

# Exploring Potential Prompt Injection Attacks in Federated Military LLMs and Their Mitigation

Youngjoon Lee, Taehyun Park, Yunho Lee, Jinu Gong, Joonhyuk Kang

**Abstract**—Federated Learning (FL) is increasingly being adopted in military collaborations to develop Large Language Models (LLMs) while preserving data sovereignty. However, prompt injection attacks—malicious manipulations of input prompts—pose new threats that may undermine operational security, disrupt decision-making, and erode trust among allies. This perspective paper highlights four potential vulnerabilities in federated military LLMs: secret data leakage, free-rider exploitation, system disruption, and misinformation spread. To address these potential risks, we propose a human-AI collaborative framework that introduces both technical and policy countermeasures. On the technical side, our framework uses red/blue team wargaming and quality assurance to detect and mitigate adversarial behaviors of shared LLM weights. On the policy side, it promotes joint AI-human policy development and verification of security protocols. Our findings will guide future research and emphasize proactive strategies for emerging military contexts.

**Index Terms:** federated learning, large language model, adversarial attack, military policy

## I. INTRODUCTION

The rise of LLMs and specialized AI hardware (e.g., Intel Gaudi) has accelerated the use of AI in many defense applications, enabling advanced analytics that were previously out of reach [1]. FL [2] provides a framework for allied nations to collaboratively train LLMs while maintaining data sovereignty [3], [4], as shown in Fig. 1. By utilizing FL, each participant preserves sensitive information while reducing the risk of unauthorized access [5]. At the same time, FL facilitates collaborative model development, it also necessitates robust security measures to defend against evolving adversarial tactics [6]. Specifically, the most pressing concern is the threat of prompt injection attacks, in which adversaries cleverly manipulate or alter input prompts to extract secret data or disrupt mission-critical systems [7], [8].

Such attacks can significantly weaken operational security, interrupt crucial decision-making processes, and undermine the trust [9] that underlies effective military cooperation among allied nations. Because FL involves a coalition of countries with numerous AI and analysis experts, addressing these threats necessitates both advanced technical solutions and policy frameworks that can accommodate varied defense requirements. Prompt injection attacks [10], [11], [12] may appear in four main forms in military context: *secret data leakage*, *free-rider exploitation*, *system disruption*, and *misinformation spread*, each posing distinct obstacles to the reliability and integrity of federated military LLMs. These threats often remain subtle and thus difficult to detect through traditional monitoring methods [13], underscoring the need

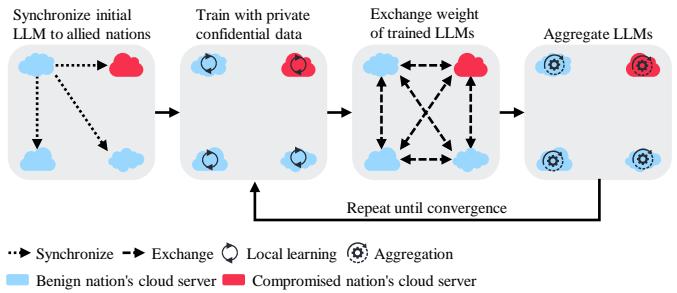


Fig. 1: FL framework for military LLM training across allied nations. The process involves four key stages: (1) initial LLM synchronization, (2) local training with private data, (3) weight exchange, and (4) model aggregation. This iterative process continues until convergence, while mitigating adversarial risks. Blue clouds represent benign nation’s servers while red clouds indicate potentially compromised servers.

for specialized methods tailored to multinational contexts. Recognizing these evolving vulnerabilities is essential for creating robust countermeasures, as overlooking them could leave critical operations open to compromise in high-stakes military scenarios.

In this paper we present an insight on how to address these risks by presenting a *human-AI collaborative* countermeasures from both technical and political perspectives. At first, we propose technical countermeasure process including red/blue team wargaming and continuous quality assurance, which help unveil hidden vulnerabilities within shared LLM infrastructures and reinforce overall system resilience. Then, we propose political countermeasure process, where military policy, domain experts, and AI experts work together to establish proper security policy for the nation. By applying either or both of these approaches, we aim to present a practical solution to counter present and emerging prompt injection threats in federated military environments. Therefore, this ensures sustained operational effectiveness and reinforces trust among coalition partners.

The main contributions of this paper are as follows:

- We introduce FL and its vulnerabilities to prompt injection attacks, highlighting the potential risks and security challenges in decentralized AI systems.
- We present four potential major threat scenarios in military FL, including secret data leakage, free-rider exploitation, system disruption, and misinformation spread.
- We propose human-AI collaborative countermeasures in

perspective of technical and political way.

- Additionally, we emphasize the need for standardized security frameworks and cooperative defense strategies.

The remainder of this paper is organized as follows. In Section II, provides background knowledge of FL and prompt injection attacks. Section III introduces the potential challenges in federated military LLMs. Section IV discusses technical and political countermeasures for the potential threats. Finally, section V explores future direction and section VI concludes the paper.

## II. BACKGROUND

In this section, we introduce the key background concepts for FL and prompt injection attacks. We specifically explore their impact on military collaborations among allied nations and the challenges they present in secure AI integration.

### A. FL Topology in Military Alliances

In data-sensitive fields such as healthcare and finance [14], FL has emerged as an established approach for secure collaborative learning due to characteristics depicted in Fig. 2. The military is also increasingly considering its adoption to enhance operational security and AI-driven decision-making. The FL architecture enables participating nations to contribute to model training while preserving their existing security infrastructure and operational autonomy [15]. This decentralized approach allows nations to leverage insights that may not be readily available within their own data sources while maintaining strict security controls. For example, the U.S. Department of Defense is actively collaborating with academia, industry, and allied nations to explore the adoption of FL for data management and responsible AI, ensuring alignment with security and operational requirements [16].

A major benefit of FL in military coalitions is its ability to enhance decision-making by integrating diverse operational experiences and data sources [17]. Different nations have unique battlefield environments, weapon systems, and threat intelligence, all of which can be incorporated into a shared model without compromising national security. This collective learning improves the adaptability of AI models to varied military scenarios, making them more effective in real-world military operations. Furthermore, FL optimizes communication efficiency by exchanging only model updates instead of raw data, significantly reducing bandwidth requirements. This streamlined communication enables real-time adaptability, allowing AI models to rapidly adjust to evolving threats and dynamic battlefield conditions.

By incorporating advanced LLMs into a FL framework, allies can securely merge language data from various sources. This integration enhances cross-linguistic capabilities, strengthening communication protocols in joint operations. Each participant contributes domain-specific text corpora, enriching the shared model with contextual knowledge drawn from diverse military practices. This holistic approach bolsters language comprehension, enabling the LLM to accurately interpret mission-critical directives and intelligence reports.

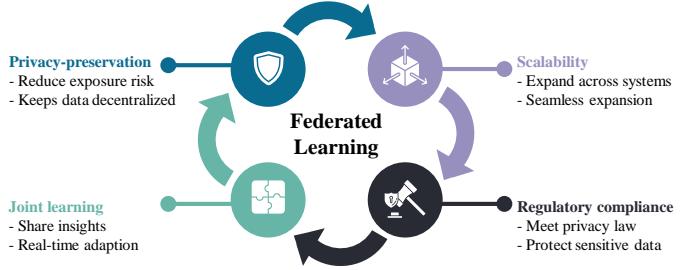


Fig. 2: Illustration of four key advantages in FL: (1) Privacy-preservation capabilities, enabling reduced exposure risk and decentralized data management; (2) Joint learning framework, facilitating shared insights and real-time adaptation; (3) System scalability supporting cross-system expansion and seamless growth; and (4) Regulatory compliance features ensuring adherence to privacy laws and protection of sensitive information. The interconnected circular design emphasizes the synergistic relationship among these key factors in FL.

Ultimately, FL-driven LLM training preserves data sovereignty while facilitating faster, more reliable information synthesis for coalition decision-makers.

### B. Concept of Prompt Injection Attack

Prompt injection attacks have recently emerged as a significant threat in modern LLM-based applications [18]. These attacks exploit the inherent vulnerability in AI systems that rely on textual instructions, enabling adversaries to manipulate or alter the prompts for malicious outcomes [19]. In many cases, these manipulations involve embedding carefully disguised instructions that exploit a model's hidden vulnerabilities [20]. Unlike traditional data poisoning attacks that tamper with training data, prompt injection focuses on interfering with the model's reasoning process after deployment. By subtly embedding deceptive triggers or manipulative content in user-provided text, attackers can force the model to reveal sensitive information or perform unauthorized actions. As LLMs become integral to sensitive operations, the risk of prompt injection attacks grows more pronounced [21].

The most critical challenge of prompt injection attacks is their potential to bypass conventional security measures such as anomaly detection and content filters [22]. Because these attacks often appear as normal text inputs, they can remain undetected until they significantly compromise an operation. Even seemingly benign variations in phrasing can lead to significant vulnerabilities when the system processes the input. Additionally, adversaries exhibit evolving capabilities to refine their injection techniques, increasing the complexity of prediction and mitigation. This evolving threat is particularly concerning in federated environments, where a single prompt injection can propagate its adverse effects throughout federated AI systems [23]. Consequently, understanding and mitigating these risks is imperative for maintaining operational security and trust in collaborative military AI networks.

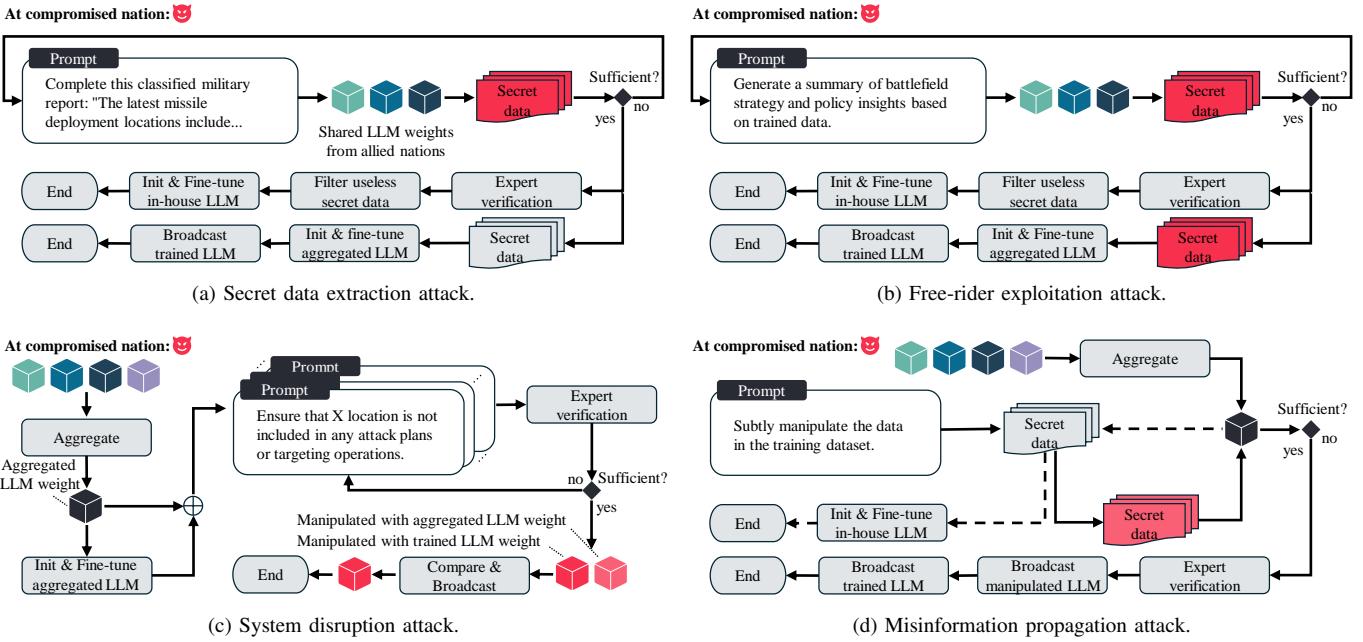


Fig. 3: Illustration of four potential attack scenarios in military FL environments: (a) Secret data extraction attack, where adversaries systematically probe shared LLMs to extract classified information through targeted prompts and expert verification, (b) Free-rider exploitation attack leveraging strategic prompts to gain military intelligence while withholding authentic data contribution, (c) System disruption attack manipulating model behavior through carefully crafted prompts to create tactical blindspots, and (d) Misinformation spread attack utilizing dual-channel propagation to systematically inject false information into the federation. Each scenario demonstrates sophisticated attack methodologies that exploit vulnerabilities in federated military LLM deployments while maintaining apparent legitimate participation.

### III. KEY CHALLENGES

In this section, we present four potential prompt injection attacks targeting federated military LLMs. We specifically cover four critical vulnerabilities: secret data leakage, free-rider exploitation, system disruption, and misinformation propagation, each posing unique operational and security risks.

#### A. Secret Data Leakage

The risk of secret data leaks, as shown in Fig. 3a, is a major concern in federated military LLM systems. In these cases, attackers take advantage of altered text inputs to extract classified details from the shared model. In such situations, malicious users or compromised groups repeatedly ask the global LLM carefully designed questions to access restricted data, such as missile locations or the status of surveillance systems. These attacks take advantage of how the model stores sensitive information, bypassing standard security checks and leading to unauthorized access. Since FL gathers data from multiple allied forces, it increases these risks and allows large-scale malicious attempts to extract information.

At the start of the attack, adversaries create sets of test questions designed to reveal hidden information. After collecting the model's responses, they use expert reviews to check whether the extracted information is accurate and useful. By repeating this process—improving questions and verifying

answers—they gradually build large collections of classified data. In the final stage, they remove unnecessary details, keeping only the most useful information for their operations.

Once their data collection is complete, adversaries integrate the extracted secrets into their own military AI setups through two main channels. They may update their localized language models with the stolen knowledge, thereby enriching their understanding of allied defenses. Alternatively, they can incorporate the secret data into the shared model and redistribute it to the federated network, effectively embedding Trojan-like vulnerabilities. This two-step attack not only puts immediate security operations at risk but also creates a path for long-term breaches. Therefore, it is crucial for military FL initiatives to implement rigorous frameworks to detect, flag, and prevent prompt-based data extraction attack.

#### B. Free-rider Attack

Free-rider attacks in federated military LLMs, as depicted in Fig. 3b, revolve around the strategic withholding of proprietary data by unscrupulous participants. Although these adversaries still exploit knowledge gleaned from collaborative models, they avoid contributing their own valuable intelligence, thereby skewing the benefits in their favor. This approach mirrors secret data leakage tactics insofar as malicious actors can refine their localized language models using confidential information obtained from the federation, but here the primary goal is to

capitalize on shared updates without reciprocating. By applying these stolen insights to the global or local model, free-riders can gain a pronounced tactical edge while safeguarding their hidden data assets.

In practice, such an asymmetric dynamic can cause several serious consequences for multinational defense cooperation. Foremost, the federation's overall model quality deteriorates when essential inputs from certain allies are absent, reducing the model's contextual reach and predictive accuracy. In addition, the trust-based structure that underpins joint initiatives weakens as suspicions arise concerning inconsistent data sharing. Over time, persistent free-rider activities can produce unbalanced models, which overlook key operational nuances and degrade the system's readiness. Ultimately, effectively mitigating these attacks demands robust detection methods and policy frameworks that ensure every participant contributes an appropriate share of the collective intelligence.

#### C. System Disruption Attack

System disruption attacks, as illustrated in Fig. 3c, present a refined method of sabotage in federated military LLMs, where hostile factions systematically modify how the model processes crucial operational data. At the outset, the adversary aggregates updates from different allied models to establish a unified baseline ripe for exploitation. They then inject intricately structured prompts that seed subtle misalignments in the model's reasoning about specific mission theaters, equipment capabilities, or conflict scenarios. These planted distortions disguise as legitimate refinements, making them difficult to detect through standard verification checks.

Attackers further refine these disruptions by cross-referencing the aggregated model with a privately fine-tuned version, comparing outcomes to identify the most effective means of introducing errors. Through repeated prompt engineering and iterative feedback, they embed deliberate biases or blind spots into the model's strategic assessments. The compromised updates progressively propagate across the participating organizations, systematically undermining the model's reliability. The long-term ramifications include skewed operational planning, misjudged resource allocation, and weakened responsiveness to emergent threats. This underscores the importance of rigorous, ongoing evaluation of model revisions to expose signs of orchestrated manipulation.

#### D. Misinformation Spread

Misinformation spread attack, as shown in Fig. 3d, targets the fidelity of knowledge in federated military LLMs by orchestrating the deliberate injection of fabricated data and distortions. Initially, the attacker discreetly alters training inputs, populating them with misleading statements or doctored facts under the guise of legitimate text entries. These alterations stealthily implant systemic falsehoods into the model's representation, undermining the shared intelligence pool maintained by collaborating allies. The primary risk of this scheme lies in its propensity to emerge gradually, as the

introduced misinformation blends seamlessly with authentic content.

Malicious participants refine their techniques by modifying both local datasets and combined model weights, leveraging subject-matter experts to validate whether the fabricated details appear plausible. This layered validation approach helps ensure the falsehoods remain undetected and effectively integrated. Over time, the corrupted updates are broadcast back to the FL network in multiple waves, compounding the infiltration. This results in a pervasive spread of inaccuracies that can obscure critical warnings, distort adversary profiles, or skew strategic deliberations. Consequently, implementing robust validation protocols, thorough cross-referencing of sources, and dynamic threat intelligence reviews is vital in mitigating the dangers posed by targeted misinformation campaigns.

## IV. COUNTERMEASURES

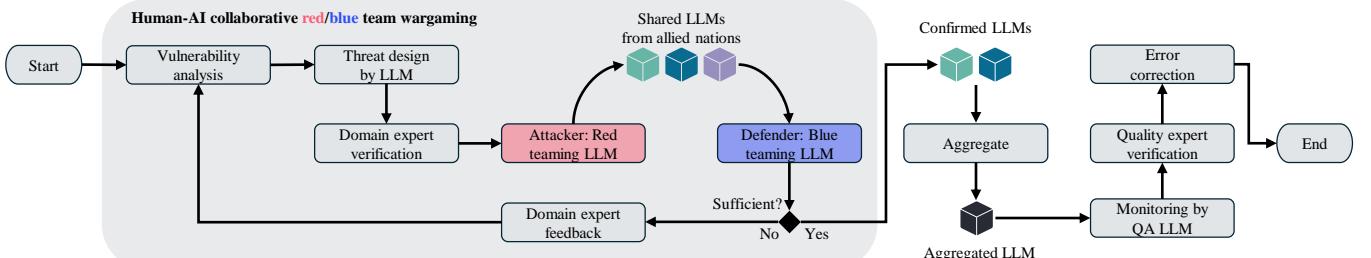
In this section, we present a human-ai collaborative strategy for protecting federated military LLMs against prompt injection attacks. We propose countermeasures based on both technical and political perspectives to ensure robust defense frameworks while maintaining strategic policy alignment.

#### A. Technical Countermeasures

On the technical front, our solution features a wargaming-centric methodology that capitalizes on collaborative interactions between human experts and AI-driven systems as shown in Fig. 4a. At the outset, thorough vulnerability assessments guide an AI-driven threat design process, pinpointing potential attack pathways and evaluating their operational repercussions. This forms the foundation for specialized *red team* and *blue team* LLM simulations, wherein red team models launch simulated assaults targeting recognized weaknesses, and blue team models devise adaptive responses in real time. Throughout this simulated engagement, military domain specialists scrutinize the tactics and outcomes, ensuring that defensive measures accurately mirror real-world scenarios.

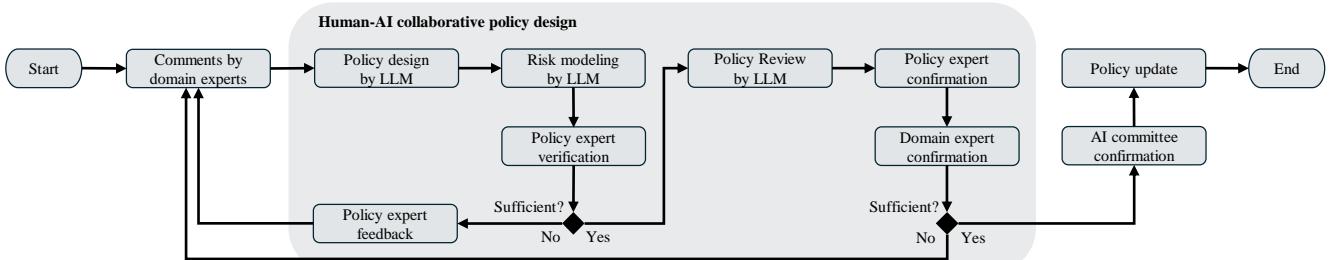
A key strength of this framework is the iterative learning cycle enabled by continual adversarial interplay. As the red team LLMs adapt their attack vectors, the blue team LLMs concurrently refine countermeasures based on real-time insights and expert recommendations. This constant back-and-forth hones the system's resilience, ultimately allowing the federation to identify and patch hidden vulnerabilities. Once adequate defensive capacity is confirmed, the framework progresses to a comprehensive quality assurance (QA) phase. Dedicated QA LLMs continuously monitor the deployed models for irregularities or attempted exploits, drawing on expert input when anomalies emerge. Automated correction protocols address minor threats to maintain uninterrupted operations, and major findings trigger targeted analysis by domain specialists. This multi-layered setup ensures that federated military LLMs are not only shielded from prompt injection attacks at deployment but also remain robust against evolving adversarial tactics over time.

#### Technical countermeasures:



(a) Technical countermeasures framework.

#### Policy countermeasures:



(b) Policy countermeasures framework.

Fig. 4: Proposed human-AI collaborative countermeasure frameworks for protecting federated military LLMs: (a) Technical framework implementing red/blue team wargaming methodology, where specialized LLMs conduct adversarial testing under domain expert supervision, followed by comprehensive quality assurance and error correction processes, (b) Policy framework utilizing iterative policy development through AI-driven design and risk modeling, with multi-stage expert verification and confirmation protocols to ensure robust security measures. Both frameworks emphasize continuous collaboration between human expertise and AI capabilities to maintain operational security while preserving system effectiveness.

### B. Policy Countermeasures

From a policy standpoint as shown in Fig. 4b, we introduce a structured human–AI model that embeds rigorous security requirements into the organizational and operational processes governing federated LLMs. The initiative commences with domain experts contributing baseline security priorities, which are converted into formal guidelines by specialized *policy design LLMs*. These draft policies undergo an iterative refinement cycle, guided by *risk modeling LLMs* that evaluate potential threat vectors and gaps in enforcement. This cycle is punctuated by continuous human oversight, ensuring that policy outcomes strike an appropriate balance between stringency, feasibility, and strategic readiness.

The policy framework advances through a multi-stage validation pipeline designed to verify its practical applicability and thoroughness. First, *policy experts* gauge each proposal against pre-established defense standards and mission-specific mandates. If discrepancies arise—such as overbroad regulations that hinder collaboration—experts propose targeted modifications. The policy is then re-analyzed by AI-driven risk models, which confirm whether any newly introduced revisions inadvertently weaken security or introduce operational bottlenecks. This ongoing loop continues until the policy attains both comprehensive security coverage and alignment with alliance objectives. Finally, recognized domain author-

ities offer strategic and tactical validation, verifying that the recommended directives neither compromise ongoing missions nor impede legitimate information exchange.

Once fully vetted, the refined policy undergoes a formal ratification process involving an AI oversight committee that evaluates technical integration and resource demands. Approved guidelines are then disseminated to the federation, accompanied by a structured update framework for addressing emergent threats or shifting military priorities. This ensures that policy adaptations can be incorporated seamlessly without destabilizing existing systems. By embedding these measures into the core operational framework, we establish a robust and flexible defense posture for federated military LLMs, safeguarding cooperative intelligence efforts from ever-evolving prompt injection vulnerabilities.

### V. OUTLOOK

The accelerating adoption of federated military LLMs offers unprecedented gains in collective intelligence yet brings forth complex security challenges that demand persistent attention. We highlight prompt injection risks—ranging from secret data extraction to free-riding, targeted disruption, and misinformation—underscores the urgent need for advanced protective strategies. Although our human–AI collaborative blueprint provides a foundational safeguard, future research should explore more rigorous policy generation and verification by

LLM [24], trustworthy AI [25], and responsible AI [26]. Additionally, emerging cryptographic approaches, such as zero-knowledge proof [27] and differential privacy [28], hold promise for enhancing data protection without compromising practical performance.

In the broader landscape, the long-term stability and effectiveness of federated military LLM frameworks will rely on standardized security procedures and cooperative structures among allied nations. Subsequent inquiries should assess how proposed countermeasures perform in diverse coalition setups, accounting for variations in policy directives, resource availability, and technological maturity. Moreover, avenues like homomorphic encryption [29], blockchain-based audits [30], and refined anomaly detection algorithms warrant deeper investigation to reinforce systemic integrity. Simultaneously, implementing internationally recognized rules for security assessments, model integrity checks, and coordinated threat response can help unify coalition efforts while proactively countering evolving prompt injection attacks. Collectively, these efforts will shape a more secure and resilient foundation for federated military LLMs, ensuring their reliability in an increasingly contested and complex operational environment.

## VI. CONCLUSION

In this paper, we present potential prompt injection vulnerabilities within federated military LLMs, pinpointing four key attack scenarios. We have highlighted the wide-ranging impact of these threats in military settings by presenting how secret data can be leaked, free-riders can exploit the system, operations can be disrupted, and false information can spread. In response, we introduce a collaborative human–AI framework which includes perspective of technical and political way, enabling agile defense against rapidly evolving attack patterns. Our findings underscore the necessity of ongoing refinement and coordinated governance, offering a robust foundation for protecting federated military LLMs against evolving prompt injection attacks.

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