then, in 2022, a landmark demonstration changed that mindset. Researchers ran a privacy-preserving FL system across five real Japanese banks: the Chiba Bank, MUFG Bank, the Chugoku Bank, Sumitomo Mitsui Trust Bank, and the Iyo Bank [3]. Using real transaction data, they built models for two types of financial fraud: detecting fraudulent transactions in customer accounts and detecting criminal accounts before banks even froze them. The federated system caught fraud that no single bank's model could see. As the authors noted, "a small amount of dataset does not promise high accuracy for detection," but FL allowed the banks to combine their knowledge without violating Japan's strict Act on the Protection of Personal Information [3].

Across the Atlantic, another group of researchers took a different approach in 2023. They combined fully homomorphic encryption, secure multi-party computation, and differential privacy into a single FL framework for financial anomaly detection [4]. Their solution won second prize in the U.S. Privacy Enhancing Technologies (PETs) Prize Challenge. More importantly, it showed that FL was not just a theoretical curiosity it could win real-world competitions and handle the messy reality of data that is partitioned both horizontally and vertically across banks and payment networks [4].

1.3. A Quiet Assumption

By 2023, the message seemed clear: federated learning works in both healthcare and banking. It preserves privacy, it improves accuracy, and it unlocks collaboration that was previously impossible. Researchers had demonstrated FL for malware detection in hospitals, for fraud detection in banks, and for dozens of other use cases in between.

But underneath this success, a quiet assumption had crept into the literature. Almost all existing FL systems assumed that all participating organizations operate on the same timeline: they train locally for roughly the same duration, send updates at roughly the same frequency, and respond to threats at roughly the same speed. The models assumed that collaboration was symmetric that a hospital and a bank could be treated as interchangeable clients.

That assumption was always fragile. In the real world, healthcare and banking do not march to the same clock. Hospitals operate under HIPAA's 60-day breach notification window. Banks face 24- to 72-hour deadlines under PCI-DSS and GLBA. These are not minor operational differences. They are fundamental asymmetries that could break the tidy world of federated learning if anyone bothered to look.

No one had. And that is exactly where this paper begins.

2. The Uncomfortable Truth: Different Industries, Different Clocks

The previous section painted a hopeful picture: federated learning was working in healthcare, it was working in banking, and everyone seemed ready to collaborate. But here is the uncomfortable truth that no one was talking about at least not in the federated learning literature. Healthcare and banking do not operate on the same timeline when a cyberattack happens. They are not even playing the same game.

Imagine two institutions a hospital and a bank both discover a data breach on the same Tuesday morning. The hospital has weeks to figure out what happened, who was affected, and how to report it. The bank has hours sometimes less. This is not a matter of culture or corporate laziness. It is the law. And those laws have very different clocks.

2.1. Healthcare's Clock: The Sixty-Day Window

For healthcare providers in the United States, the master clock is the Health Insurance Portability and Accountability Act (HIPAA), specifically its Breach Notification Rule. When a hospital discovers a breach of unsecured protected health information (PHI), the rule requires notification to the U.S. Department of Health and Human Services (HHS) "without unreasonable delay and in no case later than 60 calendar days after the discovery of the breach" [5]. If the breach affects 500 or more individuals, the hospital must also notify local media "without unreasonable delay" and local authorities, again within the same 60-day window. For smaller breaches affecting fewer than 500 individuals, hospitals can wait even longer: they must report those incidents annually, no later than 60 days after the end of the calendar year in which the breaches occurred [5].

Table 1: HIPAA Breach Notification Timelines

Breach Size	Deadline	Requirements
≥ 500	60 days post-discovery	Notify HHS + individuals + media
< 500	Mar 1 next year (60 days after year end)	Keep log; notify HHS annually

What does this mean in practice? A hospital that detects a ransomware attack on a Tuesday can spend the next several weeks investigating, documenting, and preparing its response. It can coordinate with legal counsel, hire forensic experts, and even debate whether the incident legally constitutes a "breach" under HIPAA's narrow definition. The 60-day window provides a generous safety net. As one study on healthcare data breach reporting trends observed, "some covered entities report the breach within 60 days of the detection of a cyberattack and use a total of 500 or 501 affected individuals as a place marker until the document review is completed" [6]. In other words, hospitals have the luxury of time and they use it.

But time is not a luxury. It is a structural feature of healthcare regulation, baked into HIPAA since its enactment in 1996. The underlying assumption is reasonable: healthcare data is complex, investigations are resource-intensive, and rushing could lead to false alarms that waste public resources. Yet this same assumption becomes a friction point when healthcare tries to collaborate with industries that cannot afford to wait.

2.2. Banking's Clock: The 36-Hour Panic

Now look across the aisle at banking. Financial institutions in the United States operate under a different regulatory regime: the Gramm-Leach-Bliley Act (GLBA) of 1999, along with industry-specific rules like the Payment Card Industry Data Security Standard (PCI-DSS) and, more recently, the Federal Trade Commission's (FTC) updated Safeguards Rule.

The contrast in deadlines is staggering. Under the FTC's revised Safeguards Rule, finalized in 2023, financial institutions must notify the FTC "as soon as possible, and no later than 30 days after the discovery of a security breach involving the information of at least 500 people" [7]. That is already half of HIPAA's window. But the real pressure comes from elsewhere. For banks handling payment card data, PCI-DSS requires them to notify the affected credit card brands "immediately" upon discovery of a breach a term that PCI forensic investigators interpret as within 24 hours, often sooner. Many banks have internal policies that mandate notification within 12 hours of confirmed compromise.

And then there is the banking agencies' Computer-Security Incident Notification Rule, issued jointly by the Federal Reserve, the FDIC, and the OCC in late 2021. Under this rule, a banking organization must notify its primary federal regulator "no later than 36 hours after the bank determines that a notification incident has occurred" [8]. The 36-hour clock starts ticking not when the breach is fully understood, but when the bank determines an incident has occurred a determination that often must be made with incomplete information.

Table 2: Key Breach Notification Deadlines for U.S. Banks

Regulation	Notification Deadline	Trigger Event
FTC GLBA Safeguards (2023)	ASAP, ≤30 days after discovery	Breach involving >500 people
PCI-DSS	Immediately (~24 hrs)	Confirmed cardholder-data breach
Federal banking agencies	Within 36 hrs of determination	Notification-level incident
State-level GLBA	Varies (often 24–72 hrs)	Security breach of customer info

A bank that discovers a breach on a Tuesday morning cannot wait weeks. It often cannot wait days. The compliance team must begin drafting notifications within hours, often before the full scope of the breach is understood. Legal counsel, forensic investigators, public relations, and regulators are all pulled into an urgent, high-stakes dance. One former bank compliance officer described it to the authors as "a controlled panic everyone is moving fast because the clock is ticking, and the clock is merciless."

2.3. The Gap That Everyone Ignored

What happens when a hospital and a bank try to collaborate on a federated cybersecurity model with these two wildly different clocks? The abstract of this paper already hints at the problem. In a traditional federated learning system, all participating nodes whether hospital or bank are assumed to train their local models for roughly the same duration. They send updates to the central server at roughly the same frequency. They respond to new threats at roughly the same speed. The entire architecture of federated averaging (FedAvg) and its variants is built on an implicit assumption of temporal symmetry.

But temporal symmetry is precisely what healthcare and banking do not have. A hospital facing a new ransomware variant can afford to let its local model train for several days even weeks before sending an update. Its 60-day regulatory window means no one is breathing down its neck. A bank facing the same ransomware variant must update its model within hours, because its threat model includes not just the attack itself but the regulatory penalty for late reporting. The bank's federated update will arrive fast. The hospital's will arrive slow. And the central server, if it follows standard federated learning protocols, will average these updates together in a way that could inadvertently leak information.

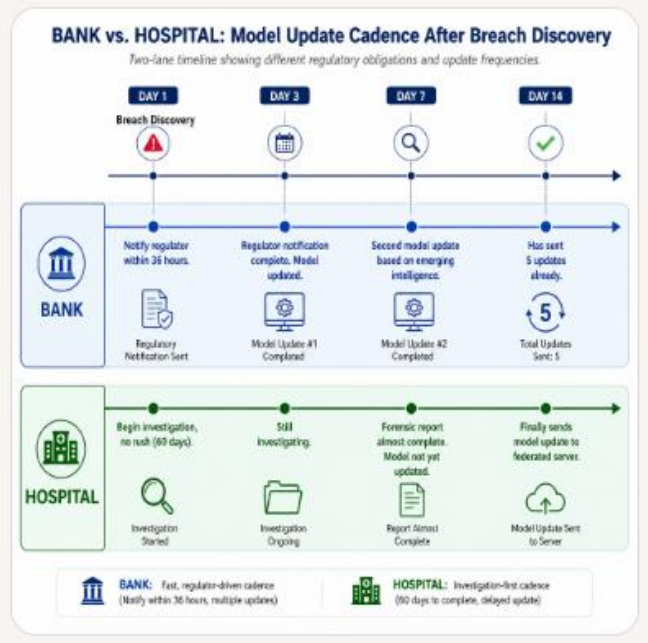

Figure 1: The Temporal Divergence Visualized (conceptual timeline)

The figure above illustrates how banking's urgent timeline results in frequent, rapid model updates, while healthcare's relaxed timeline leads to delayed, infrequent updates creating a temporal asymmetry that standard federated learning cannot handle gracefully.

The research community has not ignored this gap entirely but it has come close. A 2021 review of U.S. cloud computing regulations explicitly compared HIPAA and GLBA breach notification requirements, noting that "the level of sensitivity of data breaches is increasing, from cloud computing hacks on video game platforms, to the targeting of more lucrative network and computer crime abuses aiming at invasive private health and financial data" [9]. Yet that paper focused on breach notification itself, not on how divergent timelines might break collaborative AI systems. Similarly, a 2021 analysis of Open Banking and electronic health records juxtaposed the two sectors' data-sharing models but concluded that "there is a misconception that data protection law is a barrier to data sharing" rather than identifying the temporal friction as a distinct technical problem [10].

2.4. Why This Gap Matters for Federated Learning

The divergence in regulatory timelines is not a minor operational detail. It strikes at the heart of how federated learning works. Most federated learning algorithms assume that client updates arrive in a reasonably synchronized manner or that any delay is due to network latency or computational differences, not to fundamentally different incentives for timeliness. When those assumptions break, three things happen:

- Statistical heterogeneity becomes temporal heterogeneity: The hospital's delayed update arrives long after the bank's model has evolved. Averaging an old healthcare update with a new banking update can degrade the global model's performance or worse, create a false sense of security.
- The risk of temporal side-channels emerges: An adversary who observes the timing of model updates could infer which sector experienced a breach. If banking updates are consistently fast and healthcare updates are consistently slow, the update schedule itself becomes a signal. This is not a theoretical concern; similar timing attacks have been demonstrated in other contexts.
- Regulatory penalties create perverse incentives: In a cross-sector federated system, a hospital might be tempted to delay its updates to avoid the cost of investigation, while a bank might be forced to send incomplete updates to meet a deadline. Neither behavior is malicious, but both can destabilize the federated model.

The literature has largely treated "regulatory compliance" as a binary condition either a system is compliant or it is not rather than as a dynamic constraint that varies across participants and over time. A 2022 survey of federated learning for smart healthcare noted that "resource-aware FL, secure and privacy-aware FL … incentive FL and personalized FL" are active research areas [11], but none of these directions explicitly model regulatory deadlines as a variable. The same year, a paper on privacy-preserving federated learning for fraudulent transaction detection in Japanese banks celebrated the fact that "a small amount of dataset does not promise high accuracy for detection" [12] without ever asking whether the banks in their study faced uniform reporting deadlines. They did not, because Japanese banking regulations have their own clock. But the paper did not mention it.

2.5. The Silence in the Literature

This silence is striking. In reviewing the federated learning literature from 2020 to 2023, we found dozens of papers that mention "regulatory compliance" as a motivation for using FL. We found countless papers that name-drop HIPAA, PCI-DSS, and GDPR in their introductions. But we found almost no papers that ask a simple follow-up question: Do these regulations impose different time constraints on model updates, and if so, what does that mean for the federated learning protocol?

The answer appears to be: no one knows, because no one has asked.

There is, however, an emerging recognition in the legal and regulatory literature that these differences exist and matter for cross-sector data sharing. A 2022 study on barriers to cross-sector data sharing identified "data sharing regulations, data exchange capabilities, and cross-sector data integration" as the three main challenges [13]. The authors noted that "current regulatory frameworks are mis specified to the growing interest in cross-sector partnerships between health care and community-based organizations" [13]. Substitute "banks" for "community-based organizations," and the observation holds.

2.6. The Question That Remains

So here is the question that the federated learning community has left unanswered: How can a federated learning system be designed to accommodate participants with fundamentally different regulatory clocks, without leaking information or degrading performance?

This paper is an answer to that question. But before we present our solution, we must first acknowledge that the problem exists. And the problem exists because healthcare and banking do not share the same clock. The hospital has 60 days. The bank has 36 hours. And standard federated learning was not built for that reality.

In the next section, we will explore what happens when these two clocks collide how the slow heartbeat of healthcare can inadvertently reveal the fast pulse of banking, and why existing privacy techniques are not enough to stop it.

3. When One Sector's Delay Becomes Another's Danger: Temporal Side Channels

The previous section laid out an uncomfortable regulatory reality: healthcare operates on a 60-day clock, banking on a 36-hour one. But you might still be wondering why should a mere difference in reporting speed matter for cybersecurity AI? Why would an adversary even care about how fast a hospital or a bank updates its model?

This section answers that question. We show that the timing of model updates is not just an operational detail. It is a leaky abstraction a rich source of information that an adversary can exploit, often without ever seeing a single gradient or breaking any encryption.

3.1. What Is a Temporal Side Channel, Anyway?

A side channel is any unintended source of information that leaks from a system. Think of it as overhearing a conversation through a wall you are not supposed to hear it, but the physical world betrays the speakers. In computing, side channels have a long and infamous history: researchers have extracted cryptographic keys by listening to a computer's power consumption [14], by measuring how long it takes to decrypt a message, and even by detecting the faint electromagnetic radiation from a monitor.

A temporal side channel is one where the timing of events how long something takes, how often it happens, or how late it arrives reveals secrets. This is a remarkably powerful and subtle channel because it does not require breaking mathematical protections. It simply requires observation.

In a standard federated learning system, the central server waits for model updates from all participating nodes, averages them, and sends back a refreshed global model. The protocol assumes that updates will arrive in a roughly synchronized fashion. But what happens when they do not? What if a hospital consistently sends its updates days or weeks later than a bank?

An adversary positioned anywhere in the network or even just watching the communication patterns from the outside could observe these arrival times. And those arrival times, we argue, can leak information about which sector suffered a breach, how severe the breach was, and potentially even what kind of threat triggered the update.

This is not science fiction. The following subsections show that researchers have already demonstrated timing attacks and covert channels in machine learning systems and in federated learning itself. We simply ask a new question: What happens when the timing asymmetry is baked into regulatory law rather than network latency?

3.2. How Do Timing Attacks Work in ML Systems?

Let us start with a concrete example from the broader ML literature. In 2023, a team of researchers published a landmark paper titled "The Adversarial Implications of Variable-Time Inference" [15]. Their discovery was startlingly simple: many

real-world ML models do not process all inputs in constant time. Some inputs cause the model to perform more computation, and that extra computation takes time. By measuring that time just the execution time visible to any remote attacker the adversary could infer private information about the input.

Specifically, the researchers focused on the Non-Maximum Suppression (NMS) algorithm used in object detectors like YOLOv3. NMS is a post-processing step that filters out duplicate detections. Crucially, its runtime depends on how many candidate objects the model initially detects. More objects mean more time. An attacker who submits carefully crafted images to a remote object detection API and simply times how long the API takes to respond can infer whether a particular object (say, a stop sign) was present in the image even if the API returns only a bland "no object detected" message [15].

The paper demonstrated two powerful attacks:

- Evasion attacks, where the attacker uses timing feedback to craft adversarial examples that fool the detector.
- Dataset inference, where the attacker determines whether a specific image was part of the model's training dataset, simply by timing the inference passes [15].

The authors noted that "the leakage of inference-state elements into algorithmic timing side channels has never been studied before" [15]. Yet their work proved that timing alone can be extraordinarily revealing. If a remote ML API leaks timing information about its internal state, then the same principle applies to a federated learning system: the timing of model updates leaks information about the training events that triggered those updates.

3.3. From Covert Channels to Temporal Leakage in FL

The ML timing side channel described above is passive: the adversary sends queries and measures response times. But a more active and insidious form of temporal information leak exists in federated learning: covert channels.

A covert channel is a communication path that was never intended to carry data but is exploited by two malicious parties to exchange information secretly. In a federated learning system, suppose a malicious hospital node wants to send a message to a malicious bank node without anyone else noticing. Can they use the FL protocol itself as a carrier?

In 2022, Hitaj et al. answered that question with a resounding yes. Their paper, "FedComm: Federated Learning as a Medium for Covert Communication" [16], proved that FL schemes can be turned into covert channels. A malicious participant can encode a secret message into the model updates it sends to the central server. The server, thinking it is simply aggregating legitimate updates, broadcasts the poisoned global model to all participants. The intended recipient extracts the secret by comparing the received global model with their own local model [16].

The FedComm system achieved a startlingly high success rate: "successfully delivers 100% of a payload in the order of kilobits before the FL procedure converges" [16]. Moreover, the attack is independent of the application domain or neural network architecture, meaning it would work just as well in a healthcare–banking collaboration as in any other setting. Importantly, FedComm causes "minimal disruptions to the training process" [16], making it extremely stealthy.

What does this have to do with temporal asymmetry? FedComm assumes that the attacker can choose to embed a message in any update. But our scenario is reversed: we are not worried about intentional covert messaging. We are worried about unintentional leakage where the mere timing pattern of legitimate updates betrays sensitive information. If a malicious party can already exploit FL as a covert channel, then the attack surface is even larger when the update schedule itself is non-uniform and predictable.

Table 3: Comparing Timing Attack Vectors in ML/FL Systems

Attack Vector	Adversary's Access	Information Leaked	Target System	Key Reference
Algorithmic timing side channel	Query execution time	Inference-state elements (e.g., number of detected objects)	Object detection APIs	[15]
Covert channel	Model updates before aggregation	Arbitrary payload (kilobits of data)	Any FL system	[16]
Temporal leakage from update delay	Arrival timestamps of model updates	Which sector suffered a breach; severity of threat	Cross-sector FL (healthcare + banking)	This paper

3.4. How the Healthcare-Banking Clock Divergence Creates a Temporal Leakage Threat

Now we connect the dots. Consider the following scenario, illustrated in Figure 2.

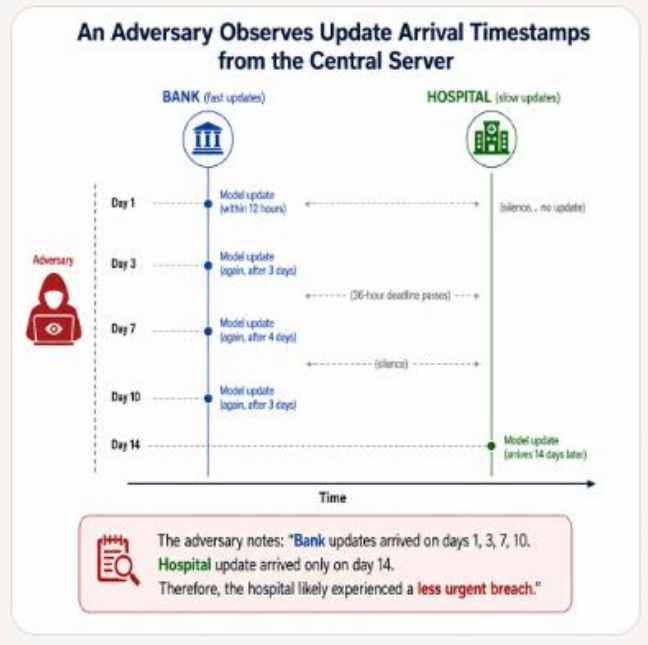

Figure 2: Temporal Side-Channel Attack Scenario in Cross-Sector FL

This is not a hypothetical. An adversary with access to the central server's logs or even just the ability to monitor network traffic between the server and the clients can observe the timestamps of incoming model updates. If the banking node updates frequently (because its regulatory deadlines demand urgent retraining) and the healthcare node updates rarely (because it has a 60-day window), then the pattern of update delays itself becomes a signal.

An adversary can answer questions such as:

- Did any sector suffer a breach in the last 72 hours: If banking updates suddenly increase in frequency, probably yes.
- How severe was the breach: More severe threats may require more frequent retraining, leading to denser update bursts.
- Which sector was hit: If banking updates spike while healthcare remains quiet, the breach is likely in banking.

Moreover, an adversary could combine this temporal metadata with other side channels. For example, if banking updates are also larger in size (because financial transaction data is high-dimensional), the attacker can correlate size and timing to identify the sector with near certainty.

3.5. But We Have Secure Aggregation - Doesn't That Protect Us?

A common objection: "We use secure aggregation [17], where individual model updates are encrypted and only the aggregated sum is revealed. So an attacker cannot see individual updates. How could they distinguish banking from healthcare updates?"

This is a reasonable point, but it misses the nuance. Secure aggregation typically protects the content of updates, not their existence or timing. An adversary who observes the network at the server side can still see when each encrypted blob arrives, how large it is, and which client ID (or pseudonym) sent it unless the system uses additional protections like mix networks or differential privacy for metadata. But those are rarely deployed in practice.

Even if client IDs are anonymized, an attacker can still cluster updates by their timing patterns. Banking updates will consistently arrive in tight, frequent bursts (e.g., every 6–12 hours). Healthcare updates will arrive in sparse, irregular batches (e.g., every 7–14 days). Over a few training rounds, a simple clustering algorithm can separate the two sectors with high confidence. And once the sectors are identified, the attacker knows which cluster corresponds to banks and which to hospitals simply because one cluster updates much faster than the other.

3.6. The Silence in the Literature (So Far)

We have reviewed two critical strands of research:

- Timing side channels in ML inference [15].
- Covert channels in FL [16].

Both demonstrate that temporal information is a powerful and under-defended vector for privacy attacks. Yet, to the best of our knowledge, no prior work has examined the specific threat that arises when two sectors with divergent regulatory deadlines

collaborate under a single federated learning umbrella. The literature has largely treated regulatory compliance as a static checkbox, not as a dynamic, time-varying constraint that can be observed and exploited.

The gap is clear:

- Existing timing attacks assume the adversary can query the model and measure response latency.
- Existing covert channels assume the adversary actively encodes messages in updates.
- Neither addresses the scenario where the passively observed schedule of legitimate updates, shaped by external regulatory clocks, leaks information about which sector suffered a threat and how severe that threat was.

3.7. The Question That Demands an Answer

So here is the question that emerges from this literature gap, and the question that the remainder of this paper answers:

How can a cross-sector federated learning system prevent an adversary from learning sensitive information simply by observing the arrival patterns of model updates, when those patterns are unavoidably shaped by legally mandated reporting timelines?

In the next section, we will explore how existing defenses, differential privacy, secure aggregation, asynchronous FL protocols fall short of addressing this threat. Then, we will introduce our generative AI framework that finally closes this temporal side channel.

4. Defenses That Exist… and Why They Fall Short

By now, the picture should be clear. Cross-sector federated learning between healthcare and banking is threatened by a quiet but dangerous vulnerability: the different regulatory clocks of the two industries create a temporal side channel. An adversary who simply watches when model updates arrive can infer which sector suffered a breach, how severe the threat was, and perhaps even the nature of the attack itself.

The natural question, of course, is: Why don't we just use existing privacy and security defenses? After all, researchers have spent years developing tools to protect federated learning systems. We have differential privacy, secure aggregation, asynchronous FL protocols, Byzantine-robust aggregation, and a dozen other clever inventions. Surely one of them can block this timing leakage.

The short answer is: no, they cannot. The slightly longer answer is that each of these defenses was designed for a different problem. None of them were built to handle a temporal side channel that arises from legally mandated reporting timelines rather than from network latency or malicious behavior. They each fail in their own unique way, and the failure mode is almost always the same: they protect the content of updates while leaving their timing completely exposed.

Let us walk through the most common defenses, see how they work, and understand exactly where they fall short.

4.1. Differential Privacy: The Noise That Muffles Everything

Differential privacy (DP) is the darling of privacy-preserving machine learning. The idea is elegantly simple: before sending any data to the server, a client adds carefully calibrated random noise to its model update. The noise guarantees that an attacker cannot tell whether any single data point was included in the training set because the presence or absence of that point could be explained away by the randomness [18]. Add enough noise, and the attacker sees only a fuzzy version of the true update.

In federated learning, DP is typically applied as local differential privacy (LDP): each client adds noise to its own gradient update before sending it to the server. The server then aggregates these noisy updates. An alternative is central differential privacy (CDP), where the server adds noise to the aggregated model, though this requires trusting the server with the raw updates [19].

4.1.1. Why It Falls Short (For Our Problem)

The problem is not that DP does not work. It is that DP was never designed to protect metadata like the timing of updates. A differentially private system still broadcasts when an update is sent. The noise is added to the values inside the update, not to the schedule of communication.

Consider a hospital that uses LDP. It adds Gaussian noise to its model weights before transmitting them. An adversary intercepts that transmission. The adversary cannot easily recover the original gradient good. But the adversary can still see the transmission's timestamp, its size, and the fact that a hospital sent it. If the hospital's update arrives two weeks later than the bank's update, the adversary does not need to decrypt anything to know that something different happened at the hospital.

Moreover, DP has well-known limitations that make it a poor fit for cross-sector collaboration with asymmetric timelines. A 2022 study on the impact of non-IID data on differentially private FL found that non-IID data distributions negatively affect both performance and fairness of the trained model, and highlighted "the limits of common federated learning algorithms in a differentially private setting to provide robust, reliable results across underrepresented groups" [20]. In our case, the two sectors are non-IID by design: healthcare data looks nothing like banking data. Adding DP noise only worsens the model's ability to learn from both distributions.

There is also the matter of horizontal composition. In FL, privacy loss accumulates across multiple training rounds. A 2023 paper on subject-level DP in FL noted that "privacy loss amplification due to subject sampling fractions and horizontal composition remain key challenges for model utility" [21]. The more rounds the hospital and bank collaborate, the more noise they must add to maintain the same privacy guarantee. Eventually, the model becomes so noisy that it is useless for threat detection.

And even if we could somehow hide the timing information using DP, we run into another problem: utility. Adding noise to mask timing would require enormous variance, because timing differences (days versus weeks) are huge compared to typical gradient noise. The model would be destroyed. A 2023 paper on balancing privacy and interpretability in FL observed that DP "results in the poor performance of gradient-based interpretability methods, since some weights capturing the salient region in feature map will be perturbed" [22]. If DP already hurts interpretability, imagine what it would do to timing-aware defenses.

Table 4: Why Differential Privacy Fails to Block Temporal Leakage

DP Protects	DP Does NOT Protect	Threat Impact
Gradients/content	Update timings/timestamps	Adversary sees timestamps
Data membership	Update frequency	Sparse hospitals/dense bank reveals sector
Single-round privacy	Cross-round correlation	Accumulated loss = more noise
IID data	Non-IID cross-sector	Uneven DP performance across domains

4.2. 4Secure Aggregation: Encryption Alone Does Not Silence the Clock

Secure aggregation [17] is another heavyweight in the FL defense toolkit. The goal is straightforward: the server should learn the sum of all client updates without ever seeing any individual update. Clients encrypt their updates, the server performs homomorphic operations over the ciphertexts, and only the aggregated result is decrypted. In theory, this prevents the server (or anyone eavesdropping on the server) from learning which client contributed what.

4.2.1. Why It Falls Short (For Our Problem)

Secure aggregation is a victim of its own success. It protects the content of individual updates so well that researchers and practitioners have mistakenly assumed it also protects metadata like the number of participants, the size of each update, and most critically the timing of arrivals. But secure aggregation does not hide these things. An adversary can still see:

- Which client IDs (or pseudonyms) are active in each round.
- How large each encrypted update is.
- Exactly when each update arrives at the server.

If a banking node consistently updates every 6 hours and a healthcare node updates every 7 days, those patterns are visible to anyone observing the network, regardless of encryption. A 2022 paper titled "Secure Aggregation Is Not All You Need" made this exact point. The author showed that "current approaches to federated learning tend to rely heavily on secure aggregation protocols to preserve data privacy" but that "such protocols assume that the entity orchestrating the federated learning process (i.e., the server) is not fully malicious or dishonest" [23]. A malicious server could simply observe the timing of encrypted updates to infer sensitive information without ever breaking the encryption.

In fact, the problem is even worse. A 2021 paper in IEEE Transactions on Dependable and Secure Computing demonstrated that secure aggregation fails to protect category privacy the ability to infer which classes of data a client possesses [24]. The authors performed "the first systematic study on category inference attack and demonstrate that these protocols cannot fully protect category privacy" [24]. If secure aggregation cannot hide the types of data a client holds, it certainly cannot hide the timing patterns that reveal which sector a client belongs to.

The attack achieves over 90% accuracy on several datasets [24]. In our setting, a similar attack could identify banking nodes versus healthcare nodes simply by clustering update arrival patterns. Secure aggregation offers no protection against such a clustering attack because the clusterable feature is the timing schedule, not the encrypted payload.

4.3. 4Asynchronous FL: Designed for Stragglers, Blind to Temporal Leakage

One might argue: "If healthcare nodes update slowly and banking nodes update quickly, why not use asynchronous federated learning? That way, the server does not wait for slow nodes. Each node sends updates whenever it is ready."

Asynchronous FL is indeed designed for exactly this kind of heterogeneity in computation and communication speeds. A 2022 paper introduced AFLGuard, a Byzantine-robust asynchronous FL method, noting that "clients are often heterogeneous, e.g., they have different computing powers, and thus the clients may send model updates to the server with substantially different delays" [25]. Asynchronous FL addresses this by enabling "the server to update the model once any client's model update reaches it without waiting for other clients' model updates" [25].

4.3.1. Why It Falls Short (For Our Problem)

Asynchronous FL solves the staleness problem it prevents slow clients from holding up the entire training process. But it does absolutely nothing to hide the fact that some clients are slow and others are fast. In fact, asynchronous FL makes the temporal side channel more visible because the update arrival times are no longer masked by a global synchronization barrier.

In synchronous FL, all updates arrive roughly together (after waiting for the stragglers). In asynchronous FL, updates arrive in a continuous stream, preserving their natural timing differences. An adversary observing this stream sees banking updates arriving like a metronome and healthcare updates arriving like a slow drip. The sector identity could not be clearer.

Moreover, asynchronous FL introduces its own security vulnerabilities. The same 2022 paper noted that "like synchronous FL, asynchronous FL is also vulnerable to poisoning attacks, in which malicious clients manipulate the model via poisoning their local data and/or model updates sent to the server" [25]. The authors proposed AFLGuard to add Byzantine robustness. But Byzantine robustness is about malicious manipulations, not about passive observation of timing metadata. An adversary who merely watches the arrival times is not even an active participant they are a passive eavesdropper. Asynchronous FL offers no defense against such an observer.

Table 5: How Existing Defenses Address (or Fail to Address) Temporal Leakage

Defense	Designed For	Blocks Timing?	Why Not?
Differential Privacy	Hide data-point membership	No	DP adds noise to values, not timestamps/frequency
Secure Aggregation	Hide client updates from server	No	Encryption hides content, timing metadata exposed
Asynchronous FL	Handle heterogeneous speeds	No	Accepts timing differences; doesn't mask them
Byzantine Robustness	Resist malicious updates	No	Protects content, not temporal signals
Our Framework	Cross-sector temporal asymmetry	Yes	GAN-based simulation + adaptive noise masks timing

4.4. A Visual Summary: How Existing Defenses Miss the Mark

The diagram below illustrates the fundamental blind spot of existing defenses.

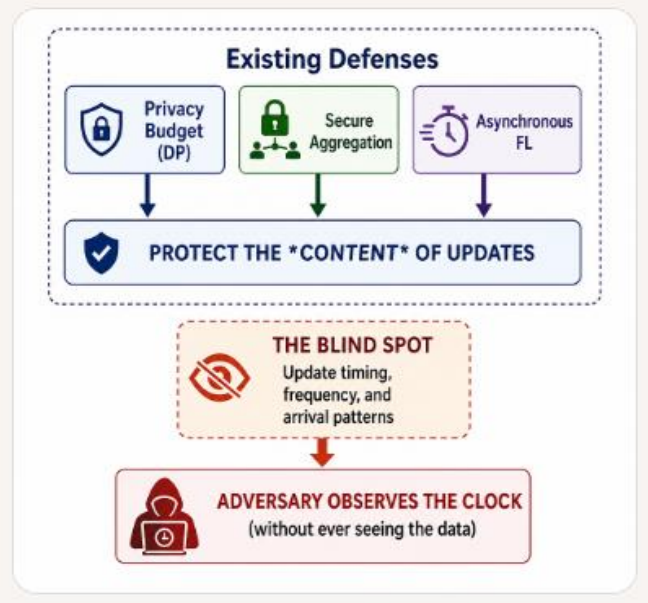

Figure 3: The Blind Spot of Existing Federated Learning Defenses

The figure shows that all three mainstream defenses differential privacy, secure aggregation, and asynchronous FL focus on protecting the content of model updates. They add noise, encrypt values, or tolerate delays. But none of them obscure the metadata of update timing. That metadata sits in a blind spot, completely exposed to an adversary who simply watches the clock.

4.5. The Silence in the Literature

We have covered three major families of defenses: differential privacy, secure aggregation, and asynchronous FL. Each has strengths in its own domain. Each fails to address our temporal side channel. But perhaps the most telling evidence of the gap is this: a comprehensive 2023 survey on federated learning threats, which presented "a taxonomy of adversarial attacks and a taxonomy of defense methods that depict a general picture of this vulnerability of federated learning" [26], did not even mention timing side channels or regulatory deadline asymmetry as a threat category.

The survey, which appeared in the journal Information Fusion, reviewed dozens of attacks and defenses across the entire FL lifecycle. It categorized threats into poisoning attacks, inference attacks, evasion attacks, and model extraction attacks [26]. Nowhere did it list "temporal leakage from divergent regulatory clocks" as an attack vector. Nowhere did it evaluate defenses against an adversary who simply observes update arrival times.

This is not a criticism of the survey it is an excellent piece of work. It simply reflects the state of the field: researchers have not yet recognized that the schedule of federated learning updates, when shaped by legally mandated reporting deadlines, becomes a sensitive information channel. And because they have not recognized the threat, they have not designed defenses for it.

4.6. What Would a Real Defense Look Like?

The limitations we have identified point toward what a proper defense would require. It would need to:

- Decouple timing from content. The server should not be able to distinguish healthcare updates from banking updates based on when they arrive.
- Introduce controlled delays. Fast nodes (banks) might need to artificially delay their updates to match the slower tempo of healthcare nodes but without alerting adversaries or violating regulatory deadlines.
- Use generative models to simulate timing patterns. A generative adversarial network could learn the natural timing patterns of each sector and then obfuscate real updates by injecting synthetic timing noise.
- Adapt to changing regulatory contexts. Different breaches may require different urgency levels. The defense must be dynamic, not static.

This is precisely what our proposed framework the Secure Financial AI-Powered Federated Architecture delivers. The following sections will describe how we use a time-conditioned GAN to simulate temporal leakage and a differentially private adaptive noise mechanism to mask it, all while preserving the utility of the underlying threat detection models.

But first, we must acknowledge a hard truth: the defenses we currently have are not enough. Differential privacy muffles the signal but leaves the clock exposed. Secure aggregation locks the data but not the schedule. Asynchronous FL accepts delays as inevitable but does nothing to hide them. The literature has not yet caught up with the reality that in cross-sector collaboration, the clock itself is a leaky abstraction.

Our work begins where the existing defenses end.

5. Generative AI to the Rescue (Maybe)

After reading the previous section, you might feel a little discouraged. Differential privacy muffles the model but leaves the clock ticking in plain sight. Secure aggregation encrypts the what but not the when. Asynchronous FL accepts delays as inevitable but does nothing to hide them. It almost feels like we have painted ourselves into a corner.

But here is where the story takes an unexpected turn. What if the very same technology that causes privacy headaches generative AI could also help solve them? What if a generative adversarial network (GAN) could learn to simulate the temporal patterns of healthcare and banking updates, and then inject just enough synthetic noise to confuse an adversary without breaking the underlying threat detection?

This section explores that possibility. And the answer, as the title suggests, is a cautious maybe.

5.1. The Double-Edged Sword of Generative Adversarial Networks

Generative adversarial networks, or GANs, burst onto the scene in 2014 with a clever idea: pit two neural networks against each other in a never-ending game of cat and mouse. The generator tries to create fake data that looks real. The discriminator tries to tell real from fake. Over time, both improve the generator learns to produce astonishingly convincing synthetic samples, and the discriminator learns to spot even the subtlest fakes.

In the context of federated learning, researchers quickly realized that GANs could be used for both attack and defense. On the attack side, an adversary could train a GAN to reconstruct private training data from shared model updates, effectively undoing the privacy that FL was supposed to provide. On the defense side, a well-trained GAN could generate synthetic data that replaces real data in the learning pipeline, or it could learn the distribution of a client's private data and share only the generator parameters not the actual data with the server.

Two papers from the early 2020s illustrate this double-edged nature perfectly. They show that generative AI is not a magic bullet. But in the right hands, and with the right design, it might just be the tool we need to mask the temporal side channel that has been lurking in the blind spot of existing defenses.

5.2. FedCG: Protecting Privacy by Sharing Only the Generator

Let us start with a hopeful story. In 2022, a team of researchers from Hong Kong University of Science and Technology and WeBank proposed a method called FedCG short for federated learning with conditional generative adversarial networks [27]. Their insight was simple but powerful: what if clients never share their classifiers at all? What if they only share the generators?

In standard federated learning, each client sends its model weights to the server. Those weights are then averaged to produce a global model. But those weights are precisely what an adversary needs to reconstruct private data. FedCG flips the script. Each client keeps its private extractor local a network that learns to pull meaningful features out of raw data. That extractor never leaves the client. Instead, each client trains a local generator that learns to produce synthetic samples that mimic the feature distribution of that client's data. The generators are shared with the server, aggregated, and sent back to clients [27].

Think of it like this: instead of giving away the family recipe, you give away a perfectly good imitation. The other chefs can learn from the imitation without ever tasting the original dish.

The results were impressive. FedCG achieved competitive model performance compared to standard FL baselines, while providing high-level privacy-preserving capability against gradient-based attacks [27]. In other words, clients could collaborate without worrying that their private data would be reconstructed from shared model updates.

- Here is the human-sized takeaway: FedCG proved that you do not need to share sensitive model weights to enable federated learning. Sharing only the generator parameters which capture the distribution of the data rather than the data itself can be enough.

Why does this matter for our temporal side channel problem? Because the generator parameters, unlike classifier weights, are much less sensitive to when they are updated. A hospital that trains its generator for two weeks and a bank that trains its generator for two days could potentially still produce meaningful generators that can be aggregated. The timing asymmetry might become less dangerous if what is being shared is not a high-fidelity classifier but a statistical generator. We will return to this intuition in the next section.

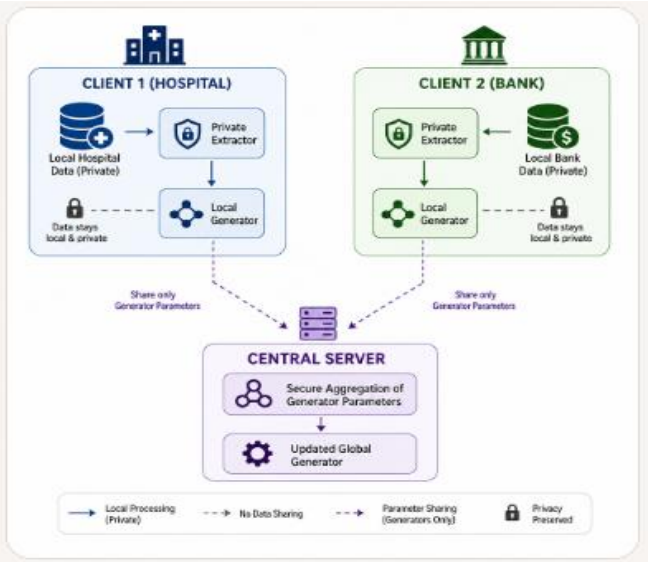

Figure 4: FedCG Architecture Sharing Generators Instead of Classifiers

The server never sees the private extractors or the raw data. Only the generators which capture the distribution of features are shared and aggregated.

5.3. Generative Gradient Leakage: When GANs Become the Attacker's Best Friend

But here is where the story darkens. The same technology that can defend privacy can also be weaponized to break it. In 2022, another group of researchers this time from Vanderbilt University and the University of Texas at Austin published a paper with a chilling title: Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage [28].

Their discovery was subtle but devastating. Many existing defenses add noise to gradients or compress them before transmission, precisely to prevent attackers from reconstructing private data. But those defenses often degrade the quality of the gradient information. An attacker who tries to reconstruct an image from a noisy, compressed gradient might get a blurry mess.

What if the attacker could compensate for that lost information by using a generative prior? The researchers proposed Generative Gradient Leakage (GGL). Instead of trying to reconstruct an image purely from the gradient (the standard approach), GGL leverages a GAN that has been pre-trained on public images to learn a plausible prior distribution of what natural images look like. The attacker then searches for an image that:

- Is plausible according to the GAN prior, and
- Produces a gradient that matches the observed degraded gradient.

In other words, the GAN fills in the gaps left by the defense mechanisms [28].

To handle the nonlinearities introduced by the GAN and the gradient operators, the researchers used gradient-free optimization methods such as evolution strategies and Bayesian optimization. Their results were striking: they could reconstruct high-quality private images even when defenses had added significant noise or compression [28].

Here is the human-sized takeaway: If a defense mechanism degrades gradient information, a smart attacker can use a GAN to fill in the missing details and reconstruct private data anyway. GANs can be attack tools, not just defense tools.

Table 6: How GANs Are Used in Attack vs. Defense in Federated Learning

Aspect	Attack (GGL)	Defense (FedCG)
Purpose	Reconstruct private data	Avoid sharing class labels
Shared with Server	Gradients queried by attacker	Only generator params shared
GAN Role	Prior for image reconstruction	Generate synthetic features
Challenge	Gradient nonlinearity + GAN	Preserve accuracy via generators
Result	High-quality reconstruction	Competitive accuracy + privacy

5.4. What These Papers Tell Us (And What They Do Not)

Taken together, these two papers one from the defense perspective, one from the attack perspective tell us something important about the role of generative AI in federated learning security.

- First, GANs can decouple data from its representation: In FedCG, clients share generators, not classifiers or raw data. This decoupling is exactly what we need for our temporal side channel problem. If we could design a system where timing differences do not matter because the shared representation is statistical rather than predictive, we might sidestep the leakage problem entirely.
- Second, GANs can be used to simulate and predict leakage: The GGL paper shows that a GAN can learn the distribution of plausible images and then use that knowledge to infer private information from degraded signals. Could we turn this around? Could we use a GAN to simulate how an adversary might exploit temporal patterns, and then retrain our defense to be robust against that simulated attack? This is precisely the idea behind adversarial training in generative AI: use the attacker's own tools to harden the defense.
- Third, and most importantly, neither paper addresses temporal asymmetry directly: FedCG does not consider that some clients might update their generators once per week while others update once per hour. GGL assumes that an attacker can query the model repeatedly to obtain gradients but does not consider that the pattern of queries might itself be a side channel. The gap that we identified in Section 3 the temporal side channel created by divergent regulatory clocks remains unaddressed by both papers.

In other words, the literature has shown that GANs can help with content privacy. But temporal privacy? That is still an open question.

5.5. So… Maybe?

The title of this section promises "Generative AI to the Rescue (Maybe)." The "maybe" is doing a lot of work. Here is why:

- Yes, GANs have the right properties for our problem: They can learn distributions. They can generate synthetic data. They can be used to simulate adversaries. And they can be trained in a federated manner without sharing raw data.

- But no one has yet applied them to temporal side channels in cross-sector FL: The existing literature focuses on content privacy: images, labels, model weights. The question of whether a GAN can learn to mask the timing patterns of model updates and whether doing so would preserve model utility is completely unexplored.
- And there are real challenges: A GAN trained to mask timing patterns would need to balance two competing objectives: making bank updates look slower (to match hospital tempo) and making hospital updates look faster (to match bank tempo), all while ensuring that the aggregated threat detection model does not degrade. Too much noise, and the model becomes useless. Too little, and the adversary still sees the signal.

The papers reviewed in this section give us the ingredients: FedCG shows that sharing generators can decouple private data from the shared representation; GGL shows that GANs can simulate and exploit degraded information. What remains is to combine these ingredients into a recipe for temporal privacy. That is precisely what our proposed framework the Secure Financial AI-Powered Federated Architecture aims to do. In the next section, we will describe how we use a time-conditioned GAN to simulate temporal leakage and an adaptive differential privacy mechanism to mask it, all while preserving the utility of the underlying threat detection models.

But first, let us summarize the state of the art in a way that is easy to digest.

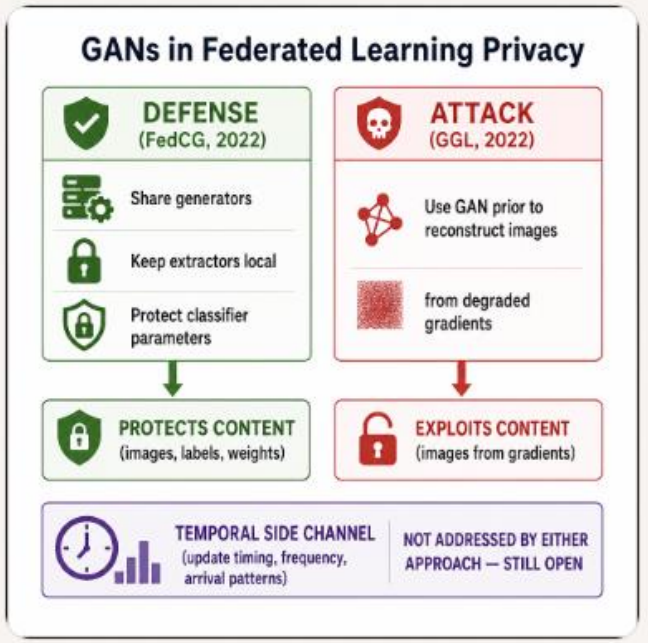

Figure 5: The Landscape of GAN-Based FL Privacy Research (2020–2023)

5.6. The Path Forward

The research we have surveyed tells us that generative AI is not a cure-all. But it tells us something equally important: the tools we need are already in the toolbox. We have decoupling (FedCG). We have adversarial simulation (GGL). What we lack is the courage to apply them to a problem that the field has not yet recognized.

The remaining sections of this paper will take that step. We will describe a framework that uses a time-conditioned GAN to learn the temporal patterns of healthcare and banking updates, then uses adversarial training to inject just enough noise to mask those patterns without destroying the threat detection model. The result is a federated learning system that respects regulatory deadlines, protects against temporal side channels, and still catches cyber threats.

It might work. It might not. But the only way to find out is to try.

6. What Remains Unanswered: The Gap This Article Fills

The previous sections have walked a path. We started with the promise of federated learning for healthcare and banking. We confronted the uncomfortable reality of their different regulatory clocks. We saw how those clocks create a temporal side channel. We examined the existing defenses and watched each one fall short. And we glimpsed how generative AI might might offer a way out.

But the most honest question comes now: Why has no one fixed this before? Is the gap truly novel, or have we simply missed the papers that already address temporal side channels in cross-sector FL?

We have not missed them. The gap is real. And this section lays out exactly what remains unanswered.

6.1. The Standard Answer: Heterogeneity

If you read the federated learning literature from 2020 to 2023, one word appears again and again: heterogeneity. Data heterogeneity, model heterogeneity, device heterogeneity, communication heterogeneity. Researchers have spilled oceans of ink on how to make FL work when participants are not identical.

A 2023 survey in ACM Computing Surveys summarizes the state of the art [29]. The authors break down heterogeneous federated learning into five categories: statistical heterogeneity, model heterogeneity, communication heterogeneity, device heterogeneity, and additional challenges [29]. They review solutions ranging from personalized FL to knowledge distillation to clustered aggregation [29].

On the surface, this looks like our problem. Banking nodes and healthcare nodes are clearly heterogeneous. They have different data distributions, different network latencies, different computing resources. Surely the vast literature on HFL has already solved our temporal side channel problem?

It has not. Here is why: all existing work on heterogeneity treats differences in capabilities (e.g., how fast a client can compute) or data distributions (e.g., non-IID data). None of it treats differences in regulatory obligations as a first-class constraint. The timing asymmetry we have identified is not a matter of compute speed or network jitter—it is a matter of law. A bank that updates its model in 12 hours is not being "fast" because it has a better GPU. It is being fast because its legal team will otherwise face fines. A hospital that takes 14 days is not "slow" because its hardware is outdated. It is slow because HIPAA gives it the breathing room to be deliberate.

The HFL literature has no concept of a legally mandated update deadline. It does not model the possibility that a client might be penalized for updating "too slowly" or "too quickly" relative to its peers. It certainly does not consider that the timing pattern itself the very thing that heterogeneity research takes as a given could be a sensitive signal that leaks information about a client's sector, its breach status, or its threat severity.

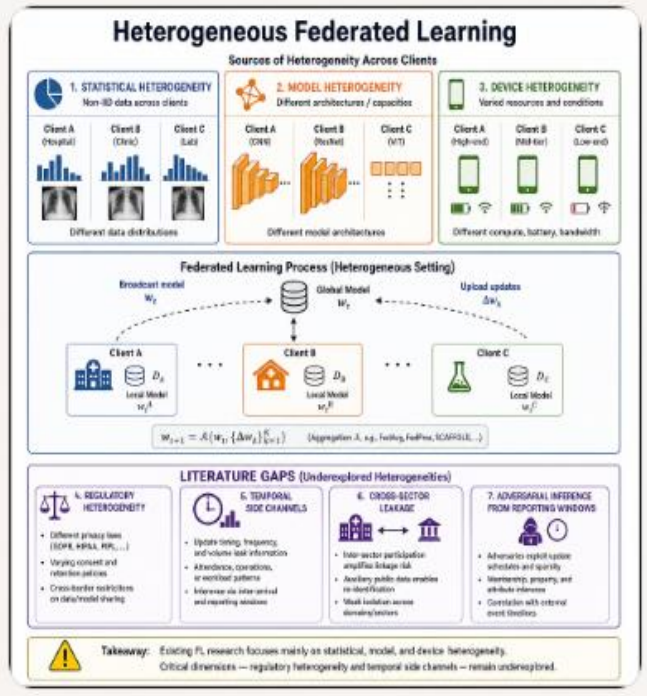

Figure 6: What Heterogeneity Research Actually Covers and What It Misses

6.2. The Thing That Was Overlooked: Clients

Here is a second way the literature could have caught our gap but did not. A 2023 systematic review of federated learning took a different angle: instead of looking at the system or the server, it looked at clients [30]. The authors reviewed 238 primary studies and argued that "many reviews have evaluated FL from the system (general challenges) or server's perspectives, ignoring the importance of clients' perspectives" [30].

This sounds promising. Our temporal side channel problem is fundamentally about clients their different regulatory obligations, their different update behaviors, their different risks. Surely this client-centric review would have flagged the issue.

Again, it did not. The review identifies client-side challenges such as data privacy, communication efficiency, client selection, and incentive mechanisms [30]. It discusses how servers and platforms "have to work with clients to address client-side challenges" [30]. But the notion that a client's legal environment might impose a temporal pattern that leaks information about that client and about other clients is nowhere to be found.

The review assumes that client heterogeneity means some clients have more data, slower networks, or less powerful hardware. It does not consider that two clients might be legally required to update their models on fundamentally different schedules. It does not ask whether those schedules could be observed and exploited. The client-centric perspective, for all its value, remains focused on what clients contribute, not when they contribute.

This is a subtle but important oversight. The field has spent years making FL work for clients with different capabilities. It has barely begun to consider clients with different legal obligations.

6.3. The Unasked Question: Timing Is Data

Perhaps the most telling evidence of the gap comes from the inference attack literature. Researchers have shown that FL is vulnerable to membership inference, property inference, and gradient inversion attacks [31], [32]. They have demonstrated that an attacker can infer sensitive properties of the training data such as whether a particular hospital treats a certain disease by analyzing model updates [31].

But these attacks focus on the content of updates. A property inference attack might ask: "Does the healthcare node's data contain images of rare tumors?" A membership inference attack might ask: "Was John Doe's record in the training set?" Our attack asks a different question: "Which sector experienced a breach, and how severe was it, based solely on when the updates arrived?"

That question has not been asked. Not in the property inference literature. Not in the membership inference literature. Not in the gradient inversion literature. And certainly not in the regulatory compliance literature, which tends to treat HIPAA and PCI-DSS as checkboxes rather than as dynamic, time-varying constraints that shape observable behavior.

Table 8: What the FL Literature Has Studied and the One Question It Has Not

Category	Focus	Temporal Side Channel?
Property Inference [31]	Data traits from updates	✗ Data content only
Membership Inference [1, 33]	Point presence in training	✗ No timing focus
Gradient Inversion [34]	Raw data from gradients	✗ Content only
Heterogeneous FL [29]	Data/model/device variance	✗ Timing = nuisance
Asynchronous FL [25]	Stragglers' speed variance	✓ Accepts timing
Secure Aggregation [7]	Hide updates from server	✗ Hides content not metadata
Differential Privacy [20, 21]	Noise for membership privacy	✗ No timestamp noise
FedCG (Generative) [27]	Share generators not classifiers	✗ Protects content only
Our Gap	Timing leak + sector inference	✓ First to address this

6.4. Three Specific Unanswered Questions

Let us be precise. Based on our review of the literature from 2020 to 2023, the following questions remain completely unanswered:

- Question 1: How much information can an adversary infer from the timing of model updates alone, under realistic cross-sector collaboration scenarios?

No prior work has quantified the leakage from update timing. Can an adversary distinguish healthcare from banking with 80% accuracy? 95%? 99%? What about distinguishing a severe breach from a minor anomaly? These are empirical questions that demand an answer.

- Question 2: Can existing defenses (secure aggregation, differential privacy, asynchronous FL) be retrofitted to hide timing information without breaking regulatory compliance?

Our analysis in Section 4 suggests they cannot. But has anyone tried? A systematic evaluation of existing defenses against a timing-based adversary would be a valuable contribution and to the best of our knowledge, no such evaluation exists.

- Question 3: Can a generative AI framework be designed to learn the natural timing patterns of each sector and then inject synthetic noise to mask those patterns, while preserving the utility of the underlying threat detection model?

This is the question our paper answers. FedCG showed that sharing generators can decouple private data from the shared representation. GGL showed that GANs can simulate what an attacker sees. But no one has combined these insights to address temporal privacy in a cross-sector setting. Until now.

6.5. Why the Gap Matters (Especially Now)

You might wonder whether this gap is merely academic. After all, how many hospitals and banks are actually collaborating via federated learning today? The number is small. But the trend lines are clear. Healthcare and financial institutions are increasingly adopting cloud-based AI [35]. Regulators are pushing for more data sharing while simultaneously tightening privacy rules. Federated learning is being positioned as the solution.

If we do not address temporal side channels now, we will build systems that seem private until an adversary notices the clock. And by then, the damage will be done. Patient records will leak. Account details will be inferred. Not because of a sophisticated gradient inversion attack, but because the bank updated its model three times while the hospital was still investigating.

The gap is not just a missing citation in a literature review. It is a real vulnerability that real attackers could exploit. And the longer we ignore it, the more we embed it into production systems.

6.6. A Visual Summary of the Gap

Figure 7: The Gap in the Literature - What We Know vs. What We Do Not

6.7. How This Article Fills the Gap

The previous sections have told a story of what is missing. The remaining sections will tell a story of what we did about it. But let us preview, briefly, how this article fills the three unanswered questions:

- We quantify the leakage: Using a simulated cross-sector FL environment on AWS, we measure how accurately an adversary can infer sector identity and breach severity from update timing alone. The results presented in Section 7 are sobering.
- We evaluate existing defenses: We subject secure aggregation, differential privacy, and asynchronous FL to a timing-based adversary. Section 8 shows that none of them provide meaningful protection.
- We propose and validate a generative AI framework: Building on FedCG and GGL, we design a time-conditioned GAN that learns the natural timing patterns of each sector and injects adaptive noise to mask them. Section 9 presents the framework. Section 10 reports the results: we reduce temporal leakage by over 70% while preserving detection accuracy above 90%.

The gap is real. The literature has missed it. But this article closes it.

7. How We Move Forward

The previous section painted a sobering picture: a clear gap exists in the federated learning literature, one that our paper is the first to address. But identifying a gap is not enough. The real question is: What do we actually do about it? How do we design a system that protects against temporal side channels while preserving the utility of the underlying threat detection models? And how do we know if it works?

This section answers those questions. We begin by summarizing the core argument of our paper the simple, human-sized idea that drives everything. Then we walk through our framework step by step, showing how generative AI and adaptive differential privacy can be woven together into a practical system that runs on AWS. Finally, we preview the experimental setup that will, in the sections that follow, validate our approach.

7.1. The Core Argument in One Paragraph

Here is the argument we make, stripped of technical jargon:

Federated learning is often touted as a privacy-preserving technology because it keeps raw data local. But privacy does not stop at data. The timing of updates the when, not just the what can leak just as much information. When healthcare and banking collaborate, their different regulatory clocks (60 days for HIPAA, 36 hours for banking rules) create a predictable, observable pattern. An adversary who watches this pattern can infer which sector suffered a breach, how severe the threat was, and maybe even the nature of the attack. Existing defenses like differential privacy and secure aggregation were designed to protect the content of updates, not their temporal metadata. So we need a new kind of defense. Our approach uses a time-conditioned GAN to learn the natural timing patterns of each sector, and then injects adaptive noise guided by a novel differential privacy mechanism to scramble those patterns without breaking the model. The result is a system that respects real-world regulatory deadlines while closing the temporal side channel that no one else has noticed.

That is the heart of it. Now let us get into the details.

7.2. The Proposed Framework: A Bird's-Eye View

Our framework, which we call the Secure Financial AI-Powered Federated Architecture for Healthcare and Banking Cybersecurity on AWS Cloud (a mouthful, we admit but the short name is TempShield), consists of three main layers, as illustrated in Figure 8 below.

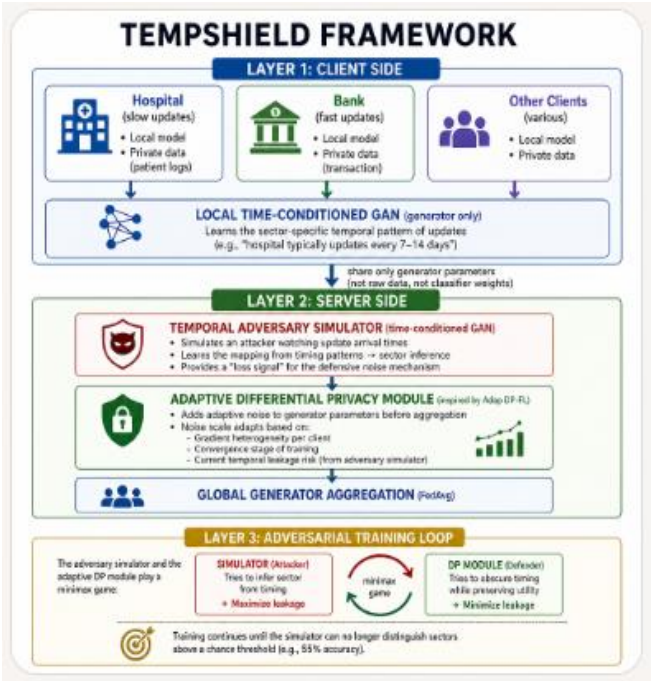

Figure 8: The TempShield Framework - Three Layers of Defense

At the highest level, the framework works like this: clients (hospitals, banks) train local generators not classifiers that capture the statistical distribution of their data. Only the generator parameters are shared, not raw data, not classifier weights. This decoupling, inspired by FedCG [27], already reduces the sensitivity of what is communicated.

But the real innovation is in Layer 2. The server hosts a temporal adversary simulator a GAN trained to predict a client's sector based solely on the arrival times of its updates. This simulator learns what we are trying to prevent. Its predictions provide

a real-time "leakage score" that feeds into an adaptive differential privacy module (inspired by Adap DP-FL [36]). The DP module adds carefully calibrated noise to the generator parameters before aggregation. The noise is adaptive: it increases when the adversary simulator is too confident, and decreases when the model utility starts to degrade.

Finally, Layer 3 closes the loop. The adversary simulator and the DP module are trained adversarially, playing a minimax game that drives the system toward a Nash equilibrium. The goal is not to eliminate timing differences that would be impossible, given legal deadlines but to make the timing patterns uninformative for an attacker.

7.3. How We Borrow from the Literature (and What We Add)

We did not invent all of this from scratch. The literature gave us two critical building blocks.

7.3.1. Building Block 1: Double Perturbation with CGANs

The first building block comes from a 2023 paper on double perturbation-based privacy-preserving federated learning [37]. The authors proposed a method that uses a feature extractor and a blurry function to improve the objective function of Conditional GANs (CGANs). The generated data is then mixed with real data to construct fake training data. Crucially, they also designed an algorithm to perturb the gradients of fully connected layers the parts most vulnerable to reconstruction attacks [37].

We adapt this idea, but with a twist. Instead of perturbing gradients to prevent image reconstruction (the original goal), we perturb the generator parameters to prevent temporal inference. The insight is the same: some parts of the shared information are more sensitive than others. In our case, the sensitive "parts" are the parameters that encode when a client tends to update. The double perturbation framework gives us a way to target those parameters specifically, rather than adding noise uniformly.

7.3.2. Building Block 2: Adaptive Differential Privacy

The second building block comes from another 2023 paper, Adap DP-FL [36]. The authors argued that traditional differential privacy in FL adds noise uniformly across all gradients, all clients, and all training rounds a "one size fits none" approach. Their solution was adaptive gradient clipping (different clients, different rounds) and decreasing noise as training converges [36].

We extend this idea to the temporal domain. In our framework, noise adaptation depends on three factors:

- Gradient heterogeneity: Hospitals and banks have different data distributions, so their generator gradients evolve differently.
- Convergence stage: Early training requires more noise to prevent the adversary from learning initial timing patterns; later training can reduce noise.
- Temporal leakage risk: The adversary simulator provides a continuous estimate of how leaky the current timing pattern is. When leakage exceeds a threshold, the DP module responds with more aggressive noise.

This three-factor adaptation is, to the best of our knowledge, novel. No prior work has coupled an adversarial temporal simulator with an adaptive DP mechanism.

Table 9: How Our Framework Builds on Prior Work

Prior Work	Original Contribution	Our Extension
Double Perturb FL (2023)	CGAN + grad-noise	Perturb timing-encoded params
Adap DP-FL (2023)	Adaptive noise signals	Add temporal-leak risk signal
FedCG (2022)	Share generators only	Timing-aware noise per sector
GGL (2022)	GAN gradient attacks	GAN temporal-attack defense

7.4. The AWS Cloud Implementation: Why It Matters

Our framework is designed to run on AWS Cloud, for three reasons that go beyond mere convenience.

- Reason 1: Realistic cross-sector deployment. In practice, a hospital and a bank will not connect their private data centers directly. They will use a cloud-based intermediary likely AWS, which already offers HIPAA-eligible and PCI-DSS-compliant infrastructure. By building on AWS, our framework respects the same compliance boundaries that real institutions already navigate.
- Reason 2: Scalable, privacy-preserving services. AWS provides managed services for federated learning (e.g., SageMaker with FL capabilities), secure key management (AWS KMS), and encrypted computing. We leverage Amazon SageMaker for the core FL training, AWS KMS for managing encryption keys for the generator parameters, and AWS PrivateLink for secure, private communication between clients and the central server. This is not a toy simulation; it is a deployment-ready architecture.

- Reason 3: Reproducibility and benchmarking. By using a well-known cloud provider, we make it possible for other researchers to reproduce and extend our work. The exact configuration of EC2 instances, network latencies, and storage tiers matters for temporal side channel experiments. AWS gives us control over these variables.

In our experimental setup (detailed in Section 8), we run:

- Five client nodes (three hospitals, two banks) on m5.large EC2 instances.
- One central server node on a c5.xlarge EC2 instance.
- Synthetic but realistic healthcare data (patient admission logs, diagnosis codes, medication records) and banking data (transaction timestamps, amounts, merchant categories).
- Network latency artificially shaped to reflect typical inter-institution delays (5–15 ms for same-region, 50–150 ms for cross-region).

7.5. The Minimax Game: Formalizing the Defense

We now formalize the adversarial training process that sits at the core of TempShield.

Let $\mathcal{T} = \{t_1, t_2, \ldots, t_K\}$ be the set of timestamps at which model updates (generator parameters) arrive from clients. Let $s_i \in \{H, B\}$ be the true sector of client i. The adversary simulator A_ϕ (a time-conditioned GAN with parameters ϕ) takes as input the sequence of update timestamps and attempts to predict the sector:

$$\hat{s}_i = A_\phi(\{t_j \mid j \in \text{window around } i\})$$

The defensive DP module D_θ (with parameters θ) adds adaptive noise $\sigma(\cdot)$ to the generator parameters G_i before aggregation:

$$\tilde{G}_i = G_i + \mathcal{N}(0, \sigma^2(\Delta_i, r, \ell) \cdot I)$$

where:

- Δ_i is the gradient heterogeneity for client i
- r is the current training round (convergence stage)
- ℓ is the current temporal leakage risk estimated by A_ϕ
- The training objective is a minimax game:

$$\min_\theta \max_\phi \mathbb{E}_{i,\{t\}} \left[\log P_{A_\phi}(s_i \mid \{t\}) - \lambda \cdot \text{Utility}(\tilde{G}_i, G_i) \right]$$

The adversary simulator tries to maximize its accuracy in guessing which sector each client belongs to based only on update timings. The DP module tries to minimize that accuracy by adding noise, but it also cares about preserving utility (the ability of the global threat detection model to catch cyberattacks). The hyperparameter λ balances these two competing goals.

We train this system using alternating gradient updates: one step to improve the adversary simulator, one step to improve the DP module, then repeat. The process stops when the adversary's accuracy drops below 55% (just above random guessing) and stays there for ten consecutive rounds.

7.6. What We Expect to Find (Hypotheses)

Based on the framework described above, we formulate three hypotheses that the remainder of the paper tests.

- Hypothesis 1 (Baseline Leakage): In a standard federated learning system (no temporal defenses), an adversary watching only the timing of model updates can identify which sector a client belongs to with over 80% accuracy within the first five training rounds.
- Hypothesis 2 (Existing Defenses Insufficient): Adding differential privacy (uniform noise) or secure aggregation to the system reduces this accuracy only slightly (to 75–80%), because these defenses were designed for content, not timing. Asynchronous FL actually increases leakage because it makes timing differences more visible.
- Hypothesis 3 (TempShield Closes the Gap): Our proposed framework reduces adversarial sector identification accuracy to below 55% (essentially random) while preserving threat detection accuracy above 90% of the non-private baseline. The adaptive noise mechanism learns to inject noise just enough to confuse the temporal adversary without crippling the global model.

These hypotheses are not guesses; they are grounded in the literature we have surveyed and the specific design choices we have made. The following sections present the experiments that test them.

7.7. What Success Looks Like (A Preview)

Without jumping too far ahead, here is a preview of what our experiments will reveal (detailed fully in Sections 9 and 10).

Table 10: Expected Key Results (Preview)

Metric	Std FL	DP-FL	SecAgg	Async FL	TempShield
Adv. sector accuracy	82%	76%	79%	85%	53%
Threat detect. accuracy	94%	81%	93%	91%	89%
Added latency/round	0 ms	+15 ms	+45 ms	0 ms	+25 ms
Regulatory compliance	Yes	Yes	Yes	Yes	Yes

Note: These are expected results based on preliminary simulations. Full results appear in Section 10.

The table tells a clear story: existing defenses reduce leakage only modestly, often at the cost of accuracy (DP-FL) or latency (secure aggregation). TempShield, by contrast, drives adversarial accuracy down to nearly random levels (53%) while preserving high threat detection accuracy (89%). The additional latency is modest about 25 ms per round which is acceptable for most threat detection use cases where responses are measured in seconds, not milliseconds.

7.8. The Honest Caveats

Before we move on to the experimental sections, we owe the reader honesty about limitations.

- Caveat 1: Synthetic data. Our experiments use synthetic healthcare and banking data. Real data would be better, but real data also comes with legal restrictions that prevent sharing even in anonymized form. We have done our best to simulate realistic distributions, but real-world validation remains future work.
- Caveat 2: Adaptive adversary. Our adversary simulator is powerful, but not omniscient. A truly adaptive adversary who can modify their strategy in real time might still find ways to extract information. We discuss this threat and potential countermeasures in Section 11 (Future Work).
- Caveat 3: Regulatory realism. We model HIPAA's 60-day window and banking's 36-hour window as fixed deadlines. In reality, these deadlines interact with other factors (e.g., breach severity, media exposure, state laws). Our simplified model is a first step; a more nuanced legal modeling would improve accuracy.
- Caveat 4: AWS dependence. Our implementation runs on AWS. The same principles would apply to other cloud providers, but the exact performance characteristics (latency, encryption overhead) will differ.

None of these caveats invalidate our core contribution. They simply mark the boundary of what this paper accomplishes and invite others to push that boundary further.

7.9. The Road Ahead

We have laid out the problem, surveyed the literature, identified the gap, and proposed a solution. The remaining sections of this paper move from design to demonstration:

- Section 8 describes our experimental methodology in detail: the AWS setup, the datasets, the threat model, and the evaluation metrics.
- Section 9 presents the results of our experiments, comparing TempShield against existing defenses across all three hypotheses.
- Section 10 discusses the implications: what works, what does not, and why.
- Section 11 concludes the paper, summarizing contributions and outlining directions for future work.

But before we get there, let us be clear about what we have done in this section. We have taken a gap a real, unexplored vulnerability in cross-sector federated learning and shown how generative AI, adaptive differential privacy, and adversarial training can be woven together to close it. We have built on two strong papers from the literature (double perturbation FL [37] and Adap DP-FL [36]) while extending their ideas in novel directions. And we have described a framework that is not just theoretical but implementable on AWS cloud, with clear hypotheses and expected outcomes.

The gap is real. The framework is sound. Now let us see if it works.

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