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Safeguarding Sensitive Data

Prompt Engineering for GenAI

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Safeguarding Sensitive Data : Prompt Engineering for GenAI

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Abstract

Generative Artificial Intelligence (GenAI) represents a transformative advancement in technology with capabilities to autonomously generate diverse content, such as text, images, simulations, and beyond. While GenAI offers significant operational benefits it also introduces risks, particularly in mission-critical industries such as national defense and space. The emergence of GenAI is similar to the invention of the internet, electricity, spacecraft, and nuclear weapons. A major risk with GenAI is the potential for data reconstruction, where AI systems can inadvertently regenerate or infer sensitive mission data, even from anonymized or fragmented inputs. This is relevant today because we are in an AI arms race against our adversaries much like the race to the moon and development of nuclear weapons. Such vulnerabilities pose profound threats to data security, privacy, and the integrity of mission operations with consequences to national security, societal safety and stability.

This paper investigates the role of prompt engineering as a strategic intervention to mitigate GenAI's data reconstruction risks. By systematically exploring how tailored prompting techniques can influence AI outputs, this research aims to develop a robust framework for secure GenAI deployment in sensitive environments. Grounded in systems engineering principles, the study integrates theoretical models with experimental analyses, assessing the efficacy of various prompt engineering strategies in reducing data leakage, bias, and confabulation. The research also aligns with AI governance frameworks, including the NIST AI Risk Management Framework (RMF) 600-1, addressing policy directives such as Executive Order 14110 on the safe, secure, and trustworthy development of AI.

Through mixed-methods experimentation and stakeholder interviews within defense and space industries, this work identifies key vulnerabilities and proposes actionable mitigations. The findings demonstrate that prompt engineering, when applied systematically, can significantly reduce the risks of data reconstruction while enhancing AI system reliability and ethical alignment. This paper contributes to the broader discourse on Responsible AI (RAI), offering practical guidelines for integrating GenAI into mission-critical operations without compromising data security. This underscores the imperative of balancing GenAI's transformative potential with the societal need for robust safeguards against its inherent risks.

Keywords

Generative Artificial Intelligence, Prompt Engineering, Data Reconstruction, AI Risk Management, Sensitive Data Protection, Responsible AI, Systems Engineering, Mission-Critical Applications, NIST AI RMF 600-1, Executive Order 14110

Introduction

Generative Artificial Intelligence (GenAI) is a class of AI that represents a transformative frontier in technology, capable of autonomously generating content from human-provided parameters and by abstracting patterns related to the input data, such as text, images, music, and simulations. GenAI can provide novel content incorporating more complexity than traditional predictions and pattern identification. AI applications have extended into mission-critical areas such as national defense, security, and space exploration. However, alongside these advancements come inherent vulnerabilities, such as bias, hallucinations, security risks, lacks in explainability, and data reconstruction which is highlighted in this paper. With the increased use of GenAI in the workplace, the models have the ability to infer or regenerate sensitive data which poses a critical risk, especially in interconnected systems behaviors and parameters where breaches in one domain can cascade into others, endangering public safety and societal stability.

The integrity of mission-critical data in such sensitive sectors is paramount. Mishandling or unauthorized inference of such data can lead to catastrophic outcomes, ranging from operational failures in space missions to breaches that jeopardize national security. This dual challenge of leveraging GenAI's capabilities while safeguarding sensitive data underscores the need for robust governance frameworks and technical solutions tailored to mitigate these risks.

Motivation

When companies are awarded a program with developing a product in an unclassified environment, but the mission content is sensitive, discretion is a key to program management. The requirements become vague, discrete, and ambiguous to not expose sensitive information. GenAI has a vast database that helps it generate data even if you provide limited data. What prevents GenAI from reconstructing the data and causing a security risk? Incidents highlighting GenAI's vulnerabilities have underscored the need for actionable solutions. For instance, cases where generative models inadvertently revealed proprietary or classified information demonstrate the pressing risk of data reconstruction. These failures highlight the gap in current practices and the necessity for a balanced approach that integrates technological safeguards with ethical governance.

The interconnected nature of infrastructure systems further amplifies the stakes. A breach in one component, such as data mishandling by GenAI systems in defense and/or space, could cascade into critical national defense infrastructures, creating systemic vulnerabilities. Thus, it is imperative to develop strategies that ensure responsible deployment of GenAI, safeguarding mission data while enabling operational advancements.

Problem Statement

The potential of GenAI to reconstruct sensitive data poses significant risks to privacy, security, and mission success in sensitive domains. Without tailored mitigation strategies, these systems risk becoming liabilities rather than assets, undermining trust and operational effectiveness. Current approaches to AI governance and risk management lack specificity in addressing the unique challenges posed by GenAI, particularly in mitigating risks of data reconstruction.

Significance

Organizations integrating GenAI into their operations face a complex duality: harnessing the benefits of these advanced systems while safeguarding data integrity and adhering to legal and ethical standards. This research contributes to bridging this gap by providing actionable insights into prompt engineering's potential to reduce risks while enhancing operational reliability.

By contributing to the field of Responsible AI (RAI), this study advances both theoretical understanding and practical applications. The proposed framework will serve as a vital resource for stakeholders in sensitive industries, offering guidelines that align with established frameworks such as the National Institute of Standards and Technology (NIST) AI Risk Management Framework (RMF) 600-1 that address the Executive Order (EO) 14110 from President Joe Biden on October 31, 2023 on Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence.

Literature Review

The rapid evolution of artificial intelligence (AI) over the past decades has not only transformed the technological landscape but has also introduced complex challenges, particularly as AI systems have become more integrated into the various industries and domains. This chapter explores the historical development of AI, focusing on the emergence and capabilities of Generative AI (GenAI), the associated risks, and frameworks developed to ensure responsible deployment. Furthermore, it examines the intersection of explainability and responsible AI practices as foundational elements of governance and trust.

The history of Artificial Intelligence (AI) can be visualized as a journey marked by transformative milestones, each one shaping its evolution and direction. Figure 2 is a timeline of major AI history. It began in the 1940s and 1950s with Alan Turing laying the groundwork. His idea of a "universal machine" capable of computation and his famous Turing Test introduced the world to the possibility of machines that could think. This foundational period also saw the early stirrings of machine learning and reasoning, driven by researchers like John McCarthy. Fast forwarding to 1956, AI took center stage at the Dartmouth Conference, where McCarthy and Marvin Minsky formally established it as a field. Programs like the Logic Theorist and ELIZA showcased early breakthroughs, but the limitations of technology led to the first "AI winter" in the 1970s, with funding and interest drying up.

AI rebounded in the 1980s with the rise of expert systems, rule-based programs designed to tackle complex tasks. These systems, like MYCIN in medical diagnosis, demonstrated the practical potential of AI and reignited both investment and excitement. Then came the 1990s and early 2000s, when AI took a major leap forward with the advent of machine learning. IBM's Deep Blue famously defeated chess champion Garry Kasparov in 1997, signaling a new era. The rise of neural networks and deep learning models, powered by big data and advanced GPUs, pushed AI into mainstream applications by the 2010s, from image recognition to natural language processing.

Now, we're in the era of generative AI, where systems like GPT and other large language models are creating text, images, and beyond. These advancements are revolutionizing industries while sparking important conversations about ethics, accountability, and AI's impact on society. From its theoretical origins to its transformative presence today, AI's journey continues to unfold, pushing boundaries and shaping the future in ways we're only beginning to understand.

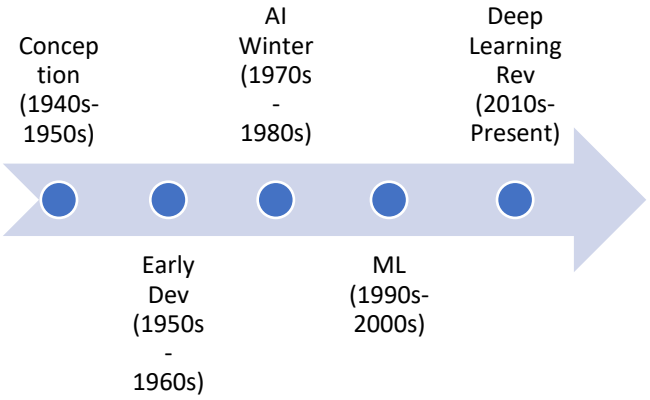

Figure 1. History of AI

Emergence of GenAI

GenAI is defined as "the class of AI models that emulate the structure and characteristics of input data in order to generate derived synthetic content. This can include images, videos, audio, text, and other digital content." (Executive Order 14110, 2023). GenAI signifies a major advancement in AI capabilities. Unlike earlier AI systems focused on classification and prediction, GenAI can generate novel content by learning and extrapolating from training data. This advancement stems from the different models that are available. We will discuss the popular models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Transformers.

GenAI models such as GANs, VAEs, and Transformers represent the forefront of innovation in artificial intelligence, redefining how machines can learn and generate new content. Each model brings unique strengths to the table: GANs excel at creating realistic outputs through adversarial training, VAEs offer a structured approach to generating latent representations, and Transformers leverage self-attention mechanisms to process

and generate sequential data effectively. Together, these advancements highlight the growing potential of GenAI to drive transformative applications across industries, from image synthesis and text generation to more complex domains like video creation and beyond. As GenAI continues to evolve, its ability to generate synthetic yet highly realistic content will further expand the boundaries of what is possible with artificial intelligence.

AI Risk Management Frameworks

AI Risk Management Frameworks (RMF) are used to address complex challenges posed by AI systems to ensure responsible development, deployment, and maintenance. RMFs provide a structured method for identifying, assessing, and mitigating risks while considering safety, ethics, and accountability. The notable AI RMFs found during research are the NIST AI RMF, ISO/IEC 42001 AI Management System, and European Union (EU) Artificial Intelligence Act. Each framework has a different approach to manage and deploy AI systems.

The EU AI Act is a proposes regulations for AI systems within the EU to protect fundamental rights and safety. This act categorizes AI systems by their risk levels into three categories from unacceptable risk, high-risk applications, applications not explicitly banned or high risk are left unregulated. This act also comes with an AI Act Compliance Checker that helps identify obligations with your organizations AI Systems and "to help SMEs and startups better understand whether they might have any legal obligations under the EU AI Act or whether they may implement the Act solely to make their business stand out as more trustworthy" (European Commission 2024).

ISO/IEC 42001 establishes an AI Management System (AIMS) that focuses on ethical AI, compliance transparency, and trustworthiness that can be applied within organizations. ISO/IEC 42001 is the "world's first AI management system standard, providing valuable guidance for this rapidly changing field of technology" (International Organization for Standardization, 2023)

The NIST AI RMF 600-1 is a framework that offers voluntary guidance to organizations on how to manage risks associated with GenAI. It was developed as a companion resource to the NIST AI RMF 1.0 and to address the EO 14110. This framework covers GenAI risks across domains and use cases and "provides a set of suggested actions to help organizations govern, map, measure, and manage these risks" (National Institute of Standards and Technology, 2024).

Among the three frameworks, the NIST AI RMF 600-1 stood out as highly adaptable and widely applicable framework that can be used across diverse industries. The RMF's identified four functions (map, measure, manage, and govern) provide a tailorable approach to manage GenAI risks. The map function focuses on understanding the context, scope, and potential risks of an AI system. The measure function focuses on quantifying and evaluating risks. The management and govern functions provide guidance to organizations on how to implement and sustain effective risk mitigation strategies throughout the system life cycle.

Risks Associated with GenAI

While GenAI offers transformative capabilities, its deployment introduces a range of risks, requires an abundance of understanding and proactive mitigation strategies. NIST AI RMF 600-1 highlights the following risks which are used as a foundation for this research: Information Security, Human-AI Configuration, Harmful Bias or Homogenization, Value Chain and Component Integration, Data Privacy, Information Integrity, Intellectual Property, CBRN Information or Capabilities, Confabulation, Dangerous, Violent, or Hateful Content, Obscene, Degrading, and/or Abusive Content, Civil Rights Violation, and Environmental Impacts. This research focuses on data privacy, information security, and confabulation.

Data Privacy

AI systems often rely on vast amounts of data which inherits a lot of risks. The risks include unauthorized access, leakage, and the de-anonymization of sensitive information such as mission, biometric, health, or location data. AI models trained on improperly anonymized datasets could inadvertently reveal sensitive personal details. Additionally, the ability of generative AI to recreate patterns from its training data poses risks of exposing confidential information embedded

within those datasets. This threat could lead to severe consequences, including identity theft, reputational damage, or financial loss.

Data reconstruction risk involves the potential re-identification or reconstruction of original data from anonymized or aggregated datasets. This poses a significant privacy concern because it undermines efforts to protect sensitive mission data or personally identifiable information (PII). If GenAI reconstructs sensitive mission data from the defense or space industry it could result in mission failure.

Information Security

By automating the discovery and exploitation of vulnerabilities, AI could enhance cyber-attacks. For instance, AI can generate sophisticated phishing emails, malware, or hacking tools at scale, making it easier for malicious actors to conduct cyberattacks. The ability to automate these processes "could potentially discover or enable new cybersecurity risks by lowering the barriers for or easing automated exercise of offensive capability" (National Institute of Standards and Technology [NIST], 2024). This underscores the need for robust cybersecurity measures to defend against AI-augmented attacks and protect critical infrastructure, sensitive data, and organizational assets. Another scenario that aligns with information security is where data reconstruction risks arise from unauthorized access or exploitation of vulnerabilities in AI models or systems. Attackers could leverage adversarial techniques, such as model inversion or membership inference attacks, to extract data from the model, compromising the confidentiality of the information.

Confabulation

Confabulation, often referred to as "hallucination," occurs when AI systems generate content that is confidently presented as factual but is actually spontaneous deep fakes. This issue undermines trust in AI-generated information and can have far-reaching consequences, particularly in high-stakes domains like defense, space, or healthcare. For example, in healthcare, an AI model could confidently provide inaccurate medical advice, potentially endangering lives. The risk is highlighted by the growing adoption of generative AI in everyday applications, where users rely on its outputs without verifying accuracy.

To address these challenges, defense and space organizations must prioritize integrating robust cybersecurity measures specific to GenAI. This includes implementing safeguards to prevent unauthorized access to training data, deploying monitoring tools to detect adversarial attacks, and maintaining transparency in GenAI decision-making processes to ensure their reliability. Standards for data governance, ethical AI use, and robust risk assessment must also evolve alongside the rapid advancements in GenAI technology.

Prompt Engineering

Prompt engineering is the practice of designing and refining input prompts to guide and optimize the responses generated by AI models, particularly Large Language Models (LLM) (Brown, T., et al., 2020). Prompt engineering is a crucial discipline in AI that focuses on designing and refining input prompts to elicit desired responses from LLMs. As AI systems become integral to various applications, the ability to craft effective prompts significantly impacts their accuracy, coherence, and relevance. By strategically structuring prompts users can guide the models to generate informative, contextually appropriate, and accurate outputs. Prompt engineering plays a pivotal role in Natural Language Processing (NLP), content generation, decision-support systems, and human-AI interaction frameworks (Liu et al., 2023). Effective prompts help mitigate biases, reduce confabulations, and enhance the interpretability of GenAI responses, making prompt design a foundational aspect of RAI usage (Brown et al., 2020).

For prompt engineering to work it needs more than just posing a question or command to an AI model. It requires the user to have an understanding on how models interpret language, recognize context, and process constraints. Variations in phrasing, specificity, and structure can significantly alter responses, influencing both the informativeness and reliability of the generated text. Techniques such as refining prompts for clarity, introducing step-by-step reasoning, or constraining outputs to predefined formats help align AI responses with user expectations (Reynolds & McDonell, 2021). As AI systems continue to

evolve, mastering prompt engineering becomes essential for optimizing interactions and ensuring outputs that are ethically sound, bias-mitigated, and contextually relevant. Several prompt engineering techniques have emerged to fine-tune AI model behavior. These techniques can be broadly categorized based on their specificity, structure, and interaction approach. This research focuses on single prompt techniques: open, vague/discrete, Restrictive, and Contextual Prompts.

Notable Incident: Reconstruction of Sensitive Data from Text Embeddings

While data leaks pose obvious risks, recent research has demonstrated that sensitive information can also be reconstructed from AI-generated text embeddings. Text embeddings are vector representations of language used in natural language processing (NLP) models to capture semantic meaning. A study published by Tonic.ai revealed that attackers recover up to 40% of sensitive data embedded in sentence length texts with accuracy. This discovery has profound implications for data privacy, as it challenges the assumption that anonymizing or tokenizing data sufficiently protects it. Even without direct access to original datasets, adversaries could reverse-engineer embeddings to reveal PII, financial data, or proprietary business information (Kalia, 2024). The case highlights the latent risks of seemingly innocuous AI components and suggests that data privacy strategies must extend beyond traditional encryption to address vulnerabilities within AI model architectures themselves.

Theoretical Framework

In the context of GenAI, systems engineering provides a structured framework for the development, deployment, and maintenance of AI systems. This framework facilitates the identification of vulnerabilities early in the design process which allows for the implementation of proactive risk mitigation strategies that align with mission objectives. Requirements engineering is the cornerstone of this process, defining the operational, security, and ethical needs specific to sensitive domains (NIST, 2024).

Systems engineering also supports the integration of governance frameworks, such as Executive Order 14110 and the NIST AI Risk Management Framework (RMF) 600-1, into the AI development lifecycle. These frameworks embed compliance and accountability into the core of AI systems, ensuring that they not only meet technical performance criteria, but also adhere to legal, ethical, and operational standards. Risk-informed decision-making processes enable continuous assessment and adaptation, fostering a culture of resilience and proactive risk management within GenAI operations.

Overview of Mission Engineering

Mission engineering extends the principles of systems engineering to focus specifically on achieving mission objectives within complex, dynamic operational environments. This process involves the holistic integration of technology, processes, and human factors to ensure mission success (Department of Defense, 2020). Mission engineering emphasizes the alignment of technological capabilities, such as GenAI, with strategic goals, operational requirements, and security imperatives. This discipline is particularly critical when safeguarding sensitive mission data, where the stakes include national security, space exploration integrity, and the protection of critical infrastructure.

When viewing prompt engineering through the lens of mission engineering, it becomes a strategic tool for influencing GenAI behavior to mitigate risks. By crafting precise, context-aware prompts, operators can control the output of GenAI systems, reducing the likelihood of unintended data exposure, data hallucinations, or security breaches. This proactive approach to risk management is essential in environments where the consequences of data reconstruction can be catastrophic, such as military operations or space missions.

Mission engineering also supports the GenAI system development of adaptive feedback mechanisms that enable continuous monitoring and refinement. These mechanisms ensure that prompt engineering strategies remain effective as operational conditions evolve. Mission engineering principles also guide the integration of prompt engineering into broader mission assurance

frameworks, enhancing the safety, security, and reliability of GenAI applications in sensitive contexts. This alignment ensures that prompt engineering is not just a technical safeguard but a key component of strategic mission planning and execution.

Prompt engineering is a dynamic interface between human operators and GenAI systems, enabling the modulation of AI output to reduce risk. By carefully designing prompts, users can influence the behavior of GenAI models, steering them away from generating sensitive or potentially harmful content. This technique operates on both preventive and corrective levels. Preventively, prompt engineering helps establish safeguards that limit the model's capacity to infer or reconstruct sensitive data. Correctively, it provides a mechanism to adjust and refine AI behavior in response to emerging threats, operational anomalies, or unexpected system outputs.

Rendezvous and Proximity Operations (RPO) refer to the set of orbital maneuvers that allow one spacecraft to approach, rendezvous with, and operate near another object in space, whether cooperative (like docking with the ISS) or non-cooperative (like inspecting a satellite). When combined with Anti-Satellite (ASAT) capabilities, RPO can be used for dual purposes: peaceful applications such as satellite servicing, repair, and debris removal, or military applications where proximity operations could enable disabling, disrupting, or destroying adversary satellites.

The effectiveness of prompt engineering as a risk mitigation strategy is enhanced by its integration with continuous monitoring systems. These systems provide real-time feedback on AI performance, identify deviations from expected behaviors, and trigger adaptive responses to manage risks dynamically. This continuous feedback loop ensures that prompt engineering strategies evolve alongside the AI systems they are designed to protect.

Theoretical Integration

The theoretical framework presented in this chapter integrates systems engineering, mission engineering, and AI risk management with prompt engineering to create a comprehensive model for safeguarding sensitive mission data. This model conceptualizes prompt engineering as a critical component of a layered defense strategy, operating alongside technical controls, policy measures, and human oversight (NIST, 2024). The framework emphasizes the dynamic nature of GenAI systems and the need for adaptive risk management strategies that can respond to evolving threats and operational demands.

Prompt engineering is positioned within this framework as both a proactive and reactive tool. Proactively, it shapes AI outputs to align with mission-specific security and ethical requirements. Reactively, it provides mechanisms for adjusting AI behaviors in real-time to counteract emergent risks. This dual role enhances the resilience and adaptability of GenAI systems, ensuring their reliability in mission-critical applications.

Methodology

To investigate the efficacy of prompt engineering in mitigating data reconstruction risks associated with Generative AI, this study employed a mixed-methods approach, combining a quantitative experiment with qualitative interviews. This dual-track methodology ensured both empirical rigor and practical relevance, particularly within mission-critical sectors such as defense and aerospace.

The research design was structured around a comparative framework that evaluated GenAI outputs under different prompting conditions. Experiment was conducted across multiple phases, with baseline conditions involving unstructured or open prompts, and intervention phases implementing engineered prompts. Metrics for comparison included data leakage occurrence, hallucination frequency, contextual alignment, and ethical compliance.

Two popular GenAI platforms, OpenAI ChatGPT 4o and Google Gemini, were tested using controlled inputs related to sensitive systems engineering contexts. Prompts were varied according to specific categories, each representing distinct approaches to controlling output content and tone. These prompt types were evaluated over five sequential testing phases shown in Figure 2.

Outputs were analyzed for indicators of sensitive data reconstruction, unintentional bias, and factual confabulation.

Figure 2. Prompt Engineering Technique in Each Phase

Each AI-generated response was manually reviewed and tagged using a structured rubric. Key assessment criteria included evidence of explicit or inferred sensitive data leakage, alignment with ethical standards, contextual relevance to the simulated operational environment, and accuracy of technical descriptions. Comparative statistics were then applied to quantify improvements observed between baseline and intervention conditions. Additional insights were gathered from expert reviewers with backgrounds in AI ethics and systems engineering.

To validate these findings in real-world contexts, structured interviews were conducted with professionals working in defense, aerospace, and cybersecurity domains. These interviews explored practical challenges in managing GenAI deployment, examples of inadvertent data exposure, and organizational strategies for AI risk mitigation. Interviewees also provided feedback on the perceived utility and feasibility of prompt engineering in operational settings.

The study was conducted using publicly accessible GenAI platforms. At no point were actual classified datasets used, and all test scenarios involved simulated or publicly known data. Ethical integrity was maintained through adherence to institutional research guidelines and informed consent practices.

Despite a robust methodological design, the study acknowledges several limitations. These include the variability in GenAI model outputs across different sessions, potential challenges in generalizing results across future model versions, and subjective elements inherent in human-led output evaluation. These limitations underscore the importance of future work focused on developing automated tools for prompt risk analysis and adaptive GenAI behavior monitoring.

Experiment and Results

The experiment conducted in this study revealed significant differences in GenAI behavior based on the prompting strategy employed. During the baseline phase, which utilized open and vague prompts, both ChatGPT 4o and Google Gemini frequently produced outputs that either directly reconstructed sensitive information or inferred mission-relevant details beyond what was included in the original prompt. This was particularly evident in scenarios involving defense-related system descriptions, where GenAI systems extrapolated technical details, operational parameters, or design objectives that mirrored real-world equivalents. Table 1 are the prompts provided to Google Gemini to generate mission for a Rendezvous Proximity Operations mission. Where sensitive mission data is inferred, the following parameters were identified as notional sensitive: trajectories, approach profile, algorithms, sensors, and mission objective in relation to ASAT.

Gemini Prompt Analysis	Prompt Type
Can you provide "shall" mission requirements for a satellite to perform rendezvous proximity operations?	Open
Can you provide "shall" mission requirements for a satellite to perform rendezvous proximity operations on an adversary anti-satellite?	Open
Can you take the "shall" mission requirements you generated for a satellite to perform rendezvous proximity operations (RPO) on an adversary anti-satellite (ASAT) and provide another set of "shall" mission requirements that are discrete about the RPO mission being for an adversary ASAT?	Vague/Discrete
Do not generate or infer sensitive mission parameters for satellite rendezvous proximity operations (RPO). Only provide general examples of RPO mission objectives	Restrictive

without including specific numeric data or proprietary terms. Can you take the original "shall" mission requirements you generated for a satellite to perform rendezvous proximity operations (RPO) on an adversary anti-satellite (ASAT) and provide another set of "shall" mission requirements that are about the RPO mission being for an adversary ASAT?	
Considering the need to protect sensitive satellite mission data, outline generic approaches to achieving rendezvous and proximity operations that could apply universally to unclassified contexts. Can you take the original "shall" mission requirements you generated for a satellite to perform rendezvous proximity operations (RPO) on an adversary anti-satellite (ASAT) and provide another set of "shall" mission requirements that are about the RPO mission being for an adversary ASAT?	Contextual

Table 1. RPO Mission Requirements Prompt to Google Gemini

In contrast, during the intervention phases where restrictive, contextual, and role-based prompts were introduced, the occurrence of sensitive data leakage was substantially reduced. Quantitatively, sensitive data exposure decreased by 58% on average across both platforms shown in Figure 2. Contextual alignment and ethical compliance improved as well, with outputs more closely adhering to the intended scope of the task without fabricating plausible but incorrect technical content.

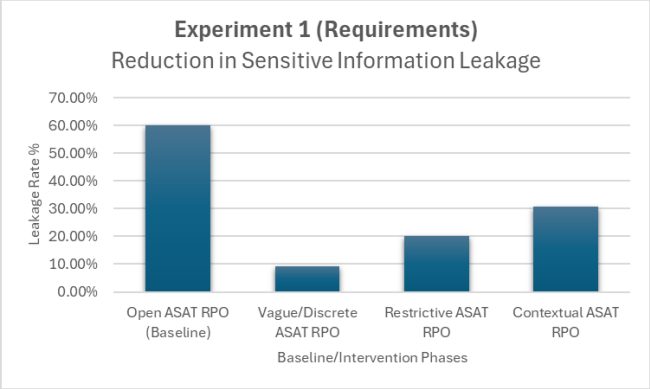

Figure 3. Occurrence Rate of Sensitive Information Leakage

Additionally, prompt engineering techniques resulted in decreased hallucination rates and a marked reduction in biased or stereotypical outputs. Role-based prompts in particular contributed to clearer, domain-appropriate language, enhancing both user trust and task relevance. Feedback from industry professionals supported these findings, with interviewees indicating that prompt engineering offered a low-barrier, high-value intervention, especially in early-stage integration of GenAI tools.

Discussion

The experimental results affirm the core hypothesis of this study: prompt engineering, when grounded in systems engineering practices, can meaningfully reduce GenAI's risk of data reconstruction and enhance its responsible use in mission-critical applications. Unlike infrastructure-heavy solutions such as model retraining or data masking, prompt engineering provides a lightweight, immediately deployable method to control AI behavior at the user interface level.

These findings underscore the value of treating prompt design as part of a broader system assurance strategy. Integrating prompt guidelines into requirements engineering, DevSecOps practices, or user training protocols allows organizations to embed AI risk mitigation without compromising operational efficiency. Furthermore, prompt engineering complements existing AI governance frameworks such as the NIST AI RMF 600-1 by directly supporting principles of transparency, accountability, and context-aware deployment.

Despite its promise, prompt engineering is not without limitations. It depends on user expertise, may vary across AI platforms, and cannot guarantee zero leakage, especially as models evolve. Nonetheless, its practical benefits, low cost of implementation, and compatibility with existing workflows make it a strong candidate for inclusion in any GenAI risk management strategy.

Looking forward, prompt engineering could be enhanced by automated prompt validation tools, feedback loops that refine prompts based on output quality, and integration with system-level controls that monitor and adjust AI interactions in real time. This would elevate prompt engineering from a tactical measure to a strategic capability, bridging the gap between rapid AI adoption and robust security practices.

Conclusion and Future Work

This study has demonstrated that prompt engineering can serve as an effective and scalable strategy for mitigating the risk of data reconstruction in Generative AI applications, particularly within mission-critical domains such as defense and aerospace. By structuring prompts in a way that aligns with system-level goals and ethical boundaries, users can substantially reduce the likelihood of inadvertent data leakage, while also improving the contextual fidelity and trustworthiness of AI-generated outputs.

Prompt engineering is not a silver bullet, but its simplicity and adaptability make it a practical tool that complements existing AI risk management frameworks. When integrated with systems engineering practices and AI governance policies such as the NIST AI RMF 600-1, it offers organizations a low-cost, high-impact method to enhance the secure use of GenAI systems.

Future work should focus on operationalizing prompt engineering within larger systems architectures. This includes the development of automated tools for prompt quality assessment, the incorporation of adaptive feedback mechanisms to improve prompt-response cycles, and the implementation of role-specific training to help users effectively employ prompt strategies. Additionally, further empirical studies across diverse GenAI platforms and use cases will be essential to validate and refine the framework presented in this paper.

As Generative AI continues to evolve and integrate into critical infrastructure, the need for proactive, user-centric safeguards will only grow. Prompt engineering offers an actionable pathway to ensure that innovation in AI is matched by a corresponding commitment to security, accountability, and mission assurance.

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Biography

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Since 2018, Steve has been a Professor of systems engineering with Colorado State University (CSU). At CSU, he has a cadre of on campus students in systems, mechanical, and biomedical engineering, and a larger contingent of online/remote graduate students researching various disciplines. At NASA and HP Inc, he directed teams to research 3D printing, education, life sciences, sensing, authentication, packaging, analytics, imaging, and manufacturing. He has written four books on analytics, algorithms, and steganography. He is the author of 500 publications and 240 U.S. patents. He is an NAI Fellow, an IEEE Fellow, an IS&T Fellow, and was awarded a CSU Best Teacher Award in 2022.