NIST Trustworthy and Responsible AI
NIST AI 600-1

Artificial Intelligence Risk Management Framework: Generative Artificial Intelligence Profile

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NATIONAL INSTITUTE OF STANDARDS AND TECHNOLOGY
U.S. DEPARTMENT OF COMMERCE

NIST 可信与负责任的人工智能
NIST AI 600-1

人工智能风险管理框架：生成式人工情报概况

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July 2024

U.S. Department of Commerce
Gina M. Raimondo, Secretary

National Institute of Standards and Technology
Laurie E. Locascio, NIST Director and Under Secretary of Commerce for Standards and Technology

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2024年7月

美国商务部
吉娜·M·雷蒙多，部长

美国国家标准与技术研究院
Laurie E.Locascio,NIST 主任兼商务部标准与技术副部长

About AI at NIST: The National Institute of Standards and Technology (NIST) develops measurements, technology, tools, and standards to advance reliable, safe, transparent, explainable, privacy-enhanced, and fair artificial intelligence (AI) so that its full commercial and societal benefits can be realized without harm to people or the planet. NIST, which has conducted both fundamental and applied work on AI for more than a decade, is also helping to fulfill the 2023 Executive Order on Safe, Secure, and Trustworthy AI. NIST established the U.S. AI Safety Institute and the companion AI Safety Institute Consortium to continue the efforts set in motion by the E.O. to build the science necessary for safe, secure, and trustworthy development and use of AI.

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Additional Information
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关于 NIST 的人工智能工作：美国国家标准与技术研究院(NIST)开发测量方法、技术、工具和标准，以推进可靠、安全、透明、可解释、增强隐私和公平的人工智能(AI)，从而在不伤害人类或地球的前提下实现其全部商业和社会效益。NIST 十多年来一直开展人工智能的基础和应用研究工作，同时也在帮助落实 2023 年关于安全、可靠和可信人工智能的行政命令。NIST 成立了美国人工智能安全研究所及配套的人工智能安全研究所联盟，以继续推进该行政命令所启动的工作，构建安全、可靠和可信地开发和使用人工智能所需的科学基础。

致谢：本报告得益于社区的许多有益评论和贡献，包括 *NIST* 生成式人工智能公共工作组，以及 *NIST* 员工和客座研究人员：*Chloe Autio*、*Jesse Dunietz*、*Patrick Hall*、*Shomik Jain*、*Kamie Roberts*、*Reva Schwartz*、*Martin Stanley* 和 *Elham Tabassi*。

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1. Introduction

This document is a cross-sectoral profile of and companion resource for the AI Risk Management Framework (AI RMF 1.0) for Generative AI,[1] pursuant to President Biden's Executive Order (EO) 14110 on Safe, Secure, and Trustworthy Artificial Intelligence.[2] The AI RMF was released in January 2023, and is intended for voluntary use and to improve the ability of organizations to incorporate trustworthiness considerations into the design, development, use, and evaluation of AI products, services, and systems.

A *profile* is an implementation of the AI RMF functions, categories, and subcategories for a specific setting, application, or technology – in this case, Generative AI (GAI) – based on the requirements, risk tolerance, and resources of the Framework user. AI RMF profiles assist organizations in deciding how to best manage AI risks in a manner that is well-aligned with their goals, considers legal/regulatory requirements and best practices, and reflects risk management priorities. Consistent with other AI RMF profiles, this profile offers insights into how risk can be managed across various stages of the AI lifecycle and for GAI as a technology.

As GAI covers risks of models or applications that can be used across use cases or sectors, this document is an AI RMF cross-sectoral profile. Cross-sectoral profiles can be used to govern, map, measure, and manage risks associated with activities or business processes common across sectors, such as the use of large language models (LLMs), cloud-based services, or acquisition.

This document defines risks that are novel to or exacerbated by the use of GAI. After introducing and describing these risks, the document provides a set of suggested actions to help organizations govern, map, measure, and manage these risks.

[1] EO 14110 defines Generative AI 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." While not all GAI is derived from foundation models, for purposes of this document, GAI generally refers to generative foundation models. The foundation model subcategory of "dual-use foundation models" is defined by EO 14110 as "an AI model that is trained on broad data; generally uses self-supervision; contains at least tens of billions of parameters; is applicable across a wide range of contexts."

[2] This profile was developed per Section 4.1(a)(i)(A) of EO 14110, which directs the Secretary of Commerce, acting through the Director of the National Institute of Standards and Technology (NIST), to develop a companion resource to the AI RMF, NIST AI 100–1, for generative AI.

1. 引言

本文档是AI 风险管理的跨部门概况和配套资源
框架(AI RMF 1.0)针对生成式人工智能，[1]依据拜登总统关于安全、可靠和可信人工智能的第 14110 号行政命令(EO)。[2] AI RMF 于 2023 年 1 月发布，旨在自愿使用，并提高组织将可信性考量纳入 AI 产品、服务和系统的设计、开发、使用和评估的能力。

概况是针对特定环境、应用或技术--在此情况下为生成式人工智能(GAI)--对 AI RMF 功能、类别和子类别的实施，基于框架用户的需求、风险容忍度和资源。AI RMF 概况帮助组织决定如何以与其目标高度一致、考虑法律/监管要求和最佳实践、并反映风险管理优先事项的方式最好地管理人工智能风险。与其他 AI RMF 概况一致，本概况提供了关于如何在人工智能生命周期各阶段以及针对 GAI 作为一项技术管理风险的见解。

由于 GAI 涵盖可跨用例或部门使用的模型或应用的风险，本文档是 AI RMF 跨部门概况。跨部门概况可用于治理、映射、度量和管理与跨部门共同活动或业务流程相关的风险，例如使用大语言模型(LLM)、云服务或采购。

本文档定义了 GAI 使用所带来新颖或加剧的风险。在介绍和描述这些风险之后，本文档提供了一组建议行动，以帮助组织治理、映射、度量和管理这些风险。

[1]第 14110 号行政命令将生成式人工智能定义为"一类模拟输入数据的结构和特征以生成衍生合成内容的人工智能模型。这可包括图像、视频、音频、文本和其他数字内容。"虽然并非所有 GAI 都源自基础模型，但就本文件而言，GAI 一般指生成式基础模型。第 14110 号行政命令将"两用基础模型"这一基础模型子类别定义为"一种在广泛数据上训练的人工智能模型；通常使用自监督；包含至少数百亿个参数；适用于广泛的情境。"

[2]本概况依据 EO 14110 第 4.1(a)(i)(A) 节制定，该节指示商务部长通过国家标准与技术研究院(NIST)主任行事，为生成式人工智能开发 AI RMF、NIST AI 100-1 的配套资源。

This work was informed by public feedback and consultations with diverse stakeholder groups as part of NIST's Generative AI Public Working Group (GAI PWG). The GAI PWG was an open, transparent, and collaborative process, facilitated via a virtual workspace, to obtain multistakeholder input on GAI risk management and to inform NIST's approach.

The focus of the GAI PWG was limited to four primary considerations relevant to GAI: Governance, Content Provenance, Pre-deployment Testing, and Incident Disclosure (further described in Appendix A). As such, the suggested actions in this document primarily address these considerations.

Future revisions of this profile will include additional AI RMF subcategories, risks, and suggested actions based on additional considerations of GAI as the space evolves and empirical evidence indicates additional risks. A glossary of terms pertinent to GAI risk management will be developed and hosted on NIST's Trustworthy & Responsible AI Resource Center (AIRC), and added to *The Language of Trustworthy AI: An In-Depth Glossary of Terms.*

This document was also informed by public comments and consultations from several Requests for Information.

2. Overview of Risks Unique to or Exacerbated by GAI

In the context of the AI RMF, *risk* refers to the composite measure of an event's **probability** (or likelihood) of occurring and the **magnitude** or degree of the consequences of the corresponding event. Some risks can be assessed as likely to materialize in a given context, particularly those that have been empirically demonstrated in similar contexts. Other risks may be unlikely to materialize in a given context, or may be more speculative and therefore uncertain.

AI risks can differ from or intensify traditional software risks. Likewise, GAI can exacerbate existing AI risks, and creates unique risks. GAI risks can vary along many dimensions:

- **Stage of the AI lifecycle:** Risks can arise during design, development, deployment, operation, and/or decommissioning.
- **Scope:** Risks may exist at individual model or system levels, at the application or implementation levels (i.e., for a specific use case), or at the ecosystem level – that is, beyond a single system or organizational context. Examples of the latter include the expansion of "algorithmic monocultures,[3]" resulting from repeated use of the same model, or impacts on access to opportunity, labor markets, and the creative economies.[4]
- **Source of risk:** Risks may emerge from factors related to the design, training, or operation of the GAI model itself, stemming in some cases from GAI model or system inputs, and in other cases, from GAI system outputs. Many GAI risks, however, originate from human behavior, including

[3] "Algorithmic monocultures" refers to the phenomenon in which repeated use of the same model or algorithm in consequential decision-making settings like employment and lending can result in increased susceptibility by systems to correlated failures (like unexpected shocks), due to multiple actors relying on the same algorithm.
[4] Many studies have projected the impact of AI on the workforce and labor markets. Fewer studies have examined the impact of GAI on the labor market, though some industry surveys indicate that that both employees and employers are pondering this disruption.

这项工作得益于公众反馈和与不同利益相关者群体的磋商，作为 NIST 生成式人工智能公共工作组(GAI PWG)的一部分。GAI PWG 是一个开放、透明和协作的过程，通过虚拟工作空间促进，以获得关于 GAI 风险管理的多利益相关者输入，并为 NIST 的方法提供信息。

GAI PWG 的重点仅限于与 GAI 相关的四个主要考虑因素：治理、内容来源、部署前测试和事件披露(在附录 A 中进一步描述)。因此，本文档中的建议行动主要涉及这些考虑因素。

本概况的未来修订版将基于随着该领域的发展对 GAI 的额外考量以及表明存在额外风险的经验证据，纳入额外的 AI RMF 子类别、风险和建议行动。与 GAI 风险管理相关的术语表将制定并托管在 NIST 的可信与负责任人工智能资源中心(AIRC)，并添加到《可信人工智能术语深入解析词汇表》中。

本文档还得益于公众评论和若干信息请求的磋商。

2. 生成式人工智能特有或加剧的风险概览

在 AI RMF 的语境中，风险指事件发生的**概率**(或可能性)与相应事件后果的**严重程度**或程度的综合度量。有些风险可被评估为在特定情境中很可能成为现实，尤其是那些已在类似情境中得到实证证明的风险。其他风险在特定情境中可能不太可能成为现实，或者可能更具推测性，因而具有不确定性。

AI 风险可能不同于或加剧传统软件风险。同样，GAI 可能加剧现有 AI 风险，并创造独特风险。GAI 风险

- **AI 生命周期阶段：**风险可能在设计、开发、部署、运营和/或退役期间出现。
- **范围：**风险可能存在于单个模型或系统层面，存在于应用或实施层面(即针对特定用例)，或存在于生态系统层面--即超出单个系统或组织情境的范围。后者的例子包括因重复使用同一模型而导致的"算法单一文化[3]"的扩大，或对机会获取、劳动力市场和创意经济的影响。[4]
- **风险来源：**风险可能源于与 GAI 模型本身的设计、训练或运营相关的因素，在某些情况下源于 GAI 模型或系统输入，在其他情况下源于 GAI 系统输出。然而，许多 GAI 风险源于人类行为，包括

[3]"算法单一文化"是指这样一种现象：在就业和借贷等具有重大后果的决策场景中重复使用同一模型或算法，可能因多个行为者依赖同一算法而导致系统对相关性故障(如意外冲击)的易感性增加。[4]许多研究已预测了人工智能对劳动力和劳动力市场的影响。考察 GAI 对劳动力市场影响的研究较少，尽管一些行业调查表明，雇员和雇主都在思考这一颠覆性变化。

the abuse, misuse, and unsafe repurposing by humans (adversarial or not), and others result from interactions between a human and an AI system.

- **Time scale:** GAI risks may materialize abruptly or across extended periods. Examples include immediate (and/or prolonged) emotional harm and potential risks to physical safety due to the distribution of harmful deepfake images, or the long-term effect of disinformation on societal trust in public institutions.

The presence of risks and where they fall along the dimensions above will vary depending on the characteristics of the GAI model, system, or use case at hand. These characteristics include but are not limited to GAI model or system architecture, training mechanisms and libraries, data types used for training or fine-tuning, levels of model access or availability of model weights, and application or use case context.

Organizations may choose to tailor how they measure GAI risks based on these characteristics. They may additionally wish to allocate risk management resources relative to the severity and likelihood of negative impacts, including where and how these risks manifest, and their direct and material impacts harms in the context of GAI use. Mitigations for model or system level risks may differ from mitigations for use-case or ecosystem level risks.

Importantly, some GAI risks are unknown, and are therefore difficult to properly scope or evaluate given the uncertainty about potential GAI scale, complexity, and capabilities. Other risks may be known but difficult to estimate given the wide range of GAI stakeholders, uses, inputs, and outputs. Challenges with risk estimation are aggravated by a lack of visibility into GAI training data, and the generally immature state of the science of AI measurement and safety today. This document focuses on risks for which there is an existing empirical evidence base at the time this profile was written; for example, speculative risks that may potentially arise in more advanced, future GAI systems are not considered. Future updates may incorporate additional risks or provide further details on the risks identified below.

To guide organizations in identifying and managing GAI risks, a set of risks unique to or exacerbated by the development and use of GAI are defined below.[5] Each risk is labeled according to the outcome, object, or source of the risk (i.e., some are risks “to” a subject or domain and others are risks “of” or “from” an issue or theme). These risks provide a lens through which organizations can frame and execute risk management efforts. To help streamline risk management efforts, each risk is mapped in Section 3 (as well as in tables in Appendix B) to relevant Trustworthy AI Characteristics identified in the AI RMF.

[5] These risks can be further categorized by organizations depending on their unique approaches to risk definition and management. One possible way to further categorize these risks, derived in part from the UK’s International Scientific Report on the Safety of Advanced AI, could be: **1) Technical / Model risks (or risk from malfunction):** Confabulation; Dangerous or Violent Recommendations; Data Privacy; Value Chain and Component Integration; Harmful Bias, and Homogenization; **2) Misuse by humans (or malicious use):** CBRN Information or Capabilities; Data Privacy; Human-AI Configuration; Obscene, Degrading, and/or Abusive Content; Information Integrity; Information Security; **3) Ecosystem / societal risks (or systemic risks)**: Data Privacy; Environmental; Intellectual Property. We also note that some risks are cross-cutting between these categories.

人类的滥用、误用和不安全再利用(对抗性或非对抗性)，以及其他源于人类与 AI 系统之间交互的风险。

- **时间尺度：** GAI 风险可能突然出现或跨越较长时间。示例包括由于传播有害深度伪造图像而导致的即时(和/或长期)情感伤害和潜在的人身安全风险，或虚假信息对公众对公共机构信任的长期影响。

风险的存在及其在上述维度上的位置将取决于 GAI 模型、系统或用例的特征。这些特征包括但不限于 GAI 模型或系统架构、训练机制和库、用于训练或微调的数据类型、模型访问级别或模型权重的可用性，以及应用或用例背景。

组织可以选择根据这些特征调整其度量 GAI 风险的方式。他们还可以希望根据负面影响的严重性和可能性分配风险管理资源，包括这些风险表现的地点和方式，以及它们在 GAI 使用背景下的直接和实质性影响危害。模型或系统级风险的缓解措施可能不同于用例或生态系统级风险的缓解措施。

重要的是，一些 GAI 风险是未知的，因此鉴于潜在 GAI 规模、复杂性和能力的不确定性，难以恰当地界定范围或进行评估。其他风险可能是已知的，但鉴于 GAI 利益相关者、用途、输入和输出的广泛多样性，难以估计。对 GAI 训练数据缺乏可见性，以及当今人工智能度量与安全科学总体上尚不成熟的状态，加剧了风险估计方面的挑战。本文件侧重于在本概况撰写之时已有现有实证证据基础的风险；例如，可能在更先进的未来 GAI 系统中出现的推测性风险未被考虑。未来的更新可能会纳入更多风险，或就下文所识别的风险提供进一步细节。

为指导组织识别和管理 GAI 风险，下文界定了一组 GAI 开发和使用所特有或因其而加剧的风险。[5]每项风险根据风险的结果、对象或来源进行标注(即有些是“针对”某一主体或领域的风险，另一些是“属于”或“来自”某一问题或主题的风险)。这些风险提供了一个视角，组织可借此构建和执行风险管理努力。为帮助简化风险管理努力，每项风险在第 3 节(以及附录 B 的表格中)被映射到 AI RMF 中识别的相关可信人工智能特征。

[5]组织可根据其定义和管理风险的独特方法对这些风险进一步分类。进一步分类这些风险的一种可能方式(部分源自英国《先进人工智能安全国际科学报告》)可以是：**1)技术/模型风险(或故障风险):**虚构；危险或暴力建议；数据隐私；价值链与组件集成；有害偏见与同质化；**2)大类滥用(或恶意使用):**CBRN信息或能力；数据隐私；人机配置；淫秽、有辱人格和/或虐待性内容；信息完整性；信息安全；**3)生态系统/社会风险(或系统性风险)**：数据隐私；环境；知识产权。我们还注意到，某些风险在这些类别之间是交叉的。

1. **CBRN Information or Capabilities:** Eased access to or synthesis of materially nefarious information or design capabilities related to chemical, biological, radiological, or nuclear (CBRN) weapons or other dangerous materials or agents.
2. **Confabulation:** The production of confidently stated but erroneous or false content (known colloquially as "hallucinations" or "fabrications") by which users may be misled or deceived.[6]
3. **Dangerous, Violent, or Hateful Content:** Eased production of and access to violent, inciting, radicalizing, or threatening content as well as recommendations to carry out self-harm or conduct illegal activities. Includes difficulty controlling public exposure to hateful and disparaging or stereotyping content.
4. **Data Privacy:** Impacts due to leakage and unauthorized use, disclosure, or de-anonymization of biometric, health, location, or other personally identifiable information or sensitive data.[7]
5. **Environmental Impacts:** Impacts due to high compute resource utilization in training or operating GAI models, and related outcomes that may adversely impact ecosystems.
6. **Harmful Bias or Homogenization:** Amplification and exacerbation of historical, societal, and systemic biases; performance disparities[8] between sub-groups or languages, possibly due to non-representative training data, that result in discrimination, amplification of biases, or incorrect presumptions about performance; undesired homogeneity that skews system or model outputs, which may be erroneous, lead to ill-founded decision-making, or amplify harmful biases.
7. **Human-AI Configuration:** Arrangements of or interactions between a human and an AI system which can result in the human inappropriately anthropomorphizing GAI systems or experiencing algorithmic aversion, automation bias, over-reliance, or emotional entanglement with GAI systems.
8. **Information Integrity:** Lowered barrier to entry to generate and support the exchange and consumption of content which may not distinguish fact from opinion or fiction or acknowledge uncertainties, or could be leveraged for large-scale dis- and mis-information campaigns.
9. **Information Security:** Lowered barriers for offensive cyber capabilities, including via automated discovery and exploitation of vulnerabilities to ease hacking, malware, phishing, offensive cyber

[6] Some commenters have noted that the terms "hallucination" and "fabrication" anthropomorphize GAI, which itself is a risk related to GAI systems as it can inappropriately attribute human characteristics to non-human entities.
[7] What is categorized as sensitive data or sensitive PII can be highly contextual based on the nature of the information, but examples of sensitive information include information that relates to an information subject's most intimate sphere, including political opinions, sex life, or criminal convictions.
[8] The notion of harm presumes some baseline scenario that the harmful factor (e.g., a GAI model) makes worse. When the mechanism for potential harm is a disparity between groups, it can be difficult to establish what the most appropriate baseline is to compare against, which can result in divergent views on when a disparity between AI behaviors for different subgroups constitutes a harm. In discussing harms from disparities such as biased behavior, this document highlights examples where someone's situation is worsened relative to what it would have been in the absence of any AI system, making the outcome unambiguously a harm of the system.

1. **CBRN 信息或能力：**与化学、生物、放射性或核(CBRN)武器或其他危险材料或制剂相关的、具有实质性恶意信息或设计能力的获取或合成变得更容易。
2. **虚构：**以自信口吻陈述但错误或虚假的内容(俗称"幻觉"或"捏造")，可能使用户被误导或欺骗。[6]
3. **危险、暴力或仇恨内容：**暴力、煽动、激进化或威胁性内容的制作和获取变得更容易，以及实施自残或进行非法活动的建议。包括难以控制公众接触仇恨、贬损或刻板印象内容。
4. **数据隐私：**因生物识别、健康、位置或其他个人可识别信息或敏感数据的泄露和未经授权的使用、披露或去匿名化而造成的影响。[7]
5. **环境影响：**因训练或运行 GAI 模型时的高计算资源利用而造成的影响，以及可能对生态系统产生不利影响的相关结果。
6. **有害偏见或同质化：**历史、社会和系统性偏见的放大和加剧；[8]子群体或语言之间的性能差异，可能由于非代表性训练数据导致，从而造成歧视、偏见放大或对性能的错误推定；不期望的同质化扭曲系统或模型输出，可能产生错误、导致缺乏依据的决策或放大有害偏见。
7. **人-AI 配置：**人与人工智能系统之间的安排或交互，可能导致人类不适当地将 GAI 系统拟人化，或经历算法厌恶、自动化偏见、过度依赖或与 GAI 系统的情感纠葛。
8. **信息完整性：**生成和支持内容交换与消费的准入门槛降低，这些内容可能无法区分事实与观点或虚构，或未承认不确定性，或被用于大规模虚假信息和错误信息活动。
9. **信息安全：**攻击性网络能力的准入门槛降低，包括通过自动发现和利用漏洞来便利黑客攻击、恶意软件、网络钓鱼、攻击性网络

6 一些评论者指出，"幻觉"和"捏造"这两个术语将生成式人工智能拟人化，这本身就是一个与生成式人工智能系统相关的风险，因为它可能不适当地将人类特征归因于非人类实体。7 什么被归类为敏感数据或敏感个人身份信息，可能高度取决于信息的性质，但敏感信息的示例包括与信息主体最私密领域相关的信息，包括政治观点、性生活或刑事定罪。8 损害的概念假定存在某种基线情景，而有害因素(例如生成式人工智能模型)使该情景变得更糟。当潜在损害的机制是群体之间的差异时，很难确定最合适的比较基线，这可能导致对人工智能行为在不同子群体之间的差异何时构成损害产生分歧。在讨论诸如偏见行为等差异所造成的损害时，本文强调了一些示例，其中某人的处境相对于没有任何人工智能系统的情况而言变得更糟，从而使结果明确成为该系统的损害。

operations, or other cyberattacks; increased attack surface for targeted cyberattacks, which may compromise a system's availability or the confidentiality or integrity of training data, code, or model weights.

10. **Intellectual Property:** Eased production or replication of alleged copyrighted, trademarked, or licensed content without authorization (possibly in situations which do not fall under fair use); eased exposure of trade secrets; or plagiarism or illegal replication.
11. **Obscene, Degrading, and/or Abusive Content:** Eased production of and access to obscene, degrading, and/or abusive imagery which can cause harm, including synthetic child sexual abuse material (CSAM), and nonconsensual intimate images (NCII) of adults.
12. **Value Chain and Component Integration:** Non-transparent or untraceable integration of upstream third-party components, including data that has been improperly obtained or not processed and cleaned due to increased automation from GAI; improper supplier vetting across the AI lifecycle; or other issues that diminish transparency or accountability for downstream users.

2.1. CBRN Information or Capabilities

In the future, GAI may enable malicious actors to more easily access CBRN weapons and/or relevant knowledge, information, materials, tools, or technologies that could be misused to assist in the design, development, production, or use of CBRN weapons or other dangerous materials or agents. While relevant biological and chemical threat knowledge and information is often publicly accessible, LLMs could facilitate its analysis or synthesis, particularly by individuals without formal scientific training or expertise.

Recent research on this topic found that LLM outputs regarding biological threat creation and attack planning provided minimal assistance beyond traditional search engine queries, suggesting that state-of-the-art LLMs at the time these studies were conducted do not substantially increase the operational likelihood of such an attack. The physical synthesis development, production, and use of chemical or biological agents will continue to require both applicable expertise and supporting materials and infrastructure. The impact of GAI on chemical or biological agent misuse will depend on what the key barriers for malicious actors are (e.g., whether information access is one such barrier), and how well GAI can help actors address those barriers.

Furthermore, chemical and biological design tools (BDTs) – highly specialized AI systems trained on scientific data that aid in chemical and biological design – may augment design capabilities in chemistry and biology beyond what text-based LLMs are able to provide. As these models become more efficacious, including for beneficial uses, it will be important to assess their potential to be used for harm, such as the ideation and design of novel harmful chemical or biological agents.

While some of these described capabilities lie beyond the reach of existing GAI tools, ongoing assessments of this risk would be enhanced by monitoring both the ability of AI tools to facilitate CBRN weapons planning and GAI systems' connection or access to relevant data and tools.

Trustworthy AI Characteristic: Safe, Explainable and Interpretable

运营或其他网络攻击；针对性网络攻击的攻击面增加，可能危及系统的可用性或训练数据、代码或模型权重的机密性或完整性。

10. **知识产权：**涉嫌受版权、商标或授权保护的内容在未经授权的情况下更容易被生产或复制(可能处于不属于合理使用的情形)；商业秘密更容易暴露；或抄袭或非法复制。
11. **淫秽、有辱人格和/或虐待性内容：**更容易生产和获取淫秽、有辱人格和/或虐待性的图像，这些图像可能造成伤害，包括合成儿童性虐待材料(CSAM)和成人的非自愿亲密图像(NCII)。
12. **价值链与组件集成：**上游第三方组件的集成不透明或不可追溯，包括因GAI自动化程度提高而improperly 获取或未经处理和清理的数据；整个人工智能生命周期中供应商审查不当；或其他削弱下游用户透明度或问责制的问题。

2.1. CBRN 信息或能力

未来，GAI可能使恶意行为者更容易获取CBRN武器和/或相关知识、信息、材料、工具或技术，这些可能被滥用于协助设计、开发、生产或使用CBRN武器或其他危险材料或制剂。虽然相关生物和化学威胁知识与信息通常可公开获取，但LLM可能促进其分析或合成，尤其是由缺乏正式科学培训或专业知识的个人进行。

近期关于该主题的研究发现，LLM在生物威胁制造和攻击规划方面的输出，相较于传统搜索引擎查询仅提供极少的帮助，这表明在这些研究进行时，最先进的LLM并未实质性增加此类攻击的操作可能性。化学或生物制剂的物理合成开发、生产和使用将继续需要适用的专业知识和配套材料及基础设施。GAI对化学或生物制剂滥用的影响将取决于恶意行为者的关键障碍是什么(例如，信息获取是否是此类障碍之一)，以及GAI能在多大程度上帮助行为者克服这些障碍。

此外，化学和生物设计工具(BDT)--基于科学数据训练的、用于辅助化学和生物设计的高度专业化的人工智能系统--可能增强化学和生物学领域的设计能力，超出基于文本的大语言模型所能提供的范围。随着这些模型变得更加有效，包括用于有益用途，评估其被用于危害的潜力将变得非常重要，例如构思和设计新型有害化学或生物制剂。

虽然其中一些所述能力超出了现有GAI工具的范围，但通过监测AI工具促进CBRN武器规划的能力以及GAI系统与相关数据和工具的连接或访问，可以增强对这一风险的持续评估。

可信人工智能特征：安全、可解释与可理解

2.2. Confabulation

"Confabulation" refers to a phenomenon in which GAI systems generate and confidently present erroneous or false content in response to prompts. Confabulations also include generated outputs that diverge from the prompts or other input or that contradict previously generated statements in the same context. These phenomena are colloquially also referred to as "hallucinations" or "fabrications."

Confabulations can occur across GAI outputs and contexts.[9,10] Confabulations are a natural result of the way generative models are designed: they generate outputs that approximate the statistical distribution of their training data; for example, LLMs predict the next token or word in a sentence or phrase. While such statistical prediction can produce factually accurate and consistent outputs, it can also produce outputs that are factually inaccurate or internally inconsistent. This dynamic is particularly relevant when it comes to open-ended prompts for long-form responses and in domains which require highly contextual and/or domain expertise.

Risks from confabulations may arise when users believe false content – often due to the confident nature of the response – leading users to act upon or promote the false information. This poses a challenge for many real-world applications, such as in healthcare, where a confabulated summary of patient information reports could cause doctors to make incorrect diagnoses and/or recommend the wrong treatments. Risks of confabulated content may be especially important to monitor when integrating GAI into applications involving consequential decision making.

GAI outputs may also include confabulated logic or citations that purport to justify or explain the system's answer, which may further mislead humans into inappropriately trusting the system's output. For instance, LLMs sometimes provide logical steps for how they arrived at an answer even when the answer itself is incorrect. Similarly, an LLM could falsely assert that it is human or has human traits, potentially deceiving humans into believing they are speaking with another human.

The extent to which humans can be deceived by LLMs, the mechanisms by which this may occur, and the potential risks from adversarial prompting of such behavior are emerging areas of study. Given the wide range of downstream impacts of GAI, it is difficult to estimate the downstream scale and impact of confabulations.

Trustworthy AI Characteristics: Fair with Harmful Bias Managed, Safe, Valid and Reliable, Explainable and Interpretable

2.3. Dangerous, Violent, or Hateful Content

GAI systems can produce content that is inciting, radicalizing, or threatening, or that glorifies violence, with greater ease and scale than other technologies. LLMs have been reported to generate dangerous or violent recommendations, and some models have generated actionable instructions for dangerous or

[9] Confabulations of falsehoods are most commonly a problem for text-based outputs; for audio, image, or video content, creative generation of non-factual content can be a desired behavior.
[10] For example, legal confabulations have been shown to be pervasive in current state-of-the-art LLMs. See also, e.g.,

2.2. 虚构

"虚构"是指GAI系统在响应提示时生成并自信地呈现错误或虚假内容的现象。虚构还包括生成的输出偏离提示或其他输入，或与同一上下文中先前生成的陈述相矛盾。这些现象通俗地也被称为"幻觉"或"捏造"。

虚构可能出现在GAI的输出和情境中。[9,10]虚构是生成模型设计方式的自然结果：它们生成近似其训练数据统计分布的输出；例如，LLM预测句子或短语中的下一个词元或单词。虽然这种统计预测可以产生事实准确且一致的输出，但也可能产生事实不准确或内部不一致的输出。当涉及长篇幅回复的开放式提示以及需要高度情境化和/或领域专业知识的领域时，这种动态尤为相关。

当用户相信虚假内容时--通常是由于回答的自信性质--可能导致用户依据或传播虚假信息，从而产生虚构内容风险。这对许多现实世界应用构成挑战，例如在医疗保健领域，虚构的患者信息报告摘要可能导致医生做出错误诊断和/或推荐错误治疗。在将GAI集成到涉及重大决策的应用中时，监测虚构内容的风险可能尤为重要。

GAI输出还可能包括虚构的逻辑或引文，声称可以证明或解释系统的答案，这可能进一步误导人类不适当地信任系统的输出。例如，大语言模型有时会提供得出答案的逻辑步骤，即使答案本身是错误的。同样，大语言模型可能错误地声称自己是人类或具有人类特征，可能欺骗人类相信他们正在与另一个人交谈。

人类在多大程度上可能被大语言模型欺骗、这种情况可能发生的机制，以及对此类行为进行对抗性提示的潜在风险，都是新兴的研究领域。鉴于GAI广泛的下游影响，很难估计虚构的下游规模和影响。

可信人工智能特征：公平且有害偏见得到管理、安全、有效且可靠、可解释且可理解

2.3. 危险、暴力或仇恨内容

GAI系统可以比其他技术更容易、更大规模地生成煽动性、激进化或威胁性内容，或美化暴力的内容。据报道，大语言模型会生成危险或暴力的建议，一些模型已生成可操作的危险或

[9]虚假内容的虚构最常见的是基于文本输出的问题；对于音频、图像或视频内容，创造性生成非事实性内容可能是期望

[10]例如，法律虚构已被证明普遍存在于当前最先进的大语言模型中。另见，例如，

unethical behavior. Text-to-image models also make it easy to create images that could be used to promote dangerous or violent messages. Similar concerns are present for other GAI media, including video and audio. GAI may also produce content that recommends self-harm or criminal/illegal activities.

Many current systems restrict model outputs to limit certain content or in response to certain prompts, but this approach may still produce harmful recommendations in response to other less-explicit, novel prompts (also relevant to CBRN Information or Capabilities, Data Privacy, Information Security, and Obscene, Degrading and/or Abusive Content). Crafting such prompts deliberately is known as "jailbreaking," or, manipulating prompts to circumvent output controls. Limitations of GAI systems can be harmful or dangerous in certain contexts. Studies have observed that users may disclose mental health issues in conversations with chatbots – and that users exhibit negative reactions to unhelpful responses from these chatbots during situations of distress.

This risk encompasses difficulty controlling creation of and public exposure to offensive or hateful language, and denigrating or stereotypical content generated by AI. This kind of speech may contribute to downstream harm such as fueling dangerous or violent behaviors. The spread of denigrating or stereotypical content can also further exacerbate representational harms (see Harmful Bias and Homogenization below).

Trustworthy AI Characteristics: Safe, Secure and Resilient

2.4. Data Privacy

GAI systems raise several risks to privacy. GAI system training requires large volumes of data, which in some cases may include personal data. The use of personal data for GAI training raises risks to widely accepted privacy principles, including to transparency, individual participation (including consent), and purpose specification. For example, most model developers do not disclose specific data sources on which models were trained, limiting user awareness of whether personally identifiably information (PII) was trained on and, if so, how it was collected.

Models may leak, generate, or correctly infer sensitive information about individuals. For example, during adversarial attacks, LLMs have revealed sensitive information (from the public domain) that was included in their training data. This problem has been referred to as data memorization, and may pose exacerbated privacy risks even for data present only in a small number of training samples.

In addition to revealing sensitive information in GAI training data, GAI models may be able to correctly infer PII or sensitive data that was not in their training data nor disclosed by the user by stitching together information from disparate sources. These inferences can have negative impact on an individual even if the inferences are not accurate (e.g., confabulations), and especially if they reveal information that the individual considers sensitive or that is used to disadvantage or harm them.

Beyond harms from information exposure (such as extortion or dignitary harm), wrong or inappropriate inferences of PII can contribute to downstream or secondary harmful impacts. For example, predictive inferences made by GAI models based on PII or protected attributes can contribute to adverse decisions, leading to representational or allocative harms to individuals or groups (see Harmful Bias and Homogenization below).

不道德行为。文本到图像模型也使得创建图像变得容易，这些图像可用于宣传危险或暴力信息。其他GAI媒体，包括视频和音频，也存在类似的担忧。GAI还可能生成推荐自残或犯罪/非法活动的内容。

许多当前系统限制模型输出以限制某些内容或响应某些提示，但这种方法在响应其他不太明确的新颖提示时可能仍产生有害建议(也与CBRN信息或能力、数据隐私、信息安全以及淫秽、贬低和/或虐待性内容相关)。故意制作此类提示被称为"越狱"，即操纵提示以规避输出控制。GAI系统的局限性在某些情境下可能有害或危险。研究观察到，用户可能在聊天机器人对话中披露心理健康问题，并且用户在痛苦情境下对这些聊天机器人的无益回应表现出负面反应。

这一风险涵盖难以控制攻击性或仇恨性语言的创建和公开暴露，以及AI生成的贬损性或刻板印象内容。此类言论可能导致下游伤害，例如助长危险或暴力行为。贬损性或刻板印象内容的传播还可能进一步加剧代表性伤害(见下文有害偏见与同质化)。

可信人工智能特征： 安全、可靠且有韧性

2.4. 数据隐私

GAI系统引发若干隐私风险。GAI系统训练需要大量数据，某些情况下可能包括个人数据。将个人数据用于GAI训练会危及广泛接受的隐私原则，包括透明度、个人参与(包括同意)和目的明确。例如，大多数模型开发者不披露模型训练所依据的具体数据来源，限制了用户对是否使用个人可识别信息(PII)进行训练以及如何收集的认知。

模型可能泄露、生成或正确推断关于个人的敏感信息。例如，在对抗性攻击期间，大语言模型已泄露敏感信息(来自公共领域)，这些信息被包含在其训练数据中。这个问题被称为数据记忆，即使对于仅存在于少量训练样本中的数据，也可能构成加剧的隐私风险。

除了在GAI训练数据中泄露敏感信息外，GAI模型还可能通过拼接来自不同来源的信息，正确推断不在其训练数据中且用户未披露的PII或敏感数据。即使推断不准确(例如虚构内容)，这些推断也可能对个人产生负面影响，尤其是当它们泄露个人认为敏感或用于使其处于不利地位或受到伤害的信息时。

除了信息暴露带来的伤害(如勒索或尊严伤害)之外，对PII的错误或不适当推断可能导致下游或二次有害影响。例如，GAI模型基于PII或受保护属性做出的预测性推断可能导致不利决策，从而对个人或群体造成代表性或分配性伤害(见下文有害偏见与同质化)。

Trustworthy AI Characteristics: Accountable and Transparent, Privacy Enhanced, Safe, Secure and Resilient

2.5. Environmental Impacts

Training, maintaining, and operating (running inference on) GAI systems are resource-intensive activities, with potentially large energy and environmental footprints. Energy and carbon emissions vary based on what is being done with the GAI model (i.e., pre-training, fine-tuning, inference), the modality of the content, hardware used, and type of task or application.

Current estimates suggest that training a single transformer LLM can emit as much carbon as 300 round-trip flights between San Francisco and New York. In a study comparing energy consumption and carbon emissions for LLM inference, generative tasks (e.g., text summarization) were found to be more energy- and carbon-intensive than discriminative or non-generative tasks (e.g., text classification).

Methods for creating smaller versions of trained models, such as model distillation or compression, could reduce environmental impacts at inference time, but training and tuning such models may still contribute to their environmental impacts. Currently there is no agreed upon method to estimate environmental impacts from GAI.

Trustworthy AI Characteristics: Accountable and Transparent, Safe

2.6. Harmful Bias and Homogenization

Bias exists in many forms and can become ingrained in automated systems. AI systems, including GAI systems, can increase the speed and scale at which harmful biases manifest and are acted upon, potentially perpetuating and amplifying harms to individuals, groups, communities, organizations, and society. For example, when prompted to generate images of CEOs, doctors, lawyers, and judges, current text-to-image models underrepresent women and/or racial minorities, and people with disabilities. Image generator models have also produced biased or stereotyped output for various demographic groups and have difficulty producing non-stereotyped content even when the prompt specifically requests image features that are inconsistent with the stereotypes. Harmful bias in GAI models, which may stem from their training data, can also cause representational harms or perpetuate or exacerbate bias based on race, gender, disability, or other protected classes.

Harmful bias in GAI systems can also lead to harms via disparities between how a model performs for different subgroups or languages (e.g., an LLM may perform less well for non-English languages or certain dialects). Such disparities can contribute to discriminatory decision-making or amplification of existing societal biases. In addition, GAI systems may be inappropriately trusted to perform similarly across all subgroups, which could leave the groups facing underperformance with worse outcomes than if no GAI system were used. Disparate or reduced performance for lower-resource languages also presents challenges to model adoption, inclusion, and accessibility, and may make preservation of endangered languages more difficult if GAI systems become embedded in everyday processes that would otherwise have been opportunities to use these languages.

Bias is mutually reinforcing with the problem of undesired homogenization, in which GAI systems produce skewed distributions of outputs that are overly uniform (for example, repetitive aesthetic styles

可信人工智能特征：可问责且透明、隐私增强、安全、可靠且有韧性

2.5. 环境影响

训练、维护和运行(运行推理)GAI系统是资源密集型活动，可能具有较大的能源和环境足迹。能源和碳排放因GAI模型的使用方式(即预训练、微调、推理)、内容模态、所用硬件以及任务或应用类型而异。

当前估计表明，训练单个transformer大语言模型可能排放多达300次旧金山与纽约之间往返航班的碳量。在一项比较大语言模型推理的能源消耗和碳排放的研究中，生成式任务(如文本摘要)被发现比判别式或非生成式任务(如文本分类)更加能源和碳密集。

创建已训练模型较小版本的方法，如模型蒸馏或压缩，可以减少推理时的环境影响，但训练和调优此类模型仍可能对其环境影响有所贡献。目前尚无公认的方法来估计GAI的环境影响。

可信人工智能特征：可问责且透明、安全

2.6. 有害偏见与同质化

偏见以多种形式存在，并可能在自动化系统中根深蒂固。人工智能系统(包括GAI系统)可能加快有害偏见显现和作用于其中的速度和规模，可能持续并放大对个人、群体、社区、组织和社会的伤害。例如，当提示生成CEO、医生、律师和法官的图像时，当前的文本到图像模型对女性和/或少数族裔以及残疾人的代表性不足。图像生成器模型还对各种人口群体产生偏见或刻板印象输出，并且即使提示明确要求与刻板印象不一致的图像特征，也难以生成非刻板印象内容。GAI模型中的有害偏见可能源于其训练数据，也可能造成代表性伤害或延续或加剧基于种族、性别、残疾或其他受保护类别的偏见。

生成式人工智能系统中的有害偏见还可能通过模型在不同子群体或语言之间表现差异而造成危害(例如，LLM 在处理非英语语言或某些方言时可能表现较差)。此类差异可能导致歧视性决策或放大现有的社会偏见。此外，生成式人工智能系统可能被不当信任为在所有子群体中表现相似，这可能使表现不佳的群体面临比不使用生成式人工智能系统更差的结果。对低资源语言的表现差异或性能下降也对模型采用、包容性和可及性构成挑战，并且如果生成式人工智能系统嵌入到原本可以使用这些语言的日常流程中，可能会使濒危语言的保护更加困难。

偏见与不期望的同质化问题相互强化，其中GAI系统产生过于统一的偏斜输出分布(例如，重复的审美风格

and reduced content diversity). Overly homogenized outputs can themselves be incorrect, or they may lead to unreliable decision-making or amplify harmful biases. These phenomena can flow from foundation models to downstream models and systems, with the foundation models acting as "bottlenecks," or single points of failure.

Overly homogenized content can contribute to "model collapse." Model collapse can occur when model training over-relies on synthetic data, resulting in data points disappearing from the distribution of the new model's outputs. In addition to threatening the robustness of the model overall, model collapse could lead to homogenized outputs, including by amplifying any homogenization from the model used to generate the synthetic training data.

Trustworthy AI Characteristics: Fair with Harmful Bias Managed, Valid and Reliable

2.7. Human-AI Configuration

GAI system use can involve varying risks of misconfigurations and poor interactions between a system and a human who is interacting with it. Humans bring their unique perspectives, experiences, or domain-specific expertise to interactions with AI systems but may not have detailed knowledge of AI systems and how they work. As a result, human experts may be unnecessarily "averse" to GAI systems, and thus deprive themselves or others of GAI's beneficial uses.

Conversely, due to the complexity and increasing reliability of GAI technology, over time, humans may over-rely on GAI systems or may unjustifiably perceive GAI content to be of higher quality than that produced by other sources. This phenomenon is an example of automation bias, or excessive deference to automated systems. Automation bias can exacerbate other risks of GAI, such as risks of confabulation or risks of bias or homogenization.

There may also be concerns about emotional entanglement between humans and GAI systems, which could lead to negative psychological impacts.

Trustworthy AI Characteristics: Accountable and Transparent, Explainable and Interpretable, Fair with Harmful Bias Managed, Privacy Enhanced, Safe, Valid and Reliable

2.8. Information Integrity

Information integrity describes the "spectrum of information and associated patterns of its creation, exchange, and consumption in society." High-integrity information can be trusted; "distinguishes fact from fiction, opinion, and inference; acknowledges uncertainties; and is transparent about its level of vetting. This information can be linked to the original source(s) with appropriate evidence. High-integrity information is also accurate and reliable, can be verified and authenticated, has a clear chain of custody, and creates reasonable expectations about when its validity may expire."[11]

[11] This definition of information integrity is derived from the 2022 White House Roadmap for Researchers on Priorities Related to Information Integrity Research and Development.

和内容多样性降低）。过度同质化的输出本身可能是错误的，或者可能导致不可靠的决策或放大有害偏见。这些现象可能从基础模型流向下游模型和系统，基础模型充当"瓶颈"或单点故障。

过度同质化的内容可能导致"模型崩溃"。当模型训练过度依赖合成数据时，可能发生模型崩溃，导致数据点从新模型输出分布中消失。除了威胁模型整体的鲁棒性外，模型崩溃还可能导致同质化输出，包括放大用于生成合成训练数据的模型中的任何同质化。

可信人工智能特征：公平且有害偏见得到管理、有效且可靠

2.7. 人机协同配置

GAI系统的使用可能涉及不同程度的错误配置风险以及系统与交互人类之间不良互动的风险。人类将其独特的视角、经验或领域特定专业知识带入与人工智能系统的交互中，但可能不具备人工智能系统及其工作原理的详细知识。因此，人类专家可能不必要地"厌恶"GAI系统，从而剥夺自己或他人使用GAI有益用途的机会。

相反，由于GAI技术的复杂性和日益提高的可靠性，随着时间的推移，人类可能过度依赖GAI系统，或可能不合理地认为GAI内容比其他来源产生的内容质量更高。这种现象是自动化偏见的一个例子，即过度服从自动化系统。自动化偏见可能加剧GAI的其他风险，如虚构风险或偏见或同质化风险。

还可能存在对人类与GAI系统之间情感纠葛的担忧，这可能导致负面心理影响。

可信人工智能特征：可问责且透明、可解释且可理解、公平且有害偏见得到管理、隐私增强、安全、有效且可靠

2.8. 信息完整性

信息完整性描述了"社会中信息的谱系及其创建、交换和消费的相关模式"。高完整性信息可以被信任；"区分事实与虚构、观点和推断；承认不确定性；并对其审查水平保持透明。此类信息可以通过适当的证据链接到原始来源。高完整性信息也是准确可靠的，可以被验证和认证，具有清晰的监管链，并对其有效性可能何时过期建立合理预期。"[11]

[11]信息完整性的这一定义源自2022年《白宫研究人员信息完整性相关研究与发展优先事项路线图》。

GAI systems can ease the unintentional production or dissemination of false, inaccurate, or misleading content (misinformation) at scale, particularly if the content stems from confabulations.

GAI systems can also ease the deliberate production or dissemination of false or misleading information (disinformation) at scale, where an actor has the explicit intent to deceive or cause harm to others. Even very subtle changes to text or images can manipulate human and machine perception.

Similarly, GAI systems could enable a higher degree of sophistication for malicious actors to produce disinformation that is targeted towards specific demographics. Current and emerging multimodal models make it possible to generate both text-based disinformation and highly realistic "deepfakes" – that is, synthetic audiovisual content and photorealistic images.[12] Additional disinformation threats could be enabled by future GAI models trained on new data modalities.

Disinformation and misinformation – both of which may be facilitated by GAI – may erode public trust in true or valid evidence and information, with downstream effects. For example, a synthetic image of a Pentagon blast went viral and briefly caused a drop in the stock market. Generative AI models can also assist malicious actors in creating compelling imagery and propaganda to support disinformation campaigns, which may not be photorealistic, but could enable these campaigns to gain more reach and engagement on social media platforms. Additionally, generative AI models can assist malicious actors in creating fraudulent content intended to impersonate others.

Trustworthy AI Characteristics: Accountable and Transparent, Safe, Valid and Reliable, Interpretable and Explainable

2.9. Information Security

Information security for computer systems and data is a mature field with widely accepted and standardized practices for offensive and defensive cyber capabilities. GAI-based systems present two primary information security risks: GAI could potentially discover or enable new cybersecurity risks by lowering the barriers for or easing automated exercise of offensive capabilities; simultaneously, it expands the available attack surface, as GAI itself is vulnerable to attacks like prompt injection or data poisoning.

Offensive cyber capabilities advanced by GAI systems may augment cybersecurity attacks such as hacking, malware, and phishing. Reports have indicated that LLMs are already able to discover some vulnerabilities in systems (hardware, software, data) and write code to exploit them. Sophisticated threat actors might further these risks by developing GAI-powered security co-pilots for use in several parts of the attack chain, including informing attackers on how to proactively evade threat detection and escalate privileges after gaining system access.

Information security for GAI models and systems also includes maintaining availability of the GAI system and the integrity and (when applicable) the confidentiality of the GAI code, training data, and model weights. To identify and secure potential attack points in AI systems or specific components of the AI

[12] See also https://doi.org/10.6028/NIST.AI.100-4, to be published.

生成式人工智能系统可以轻易助长大规模无意生成或传播虚假、不准确或误导性内容(错误信息)，尤其是当内容源于虚构时。

生成式人工智能系统还可以轻易助长大规模故意生成或传播虚假或误导性信息(虚假信息)，即行为者明确意图欺骗或对他人造成伤害。即使对文本或图像进行非常细微的改动，也可能操纵人类和机器的感知。

同样，生成式人工智能系统可能使恶意行为者能够以更高程度的复杂性制作针对特定人群的虚假信息。当前和新兴的多模态模型使得生成基于文本的虚假信息和高度逼真的"深度伪造"--即合成视听内容和照片级真实图像--成为可能。[12]未来的生成式人工智能模型在新数据模态上训练后，可能会带来更多虚假信息威胁。

虚假信息和错误信息--两者均可能被生成式人工智能助长--可能侵蚀公众信任，使人们对真实或有效证据和信息产生怀疑，并带来下游影响。例如，一张五角大楼爆炸的合成图像在网络上疯传，并短暂导致股市下跌。生成式人工智能模型还可以帮助恶意行为者制作有说服力的图像和宣传材料，以支持虚假信息活动；这些内容可能并非照片级真实，但可能使这些活动在社交媒体平台上获得更多触达和互动。此外，生成式人工智能模型还可以帮助恶意行为者制作旨在冒充他人的欺诈性内容。

可信人工智能特征：可问责且透明、安全、有效且可靠、可解释且可说明

2.9. 信息安全

计算机系统和数据的信息安全是一个成熟的领域，在进攻性和防御性网络能力方面拥有广泛接受和标准化的实践。基于生成式人工智能的系统带来两个主要的信息安全风险：生成式人工智能可能通过降低进攻能力的门槛或简化其自动化实施，从而发现或促成新的网络安全风险；同时，它扩大了可用的攻击面，因为生成式人工智能本身容易受到提示注入或数据投毒等攻击。

GAI系统所推进的进攻性网络能力可能增强网络安全攻击，例如黑客攻击、恶意软件和网络钓鱼。报告表明，LLM已经能够发现系统中的某些漏洞(硬件、软件、数据)，并编写代码来利用这些漏洞。复杂的威胁行为者可能通过开发由GAI驱动的安全副驾驶来加剧这些风险，用于攻击链的多个环节，包括指导攻击者如何主动规避威胁检测以及在获得系统访问权限后提升权限。

生成式人工智能模型和系统的信息安全还包括维持生成式人工智能系统的可用性，以及生成式人工智能代码、训练数据和模型权重的完整性及(在适用情况下)保密性。为识别和保护人工智能系统或人工智能价值链特定组件(例如数据输入、处理、生成式人工智能训练或部署环境)中的潜在攻击点，常规网络安全实践可能需要。

[12]另见 https://doi.org/10.6028/NIST.AI.100-4， 即将发布。

value chain (e.g., data inputs, processing, GAI training, or deployment environments), conventional cybersecurity practices may need to adapt or evolve.

For instance, prompt injection involves modifying what input is provided to a GAI system so that it behaves in unintended ways. In direct prompt injections, attackers might craft malicious prompts and input them directly to a GAI system, with a variety of downstream negative consequences to interconnected systems. Indirect prompt injection attacks occur when adversaries remotely (i.e., without a direct interface) exploit LLM-integrated applications by injecting prompts into data likely to be retrieved. Security researchers have already demonstrated how indirect prompt injections can exploit vulnerabilities by stealing proprietary data or running malicious code remotely on a machine. Merely querying a closed production model can elicit previously undisclosed information about that model.

Another cybersecurity risk to GAI is data poisoning, in which an adversary compromises a training dataset used by a model to manipulate its outputs or operation. Malicious tampering with data or parts of the model could exacerbate risks associated with GAI system outputs.

Trustworthy AI Characteristics: Privacy Enhanced, Safe, Secure and Resilient, Valid and Reliable

2.10. Intellectual Property

Intellectual property risks from GAI systems may arise where the use of copyrighted works is not a fair use under the fair use doctrine. If a GAI system's training data included copyrighted material, GAI outputs displaying instances of training data memorization (see Data Privacy above) could infringe on copyright.

How GAI relates to copyright, including the status of generated content that is similar to but does not strictly copy work protected by copyright, is currently being debated in legal fora. Similar discussions are taking place regarding the use or emulation of personal identity, likeness, or voice without permission.

Trustworthy AI Characteristics: Accountable and Transparent, Fair with Harmful Bias Managed, Privacy Enhanced

2.11. Obscene, Degrading, and/or Abusive Content

GAI can ease the production of and access to illegal non-consensual intimate imagery (NCII) of adults, and/or child sexual abuse material (CSAM). GAI-generated obscene, abusive or degrading content can create privacy, psychological and emotional, and even physical harms, and in some cases may be illegal.

Generated explicit or obscene AI content may include highly realistic "deepfakes" of real individuals, including children. The spread of this kind of material can have downstream negative consequences: in the context of CSAM, even if the generated images do not resemble specific individuals, the prevalence of such images can divert time and resources from efforts to find real-world victims. Outside of CSAM, the creation and spread of NCII disproportionately impacts women and sexual minorities, and can have subsequent negative consequences including decline in overall mental health, substance abuse, and even suicidal thoughts.

Data used for training GAI models may unintentionally include CSAM and NCII. A recent report noted that several commonly used GAI training datasets were found to contain hundreds of known images of

价值链(例如数据输入、处理、GAI 训练或部署环境)，传统的网络安全实践可能需要调整或演进。

例如，提示注入涉及修改提供给GAI系统的输入，使其以非预期方式运行。在直接提示注入中，攻击者可能构造恶意提示并直接输入到GAI系统中，对互连系统产生各种下游负面后果。间接提示注入攻击发生在对手远程(即没有直接接口)利用LLM集成应用时，通过将提示注入到可能被检索的数据中。安全研究人员已经展示了间接提示注入如何通过窃取专有数据或在机器上远程运行恶意代码来利用漏洞。仅仅查询一个封闭的生产模型就可能引出关于该模型此前未披露的信息。

GAI 面临的另一项网络安全风险是数据投毒，即对手破坏模型所使用的训练数据集，以操纵其输出或运行。对数据或模型部分内容的恶意篡改可能加剧与 GAI 系统输出相关的风险。

可信人工智能特征：隐私增强、安全、可靠且有韧性、有效且可靠

2.10. 知识产权

当对受版权保护作品的使用不属于合理使用原则下的合理使用时，GAI 系统可能产生知识产权风险。如果 GAI 系统的训练数据包含受版权保护的材料，显示训练数据记忆实例的 GAI 输出(见上文数据隐私)可能侵犯版权。

GAI 与版权的关系，包括与受版权保护作品相似但并非严格复制的生成内容的地位，目前正在法律论坛中辩论。关于未经许可使用或模仿个人身份、肖像或声音的类似讨论也在进行中。

可信人工智能特征：可问责且透明、公平且有害偏见受管理、隐私增强

2.11. 淫秽、有辱人格和/或辱骂性内容

用于训练生成式人工智能模型的数据可能无意中包含CSAM和NCII。指出，若干常用生成式人工智能训练数据集被发现包含数百张已知图像

生成的露骨或淫秽人工智能内容可能包括对真实个人(包括儿童)的高度逼真"深度伪造"。此类材料的传播可能产生下游负面后果：在儿童性虐待材料(CSAM)的语境下，即使生成的图像与特定个人并不相似，此类图像的泛滥也可能挤占用于寻找现实世界受害者的时间和资源。在CSAM之外，非自愿私密影像(NCII)的创建和传播对女性和性少数群体造成不成比例的影响，并可能产生后续负面后果，包括整体心理健康下降、物质滥用，甚至自杀念头。

用于训练 GAI 模型的数据可能无意中包含 CSAM 和 NCII。近期报告指出，若干常用的 GAI 训练数据集被发现包含数百张已知的

CSAM. Even when trained on “clean” data, increasingly capable GAI models can synthesize or produce synthetic NCII and CSAM. Websites, mobile apps, and custom-built models that generate synthetic NCII have moved from niche internet forums to mainstream, automated, and scaled online businesses.

Trustworthy AI Characteristics: Fair with Harmful Bias Managed, Safe, Privacy Enhanced

2.12. Value Chain and Component Integration

GAI value chains involve many third-party components such as procured datasets, pre-trained models, and software libraries. These components might be improperly obtained or not properly vetted, leading to diminished transparency or accountability for downstream users. While this is a risk for traditional AI systems and some other digital technologies, the risk is exacerbated for GAI due to the scale of the training data, which may be too large for humans to vet; the difficulty of training foundation models, which leads to extensive reuse of limited numbers of models; and the extent to which GAI may be integrated into other devices and services. As GAI systems often involve many distinct third-party components and data sources, it may be difficult to attribute issues in a system’s behavior to any one of these sources.

Errors in third-party GAI components can also have downstream impacts on accuracy and robustness. For example, test datasets commonly used to benchmark or validate models can contain label errors. Inaccuracies in these labels can impact the “stability” or robustness of these benchmarks, which many GAI practitioners consider during the model selection process.

Trustworthy AI Characteristics: Accountable and Transparent, Explainable and Interpretable, Fair with Harmful Bias Managed, Privacy Enhanced, Safe, Secure and Resilient, Valid and Reliable

3. Suggested Actions to Manage GAI Risks

The following suggested actions target risks unique to or exacerbated by GAI.

In addition to the suggested actions below, AI risk management activities and actions set forth in the AI RMF 1.0 and Playbook are already applicable for managing GAI risks. Organizations are encouraged to apply the activities suggested in the AI RMF and its Playbook when managing the risk of GAI systems.

Implementation of the suggested actions will vary depending on the type of risk, characteristics of GAI systems, stage of the GAI lifecycle, and relevant AI actors involved.

Suggested actions to manage GAI risks can be found in the tables below:

- The suggested actions are **organized by relevant AI RMF subcategories** to streamline these activities alongside implementation of the AI RMF.
- **Not every subcategory of the AI RMF is included in this document.**[13] Suggested actions are listed for only some subcategories.

[13] As this document was focused on the GAI PWG efforts and primary considerations (see Appendix A), AI RMF subcategories not addressed here may be added later.

CSAM 图像。即使使用“干净”数据训练，能力日益增强的 GAI 模型仍可合成或生成合成的 NCII 和 CSAM。生成合成 NCII 的网站、移动应用和定制模型已从小众互联网论坛转移到主流、自动化且规模化的在线业务。

可信人工智能特征：公平且有害偏见受管理、安全、隐私增强

2.12. 价值链与组件集成

生成式人工智能价值链涉及许多第三方组件，如采购的数据集、预训练模型和软件库。这些组件可能获取不当或未经适当审查，导致下游用户的透明度或问责性降低。虽然这对传统人工智能系统和某些其他数字技术而言是一种风险，但由于训练数据的规模(可能过大而人类无法审查)、基础模型训练的难度(导致有限数量模型的广泛重复使用)，以及生成式人工智能可能被集成到其他设备和服务中的程度，该风险在生成式人工智能中被加剧。由于生成式人工智能系统通常涉及许多不同的第三方组件和数据源，可能难以将系统行为中的问题归因于其中任何一个来源。

第三方 GAI 组件中的错误也可能对准确性和鲁棒性产生下游影响。例如，常用于基准测试或验证模型的测试数据集可能包含标签错误。这些标签中的不准确可能影响这些基准的“稳定性”或鲁棒性，许多 GAI 从业者在模型选择过程中会考虑这一点。

可信人工智能特征：可问责且透明、可解释且可理解、公平且有害偏见受管理、隐私增强、安全、可靠且有韧性、有效且可靠

3. 管理 GAI 风险的建议行动

以下建议行动针对的是生成式人工智能特有或因其而加剧的风险。

除了下文建议的行动外，AI RMF 1.0 和 Playbook 中提出的人工智能风险管理活动与行动已适用于管理 GAI 风险。鼓励组织在管理 GAI 系统风险时采用 AI RMF 及其 Playbook 中建议的活动。

• 建议行动按相关AI RMF子类别组织，以便在实施AI RMF的同时简化这些活动。

管理 GAI 风险的建议行动见下表：

• 建议行动按**相关 AI RMF 子类别组织**，以便与 AI RMF 的实施同步简化这些活动。

• **并非 AI RMF 的每个子类别都包含在本文档中。**[13]仅为部分子类别列出了建议行动。

[13]由于本文档聚焦于 GAI PWG 工作和主要考虑事项(见附录 A)，此处未涉及的 AI RMF 子类别可能稍后添加。

- Not every suggested action applies to **every** AI Actor[14] or is relevant to every AI Actor Task. For example, suggested actions relevant to GAI developers may not be relevant to GAI deployers. The applicability of suggested actions to relevant AI actors should be determined based on organizational considerations and their unique uses of GAI systems.

Each table of suggested actions includes:

- **Action ID:** Each Action ID corresponds to the relevant AI RMF function and subcategory (e.g., GV-1.1-001 corresponds to the first suggested action for Govern 1.1, GV-1.1-002 corresponds to the second suggested action for Govern 1.1). AI RMF functions are tagged as follows: GV = Govern; MP = Map; MS = Measure; MG = Manage.
- **Suggested Action:** Steps an organization or AI actor can take to manage GAI risks.
- **GAI Risks:** Tags linking suggested actions with relevant GAI risks.
- **AI Actor Tasks:** Pertinent AI Actor Tasks for each subcategory. Not every AI Actor Task listed will apply to every suggested action in the subcategory (i.e., some apply to AI development and others apply to AI deployment).

The tables below begin with the AI RMF subcategory, shaded in blue, followed by suggested actions.

GOVERN 1.1: Legal and regulatory requirements involving AI are understood, managed, and documented.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.1-001	Align GAI development and use with applicable laws and regulations, including those related to data privacy, copyright and intellectual property law.	Data Privacy; Harmful Bias and Homogenization; Intellectual Property
AI Actor Tasks: Governance and Oversight		

[14] AI Actors are defined by the OECD as "those who play an active role in the AI system lifecycle, including organizations and individuals that deploy or operate AI." See Appendix A of the AI RMF for additional descriptions of AI Actors and AI Actor Tasks.

- 并非每项建议行动都适用于**每个**人工智能参与者[14]，也并非与每个人工智能参与者任务都相关。例如，与GAI开发者相关的建议行动可能不适用于GAI部署者。建议行动对相关人工智能参与者的适用性应基于组织考量及其对GAI系统的独特使用来确定。

每张建议行动表包括：

- **行动ID:**每个行动ID对应相关的AI RMF功能和子类别(例如，GV-1.1-001对应治理1.1的第一项建议行动，GV-1.1-002对应治理1.1的第二项建议行动)。AI RMF功能的标记如下：GV = 治理；MP = 映射；MS = 度量；MG = 管理。
- **建议行动：**组织或人工智能参与者可采取的管理GAI风险的步骤。
- **GAI 风险：**将建议行动与相关 GAI 风险关联的标签。
- **人工智能参与者任务：**每个子类别相关的人工智能参与者任务。所列的并非每个人工智能参与者任务都适用于该子类别中的每项建议行动(即，一些适用于人工智能开发，另一些适用于人工智能部署)。

下表以AI RMF子类别开头(以蓝色底纹标示)，其后为建议行动。

治理1.1:涉及人工智能的法律和监管要求得到理解、管理和记录。		
操作 ID 建议操作		**GAI 风险**
GV-1.1-001	使GAI开发和使用符合适用的法律和法规，包括与数据隐私、版权和知识产权法相关的那些。	数据隐私；有害偏见与同质化；智力属性
人工智能行为者任务：治理与监督		

[14]人工智能参与者被OECD定义为"在人工智能系统生命周期中发挥积极作用的各方，包括部署或运营人工智能的组织和个人"。有关人工智能参与者和人工智能参与者任务的更多描述，参见AI RMF附录A。

GOVERN 1.2: The characteristics of trustworthy AI are integrated into organizational policies, processes, procedures, and practices.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.2-001	Establish transparency policies and processes for documenting the origin and history of training data and generated data for GAI applications to advance digital content transparency, while balancing the proprietary nature of training approaches.	Data Privacy; Information Integrity; Intellectual Property
GV-1.2-002	Establish policies to evaluate risk-relevant capabilities of GAI and robustness of safety measures, both prior to deployment and on an ongoing basis, through internal and external evaluations.	CBRN Information or Capabilities; Information Security
AI Actor Tasks: Governance and Oversight		

GOVERN 1.3: Processes, procedures, and practices are in place to determine the needed level of risk management activities based on the organization's risk tolerance.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.3-001	Consider the following factors when updating or defining risk tiers for GAI: Abuses and impacts to information integrity; Dependencies between GAI and other IT or data systems; Harm to fundamental rights or public safety; Presentation of obscene, objectionable, offensive, discriminatory, invalid or untruthful output; Psychological impacts to humans (e.g., anthropomorphization, algorithmic aversion, emotional entanglement); Possibility for malicious use; Whether the system introduces significant new security vulnerabilities; Anticipated system impact on some groups compared to others; Unreliable decision making capabilities, validity, adaptability, and variability of GAI system performance over time.	Information Integrity; Obscene, Degrading, and/or Abusive Content; Value Chain and Component Integration; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content; CBRN Information or Capabilities
GV-1.3-002	Establish minimum thresholds for performance or assurance criteria and review as part of deployment approval ("go/"no-go") policies, procedures, and processes, with reviewed processes and approval thresholds reflecting measurement of GAI capabilities and risks.	CBRN Information or Capabilities; Confabulation; Dangerous, Violent, or Hateful Content
GV-1.3-003	Establish a test plan and response policy, before developing highly capable models, to periodically evaluate whether the model may misuse CBRN information or capabilities and/or offensive cyber capabilities.	CBRN Information or Capabilities; Information Security

治理1.2:可信人工智能的特征被纳入组织政策、流程、程序和实践。		
操作 ID 建议操作		**GAI 风险**
GV-1.2-001	为GAI应用建立透明政策与流程，记录训练数据和生成数据的来源与历史，以推进数字 内容透明度，同时平衡训练的专有性质 方法。	数据隐私；信息 完整性；知识产权
GV-1.2-002	建立政策，评估GAI的风险相关能力和 安全措施的鲁棒性，既在部署前也在持续基础上，通过内部和外部评估进行。	CBRN 信息或能力；信息安全
人工智能行为者任务：治理与监督		

治理1.3:已建立流程、程序和实践，以根据组织的风险容忍度确定所需的风险管理活动水平。		
操作 ID 建议操作		**GAI 风险**
GV-1.3-001	在更新或定义GAI风险层级时考虑以下因素：滥用及对信息完整性的影响；GAI与其他IT或 数据系统；对基本权利或公共安全的危害；呈现 淫秽、令人反感、冒犯性、歧视性、无效或不真实的输出； 对人的心理影响(例如，拟人化、算法 厌恶、情感纠葛)；恶意使用的可能性；该 系统引入了重大的新安全漏洞；预期系统 对某些群体相较于其他群体的影响；不可靠的决策 能力、有效性、适应性以及GAI系统性能在 时间。	信息完整性；淫秽、 有辱人格和/或辱骂性 内容；价值链与 组件集成；有害 偏见与同质化； 危险、暴力或仇恨性 内容；化学、生物、放射及核信息或 能力
GV-1.3-002	建立性能或保证标准的最低阈值，并作为部署批准("go/no-go")政策、程序和流程的一部 审查流程和批准阈值反映对GAI能力和风险的度量。	CBRN信息或能力； 虚构；危险、 暴力或仇恨内容
GV-1.3-003	在开发高能力模型之前，建立测试计划和响应政策， 以定期评估该模型是否可能滥用CBRN信息或能力和/或进攻性网络能力。	CBRN 信息或能力；信息安全

GV-1.3-004	Obtain input from stakeholder communities to identify unacceptable use, in accordance with activities in the AI RMF Map function.	CBRN Information or Capabilities; Obscene, Degrading, and/or Abusive Content; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
GV-1.3-005	Maintain an updated hierarchy of identified and expected GAI risks connected to contexts of GAI model advancement and use, potentially including specialized risk levels for GAI systems that address issues such as model collapse and algorithmic monoculture.	Harmful Bias and Homogenization
GV-1.3-006	Reevaluate organizational risk tolerances to account for unacceptable negative risk (such as where significant negative impacts are imminent, severe harms are actually occurring, or large-scale risks could occur); and broad GAI negative risks, including: Immature safety or risk cultures related to AI and GAI design, development and deployment, public information integrity risks, including impacts on democratic processes, unknown long-term performance characteristics of GAI.	Information Integrity; Dangerous, Violent, or Hateful Content; CBRN Information or Capabilities
GV-1.3-007	Devise a plan to halt development or deployment of a GAI system that poses unacceptable negative risk.	CBRN Information and Capability; Information Security; Information Integrity
AI Actor Tasks: Governance and Oversight		

GV-1.3-004	获取来自利益相关者社区的输入以识别不可接受的使用，在 与 AI RMF 映射功能中的活动保持一致。	CBRN 信息或能力；淫秽、有辱人格 辱骂性内容；有害偏见 以及同质化；危险、暴力或仇恨内 容
GV-1.3-005	维护与以下方面相关的已识别和预期 GAI 风险的更新层级结构： GAI模型推进和使用的背景下，可能包括针对GAI系统的专门风险 针对生成式人工智能系统的水平，以应对模型崩溃和算法 单一化等问题。	有害偏见与同质化
GV-1.3-006	重新评估组织的风险容忍度，以考虑不可接受的负面风险 (例如重大负面影响迫在眉睫、严重危害实际发生或可能发生大规模风险的情况)；以及 包括：与人工智能和生成式人工智能设计相关的安全或风险文化不成熟， 开发和部署、公共信息完整性风险(包括对民主进程的影响)、GAI未知的长期性能特征。	信息完整性；危险的， 暴力或仇恨性内容；化学、生物、放射及核 信息或能力
GV-1.3-007	制定一项计划以停止开发或部署构成GAI系统的 不可接受的负面风险。	CBRN信息与能力； 信息安全；信息 完整性
人工智能行为者任务：治理与监督		

GOVERN 1.4: The risk management process and its outcomes are established through transparent policies, procedures, and other controls based on organizational risk priorities.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.4-001	Establish policies and mechanisms to prevent GAI systems from generating CSAM, NCII or content that violates the law.	Obscene, Degrading, and/or Abusive Content; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
GV-1.4-002	Establish transparent acceptable use policies for GAI that address illegal use or applications of GAI.	CBRN Information or Capabilities; Obscene, Degrading, and/or Abusive Content; Data Privacy; Civil Rights violations
AI Actor Tasks: AI Development, AI Deployment, Governance and Oversight		

治理1.4:风险管理过程及其结果通过基于组织风险优先级的透明政策、程序和其他控制措施予以确立。		
操作 ID 建议操作		**GAI 风险**
GV-1.4-001	建立政策和机制，防止GAI系统生成CSAM、NCII或违反法律的内容。	淫秽、有辱人格和/或辱骂性内 容；有害偏见和同质化； 危险、暴力或仇恨内容
GV-1.4-002	为生成式人工智能制定透明的可接受使用政策，以应对生成式人工智能的非法使用 或应用。	化学、生物、放射和核信息 或能力；淫秽、有辱人格和/ 或辱骂性内容；数据隐私； 公民权利侵犯
人工智能参与者任务：人工智能开发、人工智能部署、治理与监督		

GOVERN 1.5: Ongoing monitoring and periodic review of the risk management process and its outcomes are planned, and organizational roles and responsibilities are clearly defined, including determining the frequency of periodic review.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.5-001	Define organizational responsibilities for periodic review of content provenance and incident monitoring for GAI systems.	Information Integrity
GV-1.5-002	Establish organizational policies and procedures for after action reviews of GAI system incident response and incident disclosures, to identify gaps; Update incident response and incident disclosure processes as required.	Human-AI Configuration; Information Security
GV-1.5-003	Maintain a document retention policy to keep history for test, evaluation, validation, and verification (TEVV), and digital content transparency methods for GAI.	Information Integrity; Intellectual Property
AI Actor Tasks: Governance and Oversight, Operation and Monitoring		

GOVERN 1.6: Mechanisms are in place to inventory AI systems and are resourced according to organizational risk priorities.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.6-001	Enumerate organizational GAI systems for incorporation into AI system inventory and adjust AI system inventory requirements to account for GAI risks.	Information Security
GV-1.6-002	Define any inventory exemptions in organizational policies for GAI systems embedded into application software.	Value Chain and Component Integration
GV-1.6-003	In addition to general model, governance, and risk information, consider the following items in GAI system inventory entries: Data provenance information (e.g., source, signatures, versioning, watermarks); Known issues reported from internal bug tracking or external information sharing resources (e.g., AI incident database, AVID, CVE, NVD, or OECD AI incident monitor); Human oversight roles and responsibilities; Special rights and considerations for intellectual property, licensed works, or personal, privileged, proprietary or sensitive data; Underlying foundation models, versions of underlying models, and access modes.	Data Privacy; Human-AI Configuration; Information Integrity; Intellectual Property; Value Chain and Component Integration
AI Actor Tasks: Governance and Oversight		

治理 1.5:对风险管理过程及其结果进行持续监测和定期审查已纳入计划，组织角色和职责已明确界定，包括确定定期审查的频率。		
操作 ID 建议操作		**GAI 风险**
GV-1.5-001	定义组织职责用于定期审查内容来源 以及 GAI 系统的事件监测。	信息完整性
GV-1.5-002	为GAI的行动后审查建立组织政策和程序 系统事件响应和事件披露，以识别差距；根据需要更新事件响应和事件披露流程。	人机协同配置；信息安全
GV-1.5-003	维护文档保留政策，以保存测试、评估的历史记录， 验证与确认(TEVV)，以及数字内容透明度方法，用于 GAI。	信息完整性；知识产权 属性
人工智能行为者任务：治理与监督、运行与监控		

治理 1.6:已建立机制来清点人工智能系统，并根据组织风险优先级配置资源。		
操作 ID 建议操作		**GAI 风险**
GV-1.6-001	列举组织生成式人工智能系统用于纳入人工智能系统清单 并调整AI系统清单要求，以考虑GAI风险。	信息安全
GV-1.6-002	定义任何清单豁免在组织政策用于生成式人工智能系统 嵌入应用软件中。	价值链与组件 集成
GV-1.6-003	除一般模型、治理和风险信息外，在 GAI 系统清单条目中还应考虑以下事项：数据来源信息(例如来源、签名、版本控制、水印)；来自内部缺陷跟踪或外部信息共享资源(例如AI 事件数据库、AVID、CVE、NVD或OECD AI 事件监测器)的已知问题报告；人类监督角色与职责；针对知识产权、许可作品或个人、特权、专有或敏感数据的特殊权利与考量；底层基础模型、底层模型的版本以及访问模式。	数据隐私；人机配置；信息完整性；知识产权；价值链与组件 集成
人工智能行为者任务：治理与监督		

GOVERN 1.7: Processes and procedures are in place for decommissioning and phasing out AI systems safely and in a manner that does not increase risks or decrease the organization's trustworthiness.		
Action ID	**Suggested Action**	**GAI Risks**
GV-1.7-001	Protocols are put in place to ensure GAI systems are able to be deactivated when necessary.	Information Security; Value Chain and Component Integration
GV-1.7-002	Consider the following factors when decommissioning GAI systems: Data retention requirements; Data security, e.g., containment, protocols, Data leakage after decommissioning; Dependencies between upstream, downstream, or other data, internet of things (IOT) or AI systems; Use of open-source data or models; Users' emotional entanglement with GAI functions.	Human-AI Configuration; Information Security; Value Chain and Component Integration
AI Actor Tasks: AI Deployment, Operation and Monitoring		

GOVERN 2.1: Roles and responsibilities and lines of communication related to mapping, measuring, and managing AI risks are documented and are clear to individuals and teams throughout the organization.		
Action ID	**Suggested Action**	**GAI Risks**
GV-2.1-001	Establish organizational roles, policies, and procedures for communicating GAI incidents and performance to AI Actors and downstream stakeholders (including those potentially impacted), via community or official resources (e.g., AI incident database, AVID, CVE, NVD, or OECD AI incident monitor).	Human-AI Configuration; Value Chain and Component Integration
GV-2.1-002	Establish procedures to engage teams for GAI system incident response with diverse composition and responsibilities based on the particular incident type.	Harmful Bias and Homogenization
GV-2.1-003	Establish processes to verify the AI Actors conducting GAI incident response tasks demonstrate and maintain the appropriate skills and training.	Human-AI Configuration
GV-2.1-004	When systems may raise national security risks, involve national security professionals in mapping, measuring, and managing those risks.	CBRN Information or Capabilities; Dangerous, Violent, or Hateful Content; Information Security
GV-2.1-005	Create mechanisms to provide protections for whistleblowers who report, based on reasonable belief, when the organization violates relevant laws or poses a specific and empirically well-substantiated negative risk to public safety (or has already caused harm).	CBRN Information or Capabilities; Dangerous, Violent, or Hateful Content
AI Actor Tasks: Governance and Oversight		

治理 1.7:已建立流程和程序，以安全的方式停用和逐步淘汰人工智能系统，且不会增加风险或降低组织的可信度。		
操作 ID	**建议操作**	**GAI 风险**
GV-1.7-001	协议已制定并落实,以确保GAI系统能够在以下情况下被停用: 必要的。	信息安全；价值链 与组件集成
GV-1.7-002	停用生成式人工智能系统时考虑以下因素：数据保留要求；数据安全，例如遏制、协议、 在退役后；上游、下游或其他之间的依赖关系 数据、物联网(IOT)或AI系统；使用开源数据或模型； 用户与GAI功能之间的情感纠葛。	人机协同配置； 信息安全；价值链 与组件集成
AI 行为者任务：AI 部署、运行与监控		

治理 2.1:与映射、度量和管人工智能风险相关的角色、职责和沟通渠道已记录在案，并为整个组织的个人和团队所明确。		
操作 ID	**建议操作**	**GAI 风险**
GV-2.1-001	建立组织角色、政策和程序，用于向人工智能参与者和下游利益相关者(包括 可能受影响者)传达生成式人工智能事件和性能，通过社区或官方资源(例如，人工智能事件数据库、AVID、CVE、NVD或OECD人工智能事件监测器)。	人机协同配置；价值链与组件集成
GV-2.1-002	建立程序以让团队参与生成式人工智能系统事件响应与 根据具体事件类型，组成和职责各不相同。	有害偏见与同质化
GV-2.1-003	建立流程以验证人工智能参与者执行生成式人工智能事件响应任务 展示并保持适当的技能和培训。	人机协同配置
GV-2.1-004	当系统可能引发国家安全风险时，涉及国家安全 负责映射、度量和管理这些风险的专业人员。	CBRN信息或能力； 危险、暴力或仇恨性内容；信息安全
GV-2.1-005	建立机制，为举报者提供保护，依据 在合理确信的情况下，当组织违反相关法律或构成 对公共安全的具体且经实证充分证实的负面风险(或已 (已造成损害)。	CBRN信息或能力； 危险、暴力或仇恨性内容
人工智能行为者任务：治理与监督		

GOVERN 3.2: Policies and procedures are in place to define and differentiate roles and responsibilities for human-AI configurations and oversight of AI systems.		
Action ID	**Suggested Action**	**GAI Risks**
GV-3.2-001	Policies are in place to bolster oversight of GAI systems with independent evaluations or assessments of GAI models or systems where the type and robustness of evaluations are proportional to the identified risks.	CBRN Information or Capabilities; Harmful Bias and Homogenization
GV-3.2-002	Consider adjustment of organizational roles and components across lifecycle stages of large or complex GAI systems, including: Test and evaluation, validation, and red-teaming of GAI systems; GAI content moderation; GAI system development and engineering; Increased accessibility of GAI tools, interfaces, and systems, Incident response and containment.	Human-AI Configuration; Information Security; Harmful Bias and Homogenization
GV-3.2-003	Define acceptable use policies for GAI interfaces, modalities, and human-AI configurations (i.e., for chatbots and decision-making tasks), including criteria for the kinds of queries GAI applications should refuse to respond to.	Human-AI Configuration
GV-3.2-004	Establish policies for user feedback mechanisms for GAI systems which include thorough instructions and any mechanisms for recourse.	Human-AI Configuration
GV-3.2-005	Engage in threat modeling to anticipate potential risks from GAI systems.	CBRN Information or Capabilities; Information Security
AI Actors: AI Design		

GOVERN 4.1: Organizational policies and practices are in place to foster a critical thinking and safety-first mindset in the design, development, deployment, and uses of AI systems to minimize potential negative impacts.		
Action ID	**Suggested Action**	**GAI Risks**
GV-4.1-001	Establish policies and procedures that address continual improvement processes for GAI risk measurement. Address general risks associated with a lack of explainability and transparency in GAI systems by using ample documentation and techniques such as: application of gradient-based attributions, occlusion/term reduction, counterfactual prompts and prompt engineering, and analysis of embeddings; Assess and update risk measurement approaches at regular cadences.	Confabulation
GV-4.1-002	Establish policies, procedures, and processes detailing risk measurement in context of use with standardized measurement protocols and structured public feedback exercises such as AI red-teaming or independent external evaluations.	CBRN Information and Capability; Value Chain and Component Integration

治理 3.2:已建立政策和程序，以定义和区分人机配置及人工智能系统监督的角色和职责。		
操作 ID	**建议操作**	**GAI 风险**
GV-3.2-001	已制定相关政策，以通过独立 对生成式人工智能模型或系统的评估或评价，其中评估的类型和鲁棒性与已识别的风	CBRN 信息或能力；有害偏见与同质
GV-3.2-002	考虑在生命周期内调整组织角色和组成部分 大型或复杂生成式人工智能系统的阶段，包括：测试与评估、验证、 以及对 GAI 系统的红队测试；GAI 内容审核；GAI 系统 开发与工程；生成式人工智能工具、接口和 系统、事件响应与遏制。	人机协同配置； 信息安全；有害偏见 和同质化
GV-3.2-003	为GAI接口、模态及人机交互定义可接受使用政策 配置(即用于聊天机器人和决策任务)的可及性增加，包括以下标准： 生成式人工智能应用应拒绝响应的查询类型。	人机协同配置
GV-3.2-004	为GAI系统建立用户反馈机制的政策，其中包括 详尽的说明以及任何救济机制。	人机协同配置
GV-3.2-005	参与威胁建模，以预判GAI系统可能带来的风险。	CBRN 信息或能力；信息安全
人工智能参与者：AI设计		

治理 4.1:已建立组织政策和实践，以在人工智能系统的设计、开发、部署和使用中培养批判性思维和安全第一的心态，以最大限度地减		
操作 ID	**建议操作**	**GAI 风险**
GV-4.1-001	建立政策和程序，解决生成式人工智能风险测量的持续改进过程。应对与缺乏 通过使用充分的文档记录，提升GAI系统的可解释性和透明度，并 技术包括：应用基于梯度的归因、遮挡/术语 归约、反事实提示和提示工程以及嵌入分析相关的普遍风险；定期评估和更新风险测量方法 节奏。	虚构
GV-4.1-002	制定政策、程序和流程，详细说明以下方面的风险度量： 在标准化测量协议和结构化公开的使用情境下 反馈练习，如AI红队演练或独立外部评估。	CBRN信息与能力； 价值链与组件 集成

GV-4.1-003	Establish policies, procedures, and processes for oversight functions (e.g., senior leadership, legal, compliance, including internal evaluation) across the GAI lifecycle, from problem formulation and supply chains to system decommission.	Value Chain and Component Integration
AI Actor Tasks: AI Deployment, AI Design, AI Development, Operation and Monitoring		

GV-4.1-003	为贯穿生成式人工智能生命周期(从问题构建和供应链到系统退役)的监督职能(例如高级领导层、法律、合规，包括内部评估)建立政策、程序和流程。	价值链与组件集成
人工智能参与者任务：人工智能部署、人工智能设计、人工智能开发、运行与监控		

GOVERN 4.2: Organizational teams document the risks and potential impacts of the AI technology they design, develop, deploy, evaluate, and use, and they communicate about the impacts more broadly.		
Action ID	**Suggested Action**	**GAI Risks**
GV-4.2-001	Establish terms of use and terms of service for GAI systems.	Intellectual Property; Dangerous, Violent, or Hateful Content; Obscene, Degrading, and/or Abusive Content
GV-4.2-002	Include relevant AI Actors in the GAI system risk identification process.	Human-AI Configuration
GV-4.2-003	Verify that downstream GAI system impacts (such as the use of third-party plugins) are included in the impact documentation process.	Value Chain and Component Integration
AI Actor Tasks: AI Deployment, AI Design, AI Development, Operation and Monitoring		

GOVERN 4.2:组织团队记录其设计、开发、部署、评估和使用的人工智能技术的风险和潜在影响，并更广泛地就这些影响进行沟通。		
操作 ID 建议操作		**GAI 风险**
GV-4.2-001	为GAI系统制定使用条款和服务条款。 为GAI系统制定使用条款和服务条款。	知识产权；危险、暴力或仇恨内容；淫秽、有辱人格和/或辱骂性内容
GV-4.2-002	将相关的人工智能行为者纳入生成式人工智能系统风险识别过程。	人机协同配置
GV-4.2-003	验证下游 GAI 系统影响(例如使用第三方 插件)纳入影响文档化流程。	价值链与组件集成
人工智能参与者任务：人工智能部署、人工智能设计、人工智能开发、运行与监控		

GOVERN 4.3: Organizational practices are in place to enable AI testing, identification of incidents, and information sharing.		
Action ID	**Suggested Action**	**GAI Risks**
GV4.3--001	Establish policies for measuring the effectiveness of employed content provenance methodologies (e.g., cryptography, watermarking, steganography, etc.)	Information Integrity
GV-4.3-002	Establish organizational practices to identify the minimum set of criteria necessary for GAI system incident reporting such as: System ID (auto-generated most likely), Title, Reporter, System/Source, Data Reported, Date of Incident, Description, Impact(s), Stakeholder(s) Impacted.	Information Security

GOVERN 4.3:组织已建立实践，以支持人工智能测试、事件识别和信息共享。		
操作 ID 建议操作		**GAI 风险**
GV4.3--001	建立政策，以衡量所采用的内容来源溯源方法(例如密码学、水印、隐写术)的有效性， 等)	信息完整性
GV-4.3-002	建立组织实践，以确定生成式人工智能系统事件报告所需的最低标准集，例如：系统 ID(很可能是自动生成的)、标题、报告人、系统/来源、报告数据、事件日期、 描述、影响、受影响利益相关方。	信息安全

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GV-4.3-003	Verify information sharing and feedback mechanisms among individuals and organizations regarding any negative impact from GAI systems.	Information Integrity; Data Privacy
AI Actor Tasks: AI Impact Assessment, Affected Individuals and Communities, Governance and Oversight		

GV-4.3-003	验证个人和组织之间关于生成式人工智能系统任何负面影响的 information sharing 和反馈	信息完整性；数据隐私
人工智能参与者任务：人工智能影响评估、受影响的个人和社区、治理与监督		

GOVERN 5.1: Organizational policies and practices are in place to collect, consider, prioritize, and integrate feedback from those external to the team that developed or deployed the AI system regarding the potential individual and societal impacts related to AI risks.

Action ID	Suggested Action	GAI Risks
GV-5.1-001	Allocate time and resources for outreach, feedback, and recourse processes in GAI system development.	Human-AI Configuration; Harmful Bias and Homogenization
GV-5.1-002	Document interactions with GAI systems to users prior to interactive activities, particularly in contexts involving more significant risks.	Human-AI Configuration; Confabulation
AI Actor Tasks: AI Design, AI Impact Assessment, Affected Individuals and Communities, Governance and Oversight		

GOVERN 5.1:组织已建立政策和实践，以收集、考虑、优先排序并整合来自开发或部署人工智能系统的团队之外的人员的反馈，这些反馈涉及与人工智能风险相关的潜在个人和社会影响。

操作 ID	建议操作	GAI 风险
GV-5.1-001	为生成式人工智能中的外联、反馈和追索流程分配时间和资源 系统开发。	人机协同配置；有害 偏见与同质化
GV-5.1-002	在交互活动之前，向用户记录与 GAI 系统的交互情况， 尤其是在涉及更重大风险的场景中。	人机协同配置； 虚构
人工智能参与者任务：人工智能设计、人工智能影响评估、受影响的个人和社区、治理与监督		

GOVERN 6.1: Policies and procedures are in place that address AI risks associated with third-party entities, including risks of infringement of a third-party's intellectual property or other rights.

Action ID	Suggested Action	GAI Risks
GV-6.1-001	Categorize different types of GAI content with associated third-party rights (e.g., copyright, intellectual property, data privacy).	Data Privacy; Intellectual Property; Value Chain and Component Integration
GV-6.1-002	Conduct joint educational activities and events in collaboration with third parties to promote best practices for managing GAI risks.	Value Chain and Component Integration
GV-6.1-003	Develop and validate approaches for measuring the success of content provenance management efforts with third parties (e.g., incidents detected and response times).	Information Integrity; Value Chain and Component Integration
GV-6.1-004	Draft and maintain well-defined contracts and service level agreements (SLAs) that specify content ownership, usage rights, quality standards, security requirements, and content provenance expectations for GAI systems.	Information Integrity; Information Security; Intellectual Property

GOVERN 6.1:已建立政策和程序，以应对与第三方实体相关的人工智能风险，包括以下风险：
侵犯第三方知识产权或其他权利。

操作 ID	建议操作	GAI 风险
GV-6.1-001	对不同类型的生成式人工智能内容及其相关的第三方权利进行分类(例如， 版权、知识产权、数据隐私)。	数据隐私；知识产权；价 值链与组件集成
GV-6.1-002	与第三方合作开展联合教育活动和活动 以促进管理 GAI 风险的最佳实践。	价值链与组件 集成
GV-6.1-003	制定并验证衡量内容成功的方法 与第三方开展的来源溯源管理工作(例如，检测到的事件和响应时间)。	信息完整性；价值链与组件集成
GV-6.1-004	起草并维护定义明确的合同和服务级别协议(SLA) 其中规定生成式人工智能系统的内容所有权、使用权、质量标准、安全要求和内容来源	信息完整性；信息安全；知识产权

GV-6.1-005	Implement a use-cased based supplier risk assessment framework to evaluate and monitor third-party entities' performance and adherence to content provenance standards and technologies to detect anomalies and unauthorized changes; services acquisition and value chain risk management; and legal compliance.	Data Privacy; Information Integrity; Information Security; Intellectual Property; Value Chain and Component Integration
GV-6.1-006	Include clauses in contracts which allow an organization to evaluate third-party GAI processes and standards.	Information Integrity
GV-6.1-007	Inventory all third-party entities with access to organizational content and establish approved GAI technology and service provider lists.	Value Chain and Component Integration
GV-6.1-008	Maintain records of changes to content made by third parties to promote content provenance, including sources, timestamps, metadata.	Information Integrity; Value Chain and Component Integration; Intellectual Property
GV-6.1-009	Update and integrate due diligence processes for GAI acquisition and procurement vendor assessments to include intellectual property, data privacy, security, and other risks. For example, update processes to: Address solutions that may rely on embedded GAI technologies; Address ongoing monitoring, assessments, and alerting, dynamic risk assessments, and real-time reporting tools for monitoring third-party GAI risks; Consider policy adjustments across GAI modeling libraries, tools and APIs, fine-tuned models, and embedded tools; Assess GAI vendors, open-source or proprietary GAI tools, or GAI service providers against incident or vulnerability databases.	Data Privacy; Human-AI Configuration; Information Security; Intellectual Property; Value Chain and Component Integration; Harmful Bias and Homogenization
GV-6.1-010	Update GAI acceptable use policies to address proprietary and open-source GAI technologies and data, and contractors, consultants, and other third-party personnel.	Intellectual Property; Value Chain and Component Integration
AI Actor Tasks: Operation and Monitoring, Procurement, Third-party entities		

GV-6.1-005	实施基于用例的供应商风险评估框架，以评估和监控第三方实体的绩效以及对内容来源 检测异常和未经授权变更的标准与技术； 服务获取与价值链风险管理；以及法律合规。	数据隐私；信息 诚信；信息安全； 知识产权；价值链 与组件集成
GV-6.1-006	在合同中纳入条款以允许组织评估第三方 GAI 流程与标准。	信息完整性
GV-6.1-007	清点所有可访问组织内容的第三方实体并 建立经批准的GAI技术和服务提供商名单。	价值链与组件 集成
GV-6.1-008	维护记录以记录第三方对内容所做的变更以促进内容 来源信息，包括来源、时间戳、元数据。	信息完整性；价值链与组件集成； 知识产权
GV-6.1-009	更新并整合 GAI 采购与尽职调查流程， 采购供应商评估，以纳入知识产权、数据隐私、安全和其他风险。例如，更新流程以：处理以下解决方案 可能依赖嵌入式 GAI 技术；处理持续监控， 评估、警报、动态风险评估和实时报告 用于监控第三方生成式人工智能风险的工具；考虑跨生成式人工智能的政策调整 建模库、工具和 API、微调模型以及嵌入式工具；对照事件或漏洞数据库评估 GAI 供应商、开源或专有 GAI 工具或 GAI 服务提供商。	数据隐私；人机配置；信息安 全；知识产权； 价值链与组件 集成；有害偏见和 同质化
GV-6.1-010	更新生成式人工智能可接受使用政策，以涵盖专有和开源生成式人工智能 技术和数据，以及承包商、顾问和其他第三方 人员。	知识产权；价值链与组件集成
人工智能参与者任务：运行与监控、采购、第三方实体		

GOVERN 6.2: Contingency processes are in place to handle failures or incidents in third-party data or AI systems deemed to be high-risk.

Action ID	Suggested Action	GAI Risks
GV-6.2-001	Document GAI risks associated with system value chain to identify over-reliance on third-party data and to identify fallbacks.	Value Chain and Component Integration
GV-6.2-002	Document incidents involving third-party GAI data and systems, including open-data and open-source software.	Intellectual Property; Value Chain and Component Integration

GOVERN 6.2:已建立应急流程，以处理被视为高风险的第三方数据或人工智能系统中的故障或事件。

操作 ID	建议操作	GAI 风险
GV-6.2-001	记录与系统价值链相关的 GAI 风险，以识别过度依赖 关于第三方数据，并识别后备方案。	价值链与组件 集成
GV-6.2-002	记录涉及第三方 GAI 数据和系统的事件，包括开放- 数据和开源软件。	知识产权；价值链 与组件集成

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GV-6.2-003	Establish incident response plans for third-party GAI technologies: Align incident response plans with impacts enumerated in MAP 5.1; Communicate third-party GAI incident response plans to all relevant AI Actors; Define ownership of GAI incident response functions; Rehearse third-party GAI incident response plans at a regular cadence; Improve incident response plans based on retrospective learning; Review incident response plans for alignment with relevant breach reporting, data protection, data privacy, or other laws.	Data Privacy; Human-AI Configuration; Information Security; Value Chain and Component Integration; Harmful Bias and Homogenization
GV-6.2-004	Establish policies and procedures for continuous monitoring of third-party GAI systems in deployment.	Value Chain and Component Integration
GV-6.2-005	Establish policies and procedures that address GAI data redundancy, including model weights and other system artifacts.	Harmful Bias and Homogenization
GV-6.2-006	Establish policies and procedures to test and manage risks related to rollover and fallback technologies for GAI systems, acknowledging that rollover and fallback may include manual processing.	Information Integrity
GV-6.2-007	Review vendor contracts and avoid arbitrary or capricious termination of critical GAI technologies or vendor services and non-standard terms that may amplify or defer liability in unexpected ways and/or contribute to unauthorized data collection by vendors or third-parties (e.g., secondary data use). Consider: Clear assignment of liability and responsibility for incidents, GAI system changes over time (e.g., fine-tuning, drift, decay); Request: Notification and disclosure for serious incidents arising from third-party data and systems; Service Level Agreements (SLAs) in vendor contracts that address incident response, response times, and availability of critical support.	Human-AI Configuration; Information Security; Value Chain and Component Integration
AI Actor Tasks: AI Deployment, Operation and Monitoring, TEVV, Third-party entities		

GV-6.2-003	为第三方生成式人工智能技术建立事件响应计划：使事件响应计划与 MAP 5.1 中列举的影响保持一致；向所有相关人工智能参与者传达第三方生成式人工智能事件响应计划；界定生成式人工智能事件响应职能的所有权；定期演练第三方生成式人工智能事件响应计划；基于回顾性学习改进事件响应计划；审查事件响应计划，以确保其与相关违规报告、数据保护、数据隐私或其他法律保持一致。 事件响应职能；定期演练第三方生成式人工智能事件响应计划；基于回顾性学习改进事件响应计划；审查事件响应计划，以确保其与相关违规报告、数据保护、数据隐私或其他法律保持一致。	数据隐私；人机协同配置； 信息安全；价值链与 组件集成；有害偏见与同质化
GV-6.2-004	为部署中的第三方GAI系统建立持续监控的政策和程序。	价值链与组件 集成
GV-6.2-005	制定政策和程序，解决生成式人工智能数据冗余问题，包括模型权重和其他系统工件。	有害偏见与同质化
GV-6.2-006	制定政策和程序，测试和管理与生成式人工智能系统的滚动和 回退技术相关的风险，承认滚动和回退可能包括人工处理。	信息完整性
GV-6.2-007	审查供应商合同，避免任意或反复无常地终止关键生成式人工智能技术或供应商服务，以及可能以意外方式放大或推迟责任和/或助长供应商或第三方未经授权数据收集(例如二次数据使用)的非标准条款。考虑：明确的 事件责任和义务分配、生成式人工智能系统随时间的变化(例如微调、漂移、衰减)；要求：对由第三方数据和系统引起的严重事件进行通知和披露；服务水平 协议(SLA)在供应商合同中，涉及事件响应、响应时间和关键支持的可用性。	人机协同配置； 信息安全；价值链与组件集成
人工智能参与者任务：人工智能部署、运营和监控、TEVV(测试、评估、验证与确认)、第三方实体		

MAP 1.1: Intended purposes, potentially beneficial uses, context specific laws, norms and expectations, and prospective settings in which the AI system will be deployed are understood and documented. Considerations include: the specific set or types of users along with their expectations; potential positive and negative impacts of system uses to individuals, communities, organizations, society, and the planet; assumptions and related limitations about AI system purposes, uses, and risks across the development or product AI lifecycle; and related TEVV and system metrics.

Action ID	Suggested Action	GAI Risks
MP-1.1-001	When identifying intended purposes, consider factors such as internal vs. external use, narrow vs. broad application scope, fine-tuning, and varieties of data sources (e.g., grounding, retrieval-augmented generation).	Data Privacy; Intellectual Property

映射 1.1:对人工智能系统将被部署的预期目的、潜在有益用途、特定情境下的法律、规范与期望，以及预期环境予以理解和记录。考虑因素包括：特定的用户群体或用户类型及其期望；系统使用对个人、社区、组织、社会及地球可能产生的正面和负面影响；关于人工智能系统目的、用途和风险的假设及相关局限性(贯穿开发或产品人工智能生命周期)；以及相关的 TEVV 和系统指标。

操作 ID 建议操作		GAI 风险
MP-1.1-001 外部	在确定预期用途时，应考虑内部与外部等因素。 使用、窄范围与广范围应用、微调以及各种 数据源(例如，基础支撑、检索增强生成)。	数据隐私；知识产权

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MP-1.1-002	Determine and document the expected and acceptable GAI system context of use in collaboration with socio-cultural and other domain experts, by assessing: Assumptions and limitations; Direct value to the organization; Intended operational environment and observed usage patterns; Potential positive and negative impacts to individuals, public safety, groups, communities, organizations, democratic institutions, and the physical environment; Social norms and expectations.	Harmful Bias and Homogenization
MP-1.1-003	Document risk measurement plans to address identified risks. Plans may include, as applicable: Individual and group cognitive biases (e.g., confirmation bias, funding bias, groupthink) for AI Actors involved in the design, implementation, and use of GAI systems; Known past GAI system incidents and failure modes; In-context use and foreseeable misuse, abuse, and off-label use; Over reliance on quantitative metrics and methodologies without sufficient awareness of their limitations in the context(s) of use; Standard measurement and structured human feedback approaches; Anticipated human-AI configurations.	Human-AI Configuration; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
MP-1.1-004	Identify and document foreseeable illegal uses or applications of the GAI system that surpass organizational risk tolerances.	CBRN Information or Capabilities; Dangerous, Violent, or Hateful Content; Obscene, Degrading, and/or Abusive Content
AI Actor Tasks: AI Deployment		

MP-1.1-002	与社会文化和其他领域专家合作，通过评估以下内容，确定并记录生成式人工智能系统预期和可接受的使用背景：假设和限制；对组织的直接价值；预期的 操作环境和观察到的使用模式；对个人、公共安全、群体、社区、组织、民主机构和物理环境的潜在正面和负面影响；社会规范和期望。	有害偏见与同质化
MP-1.1-003	记录风险度量计划，以解决已识别的风险。计划可能包括(如适用)：参与设计的AI参与者个人和群体认知偏差(例如确认偏差、资助偏差、群体思维), 实施、使用 GAI 系统；已知的过去 GAI 系统事件和 失效模式；上下文内使用及可预见的误用、滥用和超说明书使用； 过度依赖定量指标和方法，而缺乏充分的 对其在使用背景下的局限性的认识；标准度量方法和结构化人类反馈方法；预期的人机 配置。	人机协同配置；有害 偏见与同质化； 危险、暴力或仇恨 内容
MP-1.1-004	识别并记录GAI系统可预见的非法用途或应用 超出组织风险容忍度。	CBRN信息或能力； 危险、暴力或仇恨 内容；淫秽、有辱人格、 和/或滥用内容
AI 行为体任务：AI 部署		

MAP 1.2: Interdisciplinary AI Actors, competencies, skills, and capacities for establishing context reflect demographic diversity and broad domain and user experience expertise, and their participation is documented. Opportunities for interdisciplinary collaboration are prioritized.

Action ID	Suggested Action	GAI Risks
MP-1.2-001	Establish and empower interdisciplinary teams that reflect a wide range of capabilities, competencies, demographic groups, domain expertise, educational backgrounds, lived experiences, professions, and skills across the enterprise to inform and conduct risk measurement and management functions.	Human-AI Configuration; Harmful Bias and Homogenization
MP-1.2-002	Verify that data or benchmarks used in risk measurement, and users, participants, or subjects involved in structured GAI public feedback exercises are representative of diverse in-context user populations.	Human-AI Configuration; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment		

映射 1.2:跨学科人工智能参与者、能力、技能和建立背景的能力反映人口多样性和广泛的领域及用户体验专业知识，并且他们的参与被记录。跨学科合作的机会被优先考虑。

操作 ID 建议操作		GAI 风险
MP-1.2-001	建立并赋能跨学科团队，反映广泛的能力、技能、人口群体、领域专业知识、教育 企业内不同背景、生活经历、专业和技能，以 告知并开展风险度量与管理职能。	人机协同配置；有害 偏见与同质化
MP-1.2-002	验证用于风险度量的数据或基准以及用户， 参与结构化 GAI 公众反馈活动的参与者、对象或主体 能够代表多样化的情境用户群体。	人机配置；有害 偏见与同质化
AI 行为体任务：AI 部署		

MAP 2.1: The specific tasks and methods used to implement the tasks that the AI system will support are defined (e.g., classifiers, generative models, recommenders).		
Action ID	**Suggested Action**	**GAI Risks**
MP-2.1-001	Establish known assumptions and practices for determining data origin and content lineage, for documentation and evaluation purposes.	Information Integrity
MP-2.1-002	Institute test and evaluation for data and content flows within the GAI system, including but not limited to, original data sources, data transformations, and decision-making criteria.	Intellectual Property; Data Privacy
AI Actor Tasks: TEVV		

MAP 2.2: Information about the AI system's knowledge limits and how system output may be utilized and overseen by humans is documented. Documentation provides sufficient information to assist relevant AI Actors when making decisions and taking subsequent actions.		
Action ID	**Suggested Action**	**GAI Risks**
MP-2.2-001	Identify and document how the system relies on upstream data sources, including for content provenance, and if it serves as an upstream dependency for other systems.	Information Integrity; Value Chain and Component Integration
MP-2.2-002	Observe and analyze how the GAI system interacts with external networks, and identify any potential for negative externalities, particularly where content provenance might be compromised.	Information Integrity
AI Actor Tasks: End Users		

MAP 2.3: Scientific integrity and TEVV considerations are identified and documented, including those related to experimental design, data collection and selection (e.g., availability, representativeness, suitability), system trustworthiness, and construct validation		
Action ID	**Suggested Action**	**GAI Risks**
MP-2.3-001	Assess the accuracy, quality, reliability, and authenticity of GAI output by comparing it to a set of known ground truth data and by using a variety of evaluation methods (e.g., human oversight and automated evaluation, proven cryptographic techniques, review of content inputs).	Information Integrity

映射 2.1:定义用于实施人工智能系统将支持的任务的具体任务和方法(例如分类器、生成模型、推荐器)。		
操作 ID 建议操作		**GAI 风险**
MP-2.1-001	建立已知假设和实践，用于确定数据来源和内容谱系，以用于文档和评估目的。	信息完整性
MP-2.1-002	对生成式人工智能系统内的数据和内容流进行测试和评估，包括但不限于原始数据源、数据转换和决策标准。	知识产权；数据隐私
AI行为主体任务：TEVV		

映射 2.2:记录关于人工智能系统知识限制以及系统输出如何被人类利用和监督的信息。文档提供足够信息，以协助相关人工智能参与者在做出决策和采取后续行动时。		
操作 ID 建议操作		**GAI 风险**
MP-2.2-001	识别并记录系统如何依赖上游数据源，包括内容来源，以及它是否作为其他系统的上游依赖。	信息完整性；价值链与组件集成
MP-2.2-002	观察和分析生成式人工智能系统如何与外部网络交互，并识别任何潜在负外部性，特别是在内容来源可能受损的地方。	信息完整性
AI 行为者任务：最终用户		

映射 2.3:识别并记录科学诚信和TEVV(测试、评估、验证与确认)考虑因素，包括与实验设计、数据收集和选择(例如可用性、代表性、验证		
操作 ID 建议操作		**GAI 风险**
MP-2.3-001	通过将生成式人工智能输出与一组已知地面真实数据进行比较，并使用各种评估方法(例如人工监督和自动评估、经过验证的加密技术、内容输入审查)，评估其准确性、质量、可靠性和真实性。	信息完整性

MP-2.3-002	Review and document accuracy, representativeness, relevance, suitability of data used at different stages of AI life cycle.	Harmful Bias and Homogenization; Intellectual Property
MP-2.3-003	Deploy and document fact-checking techniques to verify the accuracy and veracity of information generated by GAI systems, especially when the information comes from multiple (or unknown) sources.	Information Integrity
MP-2.3-004	Develop and implement testing techniques to identify GAI produced content (e.g., synthetic media) that might be indistinguishable from human-generated content.	Information Integrity
MP-2.3-005	Implement plans for GAI systems to undergo regular adversarial testing to identify vulnerabilities and potential manipulation or misuse.	Information Security
AI Actor Tasks: AI Development, Domain Experts, TEVV		

MP-2.3-002	审查和记录准确性、代表性、相关性、适用性的数据 在人工智能生命周期的不同阶段使用。	有害偏见与同质化； 知识产权
MP-2.3-003	部署并记录事实核查技术，以验证准确性和 生成式人工智能系统所生成信息的真实性，尤其是在 信息来自多个(或未知)来源。	信息完整性
MP-2.3-004	开发并实施测试技术以识别生成式人工智能生成的内容(例如， 合成媒体)可能无法与人类生成的内容区分。	信息完整性
MP-2.3-005	实施计划为生成式人工智能系统以接受定期对抗性测试以识别 漏洞以及潜在的操纵或滥用。	信息安全
AI 行为者任务：AI 开发、领域专家、TEVV		

MAP 3.4: Processes for operator and practitioner proficiency with AI system performance and trustworthiness – and relevant technical standards and certifications – are defined, assessed, and documented.		
Action ID	**Suggested Action**	**GAI Risks**
MP-3.4-001	Evaluate whether GAI operators and end-users can accurately understand content lineage and origin.	Human-AI Configuration; Information Integrity
MP-3.4-002	Adapt existing training programs to include modules on digital content transparency.	Information Integrity
MP-3.4-003	Develop certification programs that test proficiency in managing GAI risks and interpreting content provenance, relevant to specific industry and context.	Information Integrity
MP-3.4-004	Delineate human proficiency tests from tests of GAI capabilities.	Human-AI Configuration
MP-3.4-005	Implement systems to continually monitor and track the outcomes of human-GAI configurations for future refinement and improvements.	Human-AI Configuration; Information Integrity
MP-3.4-006	Involve the end-users, practitioners, and operators in GAI system in prototyping and testing activities. Make sure these tests cover various scenarios, such as crisis situations or ethically sensitive contexts.	Human-AI Configuration; Information Integrity; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
AI Actor Tasks: AI Design, AI Development, Domain Experts, End-Users, Human Factors, Operation and Monitoring		

映射 3.4:定义、评估并记录操作员和从业人员在人工智能系统性能和可信度方面的熟练程度流程，以及相关技术标准和认证。		
操作 ID 建议操作		**GAI 风险**
MP-3.4-001	评估生成式人工智能操作员和最终用户是否能准确理解内容谱系和来源。	人机协同配置；信息完整性
MP-3.4-002	调整现有培训计划以包括模块关于数字内容 透明度。	信息完整性
MP-3.4-003	制定认证计划以测试管理GAI风险的熟练度并 解读内容来源，与特定行业和语境相关。	信息完整性
MP-3.4-004	将人类熟练度测试与 GAI 能力测试区分开来。	人机协同配置
MP-3.4-005	实施系统以持续监测并跟踪人-GAI的结果人-GAI 用于未来完善和改进的配置。	人机协同配置； 信息完整性
MP-3.4-006	让最终用户、从业人员和操作人员参与 GAI 系统的原型设计 和测试活动。确保这些测试覆盖各种场景，例如危机情境或伦理敏感情境。	人机协同配置； 信息完整性；有害偏见与同质化；危险、暴力或仇恨内容
人工智能参与者任务：人工智能设计、人工智能开发、领域专家、最终用户、人因、运营与监控		

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MAP 4.1: Approaches for mapping AI technology and legal risks of its components – including the use of third-party data or software – are in place, followed, and documented, as are risks of infringement of a third-party's intellectual property or other rights.		
Action ID	**Suggested Action**	**GAI Risks**
MP-4.1-001	Conduct periodic monitoring of AI-generated content for privacy risks; address any possible instances of PII or sensitive data exposure.	Data Privacy
MP-4.1-002	Implement processes for responding to potential intellectual property infringement claims or other rights.	Intellectual Property
MP-4.1-003	Connect new GAI policies, procedures, and processes to existing model, data, software development, and IT governance and to legal, compliance, and risk management activities.	Information Security; Data Privacy
MP-4.1-004	Document training data curation policies, to the extent possible and according to applicable laws and policies.	Intellectual Property; Data Privacy; Obscene, Degrading, and/or Abusive Content
MP-4.1-005	Establish policies for collection, retention, and minimum quality of data, in consideration of the following risks: Disclosure of inappropriate CBRN information; Use of Illegal or dangerous content; Offensive cyber capabilities; Training data imbalances that could give rise to harmful biases; Leak of personally identifiable information, including facial likenesses of individuals.	CBRN Information or Capabilities; Intellectual Property; Information Security; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content; Data Privacy
MP-4.1-006	Implement policies and practices defining how third-party intellectual property and training data will be used, stored, and protected.	Intellectual Property; Value Chain and Component Integration
MP-4.1-007	Re-evaluate models that were fine-tuned or enhanced on top of third-party models.	Value Chain and Component Integration
MP-4.1-008	Re-evaluate risks when adapting GAI models to new domains. Additionally, establish warning systems to determine if a GAI system is being used in a new domain where previous assumptions (relating to context of use or mapped risks such as security, and safety) may no longer hold.	CBRN Information or Capabilities; Intellectual Property; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content; Data Privacy
MP-4.1-009	Leverage approaches to detect the presence of PII or sensitive data in generated output text, image, video, or audio.	Data Privacy

映射 4.1:已建立、遵循并记录用于映射人工智能技术及其组件法律风险(包括使用第三方数据或软件)的方法，以及侵犯第三方知识产权或其他权利的风险。		
操作 ID	**建议操作**	**GAI 风险**
MP-4.1-001	开展定期监测的AI生成的内容以防范隐私风险；处理任何可能的 PII 或敏感数据暴露实例。	数据隐私
MP-4.1-002	实施流程以响应潜在的知识产权侵权知识产权侵权主张或其他权利。	知识产权
MP-4.1-003	将新的 GAI 政策、程序和流程与现有的模型、数据、软件开发、IT 治理以及法律、合规和风险管理活动。	信息安全；数据隐私
MP-4.1-004	记录训练数据整理政策，在尽可能的范围内并根据按照根据适用的法律和政策。	知识产权；数据隐私；淫秽、有辱人格和/或滥用内容
MP-4.1-005	建立数据收集、保留和最低质量的政策，考虑以下风险：不当 CBRN 信息的披露；非法或危险内容的使用；攻击性网络能力；可能导致有害偏见的训练数据不平衡；个人可识别信息的泄露，包括个人面部图像。	CBRN 信息或能力；知识产权；信息安全；有害偏见和同质化；危险的、暴力或仇恨内容；数据隐私
MP-4.1-006	实施政策和实践界定如何第三方知识产权和和训练数据的使用、存储和保护方式。	知识产权；价值链与组件集成
MP-4.1-007	重新评估模型那些经过微调或增强在第三方之上第三方模型。	价值链与组件集成
MP-4.1-008	在将 GAI 模型适配到新领域时重新评估风险。此外，建立预警系统以确定 GAI 系统是:领域，在该领域中先前的假设(涉及使用情境或已映射的风险，如安全性和安全性)可能	CBRN 信息或能力；知识产权；有害与同质化；危险的、暴力或仇恨内容；数据隐私
MP-4.1-009	利用方法以检测PII的存在或敏感数据在生成的数据在生成的输出文本、图像、视频或音频。	数据隐私

MP-4.1-010	Conduct appropriate diligence on training data use to assess intellectual property, and privacy, risks, including to examine whether use of proprietary or sensitive training data is consistent with applicable laws.	Intellectual Property; Data Privacy
AI Actor Tasks: Governance and Oversight, Operation and Monitoring, Procurement, Third-party entities		

MP-4.1-010	对训练数据使用进行适当的尽职调查，以评估知识产权、 以及隐私、风险，包括审查是否使用专有或敏感 训练数据符合适用法律。	知识产权；数据隐私
人工智能参与者任务：治理与监督、运营与监控、采购、第三方实体		

MAP 5.1: Likelihood and magnitude of each identified impact (both potentially beneficial and harmful) based on expected use, past uses of AI systems in similar contexts, public incident reports, feedback from those external to the team that developed or deployed the AI system, or other data are identified and documented.

Action ID	Suggested Action	GAI Risks
MP-5.1-001	Apply TEVV practices for content provenance (e.g., probing a system's synthetic data generation capabilities for potential misuse or vulnerabilities.	Information Integrity; Information Security
MP-5.1-002	Identify potential content provenance harms of GAI, such as misinformation or disinformation, deepfakes, including NCII, or tampered content. Enumerate and rank risks based on their likelihood and potential impact, and determine how well provenance solutions address specific risks and/or harms.	Information Integrity; Dangerous, Violent, or Hateful Content; Obscene, Degrading, and/or Abusive Content
MP-5.1-003	Consider disclosing use of GAI to end users in relevant contexts, while considering the objective of disclosure, the context of use, the likelihood and magnitude of the risk posed, the audience of the disclosure, as well as the frequency of the disclosures.	Human-AI Configuration
MP-5.1-004	Prioritize GAI structured public feedback processes based on risk assessment estimates.	Information Integrity; CBRN Information or Capabilities; Dangerous, Violent, or Hateful Content; Harmful Bias and Homogenization
MP-5.1-005	Conduct adversarial role-playing exercises, GAI red-teaming, or chaos testing to identify anomalous or unforeseen failure modes.	Information Security
MP-5.1-006	Profile threats and negative impacts arising from GAI systems interacting with, manipulating, or generating content, and outlining known and potential vulnerabilities and the likelihood of their occurrence.	Information Security
AI Actor Tasks: AI Deployment, AI Design, AI Development, AI Impact Assessment, Affected Individuals and Communities, End-Users, Operation and Monitoring		

映射 5.1:基于预期用途、人工智能系统在类似情境中的过往使用、公开事件报告、来自开发或部署人工智能系统团队外部人员的反馈或其他数据，识别并记录每个已识别影响(包括潜在有益和有害影响)的可能性和严重程度。

操作 ID	建议操作	GAI 风险
MP-5.1-001	应用TEVV(测试、评估、验证与确认)实践用于内容来源(例如，探测系统的合成合成 用于潜在滥用或漏洞的数据生成能力。	信息完整性；信息 安全
MP-5.1-002	识别GAI潜在的内容来源危害，例如错误信息或 虚假信息、深度伪造(包括NCII)或被篡改的内容。列举并 根据风险的可能性和潜在影响对其进行排序，并确定 来源解决方案针对特定风险和/或危害。	信息完整性；危险、 暴力或仇恨内容； 淫秽、有辱人格和/或 滥用内容
MP-5.1-003	考虑在相关情境中向最终用户披露 GAI 的使用，同时考虑披露的目的、使用情境、披露 所构成的风险、披露的对象以及披露的频率 披露。	人机协同配置
MP-5.1-004	优先考虑GAI结构化的公开反馈流程基于风险评估风险评估风险评估 估计。	信息完整性；CBRN信息或能 危险、暴力或仇恨性 内容；有害偏见和 同质化
MP-5.1-005	开展对抗性角色扮演演练、GAI红队测试、或混沌测试以 识别异常或未预见的故障模式。	信息安全
MP-5.1-006	剖析 GAI 系统与以下方面交互时产生的威胁和负面影响， 操纵或生成内容，并概述已知和潜在的 漏洞及其发生的可能性。	信息安全
人工智能参与者任务：人工智能部署、人工智能设计、人工智能开发、人工智能影响评估、受影响个人和社区、最终用户、运营与监控		

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MAP 5.2: Practices and personnel for supporting regular engagement with relevant AI Actors and integrating feedback about positive, negative, and unanticipated impacts are in place and documented.

Action ID	Suggested Action	GAI Risks
MP-5.2-001	Determine context-based measures to identify if new impacts are present due to the GAI system, including regular engagements with downstream AI Actors to identify and quantify new contexts of unanticipated impacts of GAI systems.	Human-AI Configuration; Value Chain and Component Integration
MP-5.2-002	Plan regular engagements with AI Actors responsible for inputs to GAI systems, including third-party data and algorithms, to review and evaluate unanticipated impacts.	Human-AI Configuration; Value Chain and Component Integration

AI Actor Tasks: AI Deployment, AI Design, AI Impact Assessment, Affected Individuals and Communities, Domain Experts, End-Users, Human Factors, Operation and Monitoring

MEASURE 1.1: Approaches and metrics for measurement of AI risks enumerated during the MAP function are selected for implementation starting with the most significant AI risks. The risks or trustworthiness characteristics that will not – or cannot – be measured are properly documented.

Action ID	Suggested Action	GAI Risks
MS-1.1-001	Employ methods to trace the origin and modifications of digital content.	Information Integrity
MS-1.1-002	Integrate tools designed to analyze content provenance and detect data anomalies, verify the authenticity of digital signatures, and identify patterns associated with misinformation or manipulation.	Information Integrity
MS-1.1-003	Disaggregate evaluation metrics by demographic factors to identify any discrepancies in how content provenance mechanisms work across diverse populations.	Information Integrity; Harmful Bias and Homogenization
MS-1.1-004	Develop a suite of metrics to evaluate structured public feedback exercises informed by representative AI Actors.	Human-AI Configuration; Harmful Bias and Homogenization; CBRN Information or Capabilities
MS-1.1-005	Evaluate novel methods and technologies for the measurement of GAI-related risks including in content provenance, offensive cyber, and CBRN, while maintaining the models' ability to produce valid, reliable, and factually accurate outputs.	Information Integrity; CBRN Information or Capabilities; Obscene, Degrading, and/or Abusive Content

映射 5.2:支持与相关人工智能参与者定期互动并整合关于
积极、消极和未预期的影响均已落实并记录在案。

操作 ID 建议操作		GAI 风险
MP-5.2-001	根据具体情况确定措施，以识别是否因以下原因产生了新的影响： 生成式人工智能系统，包括与下游人工智能参与者定期互动，以识别和量化生成式人	人机协同配置；价值链与组件集成
MP-5.2-002	与负责GAI系统输入的AI行为者定期开展沟通。 包括第三方数据和算法，以审查和评估未预料到的 影响。	人机协同配置；价值链与组件集成

人工智能参与者任务：人工智能部署、人工智能设计、人工智能影响评估、受影响个人和社区、领域专家、最终用户、人因、运营与监控

度量 1.1:选择用于实施在映射功能中列举的人工智能风险度量方法和指标，从最重要的人工智能风险开始。将不会或无法度量的风险或可信度特征妥善记录。

操作 ID 建议操作		GAI 风险
MS-1.1-001	采用方法追踪数字内容的来源和修改。	信息完整性
MS-1.1-002	集成旨在分析内容来源和检测数据的工具 异常，验证数字签名的真实性，并识别与错误信息或操纵相关的模式。	信息完整性
MS-1.1-003	按人口统计因素细分评估指标，以识别任何 内容来源机制在不同领域运作方式上的差异 人群。	信息完整性；有害偏见与同质化
MS-1.1-004	开发一套指标套件用于评估结构化公众反馈演练 参考代表性 AI 行为主体的意见。	人机协同配置；有害偏见与同质化；CBRN 信息或能力
MS-1.1-005	评估用于度量 GAI 相关风险的新方法和新技术，包括内容溯源、攻击性网络和 CBRN，同时保持模型生成有效、可靠且事实准确的内容的能力 输出。	信息完整性；CBRN 信息或能力；淫秽、有辱人格和/或辱骂性内容

MS-1.1-006	Implement continuous monitoring of GAI system impacts to identify whether GAI outputs are equitable across various sub-populations. Seek active and direct feedback from affected communities via structured feedback mechanisms or red-teaming to monitor and improve outputs.	Harmful Bias and Homogenization
MS-1.1-007	Evaluate the quality and integrity of data used in training and the provenance of AI-generated content, for example by employing techniques like chaos engineering and seeking stakeholder feedback.	Information Integrity
MS-1.1-008	Define use cases, contexts of use, capabilities, and negative impacts where structured human feedback exercises, e.g., GAI red-teaming, would be most beneficial for GAI risk measurement and management based on the context of use.	Harmful Bias and Homogenization; CBRN Information or Capabilities
MS-1.1-009	Track and document risks or opportunities related to all GAI risks that cannot be measured quantitatively, including explanations as to why some risks cannot be measured (e.g., due to technological limitations, resource constraints, or trustworthy considerations). Include unmeasured risks in marginal risks.	Information Integrity
AI Actor Tasks: AI Development, Domain Experts, TEVV		

MS-1.1-006	实施对GAI系统影响的持续监测，以识别GAI输出在不同子群体中是否公平。通过结构化反馈机制或红队测试，寻求受影响社区的积极直接反馈，以监测和改进输出。	有害偏见与同质化
MS-1.1-007	评估训练所用数据的质量和完整性以及数据来源 AI生成内容，例如通过采用混沌工程等技术并寻求利益相关者反馈。	信息完整性
MS-1.1-008	基于使用情境，定义结构化人类反馈活动(例如GAI红队测试)对GAI风险度量和管理最有益的使用场景、使用情境、能力和负面影响。	有害偏见与同质化；CBRN 信息或能力
MS-1.1-009	跟踪并记录与所有无法定量度量的GAI风险相关的风险或机遇，包括解释为何某些风险无法度量(例如，由于技术限制、资源约束或可信性考量)。将未度量的风险纳入边际风险。	信息完整性
AI 行为者任务：AI 开发、领域专家、TEVV		

MEASURE 1.3: Internal experts who did not serve as front-line developers for the system and/or independent assessors are involved in regular assessments and updates. Domain experts, users, AI Actors external to the team that developed or deployed the AI system, and affected communities are consulted in support of assessments as necessary per organizational risk tolerance.

Action ID	Suggested Action	GAI Risks
MS-1.3-001	Define relevant groups of interest (e.g., demographic groups, subject matter experts, experience with GAI technology) within the context of use as part of plans for gathering structured public feedback.	Human-AI Configuration; Harmful Bias and Homogenization; CBRN Information or Capabilities
MS-1.3-002	Engage in internal and external evaluations, GAI red-teaming, impact assessments, or other structured human feedback exercises in consultation with representative AI Actors with expertise and familiarity in the context of use, and/or who are representative of the populations associated with the context of use.	Human-AI Configuration; Harmful Bias and Homogenization; CBRN Information or Capabilities
MS-1.3-003	Verify those conducting structured human feedback exercises are not directly involved in system development tasks for the same GAI model.	Human-AI Configuration; Data Privacy
AI Actor Tasks: AI Deployment, AI Development, AI Impact Assessment, Affected Individuals and Communities, Domain Experts, End-Users, Operation and Monitoring, TEVV		

度量 1.3:未担任该系统一线开发人员的内部专家和/或独立评估人员参与定期评估和更新。根据组织风险容忍度，酌情咨询领域专家、开发或部署人工智能系统的团队之外的人工智能参与者以及受影响社区，以支持评估。

操作 ID	建议操作	GAI 风险
MS-1.3-001	定义相关利益群体(例如人口统计群体、主题 专家、GAI技术经验)在使用情境中，作为收集结构化公众反馈计划的一部分。	人机协同配置；有害偏见与同质化；CBRN 信息或能力
MS-1.3-002	参与内部和外部评估、GAI红队测试、影响评估或其他结构化人类反馈活动，并咨询具有使用情境专业知识和熟悉度、和/或代表与使用情境相关人群的代表性人工智能参与者。	人机协同配置；有害偏见与同质化；CBRN 信息或能力
MS-1.3-003	核实开展结构化人类反馈活动的人员不直接参与同一GAI模型的系统开发任务。	人机协同配置；数据隐私
人工智能参与者任务：AI部署、AI开发、AI影响评估、受影响个人和社区、领域专家、最终用户、运营和监测、TEVV		

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MEASURE 2.2: Evaluations involving human subjects meet applicable requirements (including human subject protection) and are representative of the relevant population.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.2-001	Assess and manage statistical biases related to GAI content provenance through techniques such as re-sampling, re-weighting, or adversarial training.	Information Integrity; Information Security; Harmful Bias and Homogenization
MS-2.2-002	Document how content provenance data is tracked and how that data interacts with privacy and security. Consider: Anonymizing data to protect the privacy of human subjects; Leveraging privacy output filters; Removing any personally identifiable information (PII) to prevent potential harm or misuse.	Data Privacy; Human AI Configuration; Information Integrity; Information Security; Dangerous, Violent, or Hateful Content
MS-2.2-003	Provide human subjects with options to withdraw participation or revoke their consent for present or future use of their data in GAI applications.	Data Privacy; Human-AI Configuration; Information Integrity
MS-2.2-004	Use techniques such as anonymization, differential privacy or other privacy-enhancing technologies to minimize the risks associated with linking AI-generated content back to individual human subjects.	Data Privacy; Human-AI Configuration
AI Actor Tasks: AI Development, Human Factors, TEVV		

MEASURE 2.3: AI system performance or assurance criteria are measured qualitatively or quantitatively and demonstrated for conditions similar to deployment setting(s). Measures are documented.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.3-001	Consider baseline model performance on suites of benchmarks when selecting a model for fine tuning or enhancement with retrieval-augmented generation.	Information Security; Confabulation
MS-2.3-002	Evaluate claims of model capabilities using empirically validated methods.	Confabulation; Information Security
MS-2.3-003	Share results of pre-deployment testing with relevant GAI Actors, such as those with system release approval authority.	Human-AI Configuration

度量 2.2:涉及人类受试者的评估满足适用要求(包括人类受试者保护)，并具有相关人群的代表性。		
操作 ID	**建议操作**	**GAI 风险**
MS-2.2-001	评估并管理与GAI内容来源相关的统计偏差通过 重采样、重加权或对抗训练等技术。	信息完整性；信息 安全性；有害偏见与 同质化
MS-2.2-002	记录内容来源数据如何被跟踪以及该数据如何与隐私和安全交互。考虑：匿名化数据以保护人类受试者的隐私；利用隐私输出过滤器；移除任何个人可识别信息(PII)以防止潜在伤害或滥用。	数据隐私；人机配置；信息完整性；信息安全；危险、暴力或仇恨 内容
MS-2.2-003	为人类受试者提供选项以退出参与或撤销其 同意其数据在 GAI 应用中的当前或未来使用。	数据隐私；人类-人工智能 配置；信息 完整性
MS-2.2-004	使用匿名化、差分隐私或其他隐私保护技术 增强技术，以最小化将AI生成内容关联回个人人类受试者所带来的风险。	数据隐私；人类-人工智能 配置
AI行为主体任务：AI开发、人为因素、TEVV		

度量 2.3:人工智能系统性能或保证标准以定性或定量方式度量，并针对类似部署条件的场景进行演示。度量结果予以记录。		
操作 ID	**建议操作**	**GAI 风险**
MS-2.3-001	在选择模型时考虑基准套件上的基线性能一个 用于微调或通过检索增强生成进行增强的模型。	信息安全； 虚构
MS-2.3-002	使用经实证验证的方法评估模型能力声明。	虚构；信息 安全
MS-2.3-003	共享结果的部署前测试与相关GAI行为者，例如那些此类 具有系统发布审批权限。	人机协同配置

MS-2.3-004	Utilize a purpose-built testing environment such as NIST Dioptra to empirically evaluate GAI trustworthy characteristics.	CBRN Information or Capabilities; Data Privacy; Confabulation; Information Integrity; Information Security; Dangerous, Violent, or Hateful Content; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, TEVV		

MS-2.3-004	利用专门构建的测试环境(如 NIST Dioptra)进行实证 评估GAI可信特征。	CBRN信息或能力； 数据隐私；虚构； 信息完整性；信息 安全；危险、暴力或 仇恨内容；有害偏见与 同质化
AI 行为者任务：AI 部署、TEVV		

MEASURE 2.5: The AI system to be deployed is demonstrated to be valid and reliable. Limitations of the generalizability beyond the conditions under which the technology was developed are documented.

Action ID	Suggested Action	Risks
MS-2.5-001	Avoid extrapolating GAI system performance or capabilities from narrow, non-systematic, and anecdotal assessments.	Human-AI Configuration; Confabulation
MS-2.5-002	Document the extent to which human domain knowledge is employed to improve GAI system performance, via, e.g., RLHF, fine-tuning, retrieval-augmented generation, content moderation, business rules.	Human-AI Configuration
MS-2.5-003	Review and verify sources and citations in GAI system outputs during pre-deployment risk measurement and ongoing monitoring activities.	Confabulation
MS-2.5-004	Track and document instances of anthropomorphization (e.g., human images, mentions of human feelings, cyborg imagery or motifs) in GAI system interfaces.	Human-AI Configuration
MS-2.5-005	Verify GAI system training data and TEVV data provenance, and that fine-tuning or retrieval-augmented generation data is grounded.	Information Integrity
MS-2.5-006	Regularly review security and safety guardrails, especially if the GAI system is being operated in novel circumstances. This includes reviewing reasons why the GAI system was initially assessed as being safe to deploy.	Information Security; Dangerous, Violent, or Hateful Content
AI Actor Tasks: Domain Experts, TEVV		

度量 2.5:待部署的人工智能系统被证明是有效且可靠的。超出技术开发条件的泛化局限性予以记录。

操作 ID	建议操作	风险
MS-2.5-001	避免从狭窄、非外推GAI系统性能或能力 系统化、系统性及轶事性评估。	人机协同配置； 虚构
MS-2.5-002	记录在多大程度上运用人类领域知识来 通过例如RLHF、微调、检索等方式改进GAI系统性能-- 增强生成、内容审核、业务规则。	人机协同配置
MS-2.5-003	在部署前审查并核实GAI系统输出中的来源和引用 部署风险度量与持续监控活动。	虚构
MS-2.5-004	在GAI系统界面中跟踪并记录拟人化实例 提及人类情感、赛博格意象或母题)在GAI系统界面中。人机配置	
MS-2.5-005	验证GAI系统训练数据和TEVV数据来源，并确保微调 或检索增强生成数据已落地。	信息完整性
MS-2.5-006	定期审查安全与安保防护措施，尤其是在GAI系统 在新颖情境下运行。这包括审查为何 GAI 系统最初被评估为可安全部署。	信息安全；危险、 暴力或仇恨内容
AI 行为主体任务：领域专家、TEVV		

MEASURE 2.6: The AI system is evaluated regularly for safety risks – as identified in the MAP function. The AI system to be deployed is demonstrated to be safe, its residual negative risk does not exceed the risk tolerance, and it can fail safely, particularly if made to operate beyond its knowledge limits. Safety metrics reflect system reliability and robustness, real-time monitoring, and response times for AI system failures.

Action ID	Suggested Action	GAI Risks
MS-2.6-001	Assess adverse impacts, including health and wellbeing impacts for value chain or other AI Actors that are exposed to sexually explicit, offensive, or violent information during GAI training and maintenance.	Human-AI Configuration; Obscene, Degrading, and/or Abusive Content; Value Chain and Component Integration; Dangerous, Violent, or Hateful Content
MS-2.6-002	Assess existence or levels of harmful bias, intellectual property infringement, data privacy violations, obscenity, extremism, violence, or CBRN information in system training data.	Data Privacy; Intellectual Property; Obscene, Degrading, and/or Abusive Content; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content; CBRN Information or Capabilities
MS-2.6-003	Re-evaluate safety features of fine-tuned models when the negative risk exceeds organizational risk tolerance.	Dangerous, Violent, or Hateful Content
MS-2.6-004	Review GAI system outputs for validity and safety: Review generated code to assess risks that may arise from unreliable downstream decision-making.	Value Chain and Component Integration; Dangerous, Violent, or Hateful Content
MS-2.6-005	Verify that GAI system architecture can monitor outputs and performance, and handle, recover from, and repair errors when security anomalies, threats and impacts are detected.	Confabulation; Information Integrity; Information Security
MS-2.6-006	Verify that systems properly handle queries that may give rise to inappropriate, malicious, or illegal usage, including facilitating manipulation, extortion, targeted impersonation, cyber-attacks, and weapons creation.	CBRN Information or Capabilities; Information Security
MS-2.6-007	Regularly evaluate GAI system vulnerabilities to possible circumvention of safety measures.	CBRN Information or Capabilities; Information Security
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, Operation and Monitoring, TEVV		

度量 2.6:人工智能系统定期接受安全风险评估--如映射功能中所识别。待部署的人工智能系统被证明是安全的，其残余负面风险不超过风险容忍度，并且能够安全失效，特别是在被要求超出其知识限制运行时。安全度量反映系统可靠性和鲁棒性、实时监测以及人工智能系统故障的响应时间。

操作 ID 建议操作		GAI 风险
MS-2.6-001	评估不利影响，包括对价值链的健康和福祉影响 或其他接触色情、冒犯性或暴力内容的AI行为者 GAI训练和维护期间的信息。	人机配置；淫秽、 有辱人格和/或辱骂性 内容；价值链与 组件集成； 危险、暴力或仇恨 内容
MS-2.6-002	评估有害偏见的存在或程度、知识产权侵权， 数据隐私侵犯、淫秽、极端主义、暴力或 CBRN 信息在 系统训练数据。	数据隐私；知识产权； 淫秽、有辱人格和/或 滥用内容；有害偏见与 同质化；危险、暴力或仇恨内容； CBRN信息或能力
MS-2.6-003	当负面风险超过时重新评估微调模型的安全特征 组织风险容忍度。	危险、暴力或仇恨 内容
MS-2.6-004	审查GAI系统输出的有效性和安全性：审查生成的代码以 评估可能因下游决策不可靠而产生的风险。	价值链与组件 集成；危险、暴力或 仇恨内容
MS-2.6-005	验证 GAI 系统架构能够监控输出和性能，并且 在检测到安全异常、威胁和影响时处理、恢复和修复错误。	虚构；信息 完整性；信息安全
MS-2.6-006	验证系统是否能正确处理可能引发不当、 恶意或非法使用，包括助长操纵、勒索、定向冒充、网络攻击和武器制造。	CBRN 信息或能力；信息安全
MS-2.6-007	定期评估生成式人工智能系统漏洞以应对可能的规避安全措施 度量。	CBRN信息或能力； 信息安全
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、运营与监控、TEVV(测试、评估、验证与确认)		

MEASURE 2.7: AI system security and resilience – as identified in the MAP function – are evaluated and documented.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.7-001	Apply established security measures to: Assess likelihood and magnitude of vulnerabilities and threats such as backdoors, compromised dependencies, data breaches, eavesdropping, man-in-the-middle attacks, reverse engineering, autonomous agents, model theft or exposure of model weights, AI inference, bypass, extraction, and other baseline security concerns.	Data Privacy; Information Integrity; Information Security; Value Chain and Component Integration
MS-2.7-002	Benchmark GAI system security and resilience related to content provenance against industry standards and best practices. Compare GAI system security features and content provenance methods against industry state-of-the-art.	Information Integrity; Information Security
MS-2.7-003	Conduct user surveys to gather user satisfaction with the AI-generated content and user perceptions of content authenticity. Analyze user feedback to identify concerns and/or current literacy levels related to content provenance and understanding of labels on content.	Human-AI Configuration; Information Integrity
MS-2.7-004	Identify metrics that reflect the effectiveness of security measures, such as data provenance, the number of unauthorized access attempts, inference, bypass, extraction, penetrations, or provenance verification.	Information Integrity; Information Security
MS-2.7-005	Measure reliability of content authentication methods, such as watermarking, cryptographic signatures, digital fingerprints, as well as access controls, conformity assessment, and model integrity verification, which can help support the effective implementation of content provenance techniques. Evaluate the rate of false positives and false negatives in content provenance, as well as true positives and true negatives for verification.	Information Integrity
MS-2.7-006	Measure the rate at which recommendations from security checks and incidents are implemented. Assess how quickly the AI system can adapt and improve based on lessons learned from security incidents and feedback.	Information Integrity; Information Security
MS-2.7-007	Perform AI red-teaming to assess resilience against: Abuse to facilitate attacks on other systems (e.g., malicious code generation, enhanced phishing content), GAI attacks (e.g., prompt injection), ML attacks (e.g., adversarial examples/prompts, data poisoning, membership inference, model extraction, sponge examples).	Information Security; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
MS-2.7-008	Verify fine-tuning does not compromise safety and security controls.	Information Integrity; Information Security; Dangerous, Violent, or Hateful Content

度量 2.7:人工智能系统的安全性和韧性--如映射功能中所识别--得到评估和记录。		
操作 ID	**建议操作**	**GAI 风险**
MS-2.7-001	应用既定的安全措施以：评估漏洞和威胁的可能性和严重程度，例如后门、受损依赖项 违规、窃听、中间人攻击、逆向工程， 违规、窃听、中间人攻击、逆向工程， 自主智能体、模型窃取或模型权重泄露、AI 推理， 绕过、提取及其他基线安全关切。	数据隐私；信息完整性； 信息安全；价值链 与组件集成
MS-2.7-002	基准测试与内容溯源相关的 GAI 系统安全性和韧性 对照行业标准和最佳实践。将生成式人工智能系统的安全特征和内容溯源方法与行业最	信息完整性；信息 安全
MS-2.7-003	开展用户调查，收集用户对人工智能生成内容的满意度以及用户对内容真实性的看法。 与内容来源相关的关切和/或当前素养水平，以及 对内容标签的理解。	人机协同配置； 信息完整性
MS-2.7-004	识别反映安全措施有效性的指标，例如数据 溯源、未经授权的访问尝试次数、推断、绕过、萃取、渗透或溯源验证。	信息完整性；信息 安全
MS-2.7-005	度量内容认证方法的可靠性，例如水印、加密签名、数字指纹，以及访问控制、合规性评估和模型完整性验证，这些有助于支持 内容溯源技术的有效实施。评估内容溯源中的假阳性和假阴性率，以及验证的真阳性和真阴性。	信息完整性
MS-2.7-006	度量安全检查与事件中建议的采纳速率 已实施。评估人工智能系统基于安全事件教训和反馈进行适应和改进的速度。	信息完整性；信息 安全
MS-2.7-007	执行人工智能红队测试以评估对以下方面的韧性：滥用以致助长对其他系统的攻击(例如 攻击(例如提示注入)、机器学习攻击(例如对抗样本/对抗提示、数据投毒、成员推断、模	信息安全；有害偏见 与同质化；危险的、 暴力或仇恨内容
MS-2.7-008	验证微调不会损害安全与安保控制。	信息完整性；信息 安全性；危险、暴力或 仇恨内容

MS-2.7-009	Regularly assess and verify that security measures remain effective and have not been compromised.	Information Security
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, Operation and Monitoring, TEVV		

MS-2.7-009	定期评估并验证安全措施保持有效且未出现失效 已被泄露。	信息安全
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、运营与监控、TEVV(测试、评估、验证与确认)		

MEASURE 2.8: Risks associated with transparency and accountability – as identified in the MAP function – are examined and documented.

Action ID	Suggested Action	GAI Risks
MS-2.8-001	Compile statistics on actual policy violations, take-down requests, and intellectual property infringement for organizational GAI systems: Analyze transparency reports across demographic groups, languages groups.	Intellectual Property; Harmful Bias and Homogenization
MS-2.8-002	Document the instructions given to data annotators or AI red-teamers.	Human-AI Configuration
MS-2.8-003	Use digital content transparency solutions to enable the documentation of each instance where content is generated, modified, or shared to provide a tamper-proof history of the content, promote transparency, and enable traceability. Robust version control systems can also be applied to track changes across the AI lifecycle over time.	Information Integrity
MS-2.8-004	Verify adequacy of GAI system user instructions through user testing.	Human-AI Configuration
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, Operation and Monitoring, TEVV		

度量 2.8:与透明度和问责制相关的风险--如映射功能中所识别--得到审查和记录。

操作 ID	建议操作	GAI 风险
MS-2.8-001	汇编关于实际政策违规、下架请求和知识 产权侵权的统计数据，针对组织内生成式人工智能系统：分析跨人口群体、语言群体	知识产权；有害偏见与同质化
MS-2.8-002	记录提供给数据标注员或 AI 红队成员的指令。	人机协同配置
MS-2.8-003	使用数字内容透明度解决方案，以便对内容生成、修改或共享的每个实例进行记录， 内容的证明历史,促进透明度,并实现可追溯性。 稳健的版本控制系统也可应用于跟踪人工智能生命周期随时间的变化。	信息完整性
MS-2.8-004	通过用户测试验证GAI系统用户说明的充分性。	人机协同配置
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、运营与监控、TEVV(测试、评估、验证与确认)		

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MEASURE 2.9: The AI model is explained, validated, and documented, and AI system output is interpreted within its context – as identified in the MAP function – to inform responsible use and governance.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.9-001	Apply and document ML explanation results such as: Analysis of embeddings, Counterfactual prompts, Gradient-based attributions, Model compression/surrogate models, Occlusion/term reduction.	Confabulation
MS-2.9-002	Document GAI model details including: Proposed use and organizational value; Assumptions and limitations, Data collection methodologies; Data provenance; Data quality; Model architecture (e.g., convolutional neural network, transformers, etc.); Optimization objectives; Training algorithms; RLHF approaches; Fine-tuning or retrieval-augmented generation approaches; Evaluation data; Ethical considerations; Legal and regulatory requirements.	Information Integrity; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, End-Users, Operation and Monitoring, TEVV		

MEASURE 2.10: Privacy risk of the AI system – as identified in the MAP function – is examined and documented.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.10-001	Conduct AI red-teaming to assess issues such as: Outputting of training data samples, and subsequent reverse engineering, model extraction, and membership inference risks; Revealing biometric, confidential, copyrighted, licensed, patented, personal, proprietary, sensitive, or trade-marked information; Tracking or revealing location information of users or members of training datasets.	Human-AI Configuration; Information Integrity; Intellectual Property
MS-2.10-002	Engage directly with end-users and other stakeholders to understand their expectations and concerns regarding content provenance. Use this feedback to guide the design of provenance data-tracking techniques.	Human-AI Configuration; Information Integrity
MS-2.10-003	Verify deduplication of GAI training data samples, particularly regarding synthetic data.	Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, End-Users, Operation and Monitoring, TEVV		

度量 2.9:人工智能模型得到解释、验证和记录，人工智能系统输出在其情境中得到解释--如映射功能中所识别--以指导负责任的使用和治		
操作 ID 建议操作		**GAI 风险**
MS-2.9-001	应用并记录机器学习解释结果，例如：嵌入分析， 反事实提示、基于梯度的归因、模型 压缩/代理模型，遮挡/术语约简。	虚构
MS-2.9-002	记录生成式人工智能模型细节，包括：拟议用途和组织价值；假设和局限性；数据收集方法；数据溯源；数据质量；模型架构(例如卷积神经网络、 transformers等)；优化目标；训练算法；RLHF 方法；微调或检索增强生成方法；评估数据；伦理考量；法律和监管要求。	信息完整性；有害偏见 与同质化
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、最终用户、运营与监控、TEVV(测试、评估、验证与确认)		

度量 2.10:人工智能系统的隐私风险--如映射功能中所识别--得到审查和记录。		
操作 ID 建议操作		**GAI 风险**
MS-2.10-001	执行人工智能红队测试以评估以下问题：训练数据样本的输出，以及随后的逆向工程、模型萃取和成员推断风险；泄露生物特征、机密、受版权保护、 许可、专利、个人、专有、敏感或商标信息；跟踪或泄露用户或训练成员的位置信息 数据集。	人机协同配置； 信息完整性；知识产权 属性
MS-2.10-002	直接与最终用户和其他利益相关方互动，以了解他们的 关于内容来源的期望与关切。利用此反馈指导来源数据追踪技术的设计。	人机协同配置；信息完整 性
MS-2.10-003	验证去重的GAI训练数据样本，特别是关于合成 数据。	有害偏见与同质化
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、最终用户、运营与监控、TEVV(测试、评估、验证与确认)		

MEASURE 2.11: Fairness and bias – as identified in the MAP function – are evaluated and results are documented.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.11-001	Apply use-case appropriate benchmarks (e.g., Bias Benchmark Questions, Real Hateful or Harmful Prompts, Winogender Schemas[15]) to quantify systemic bias, stereotyping, denigration, and hateful content in GAI system outputs; Document assumptions and limitations of benchmarks, including any actual or possible training/test data cross contamination, relative to in-context deployment environment.	Harmful Bias and Homogenization
MS-2.11-002	Conduct fairness assessments to measure systemic bias. Measure GAI system performance across demographic groups and subgroups, addressing both quality of service and any allocation of services and resources. Quantify harms using: field testing with sub-group populations to determine likelihood of exposure to generated content exhibiting harmful bias, AI red-teaming with counterfactual and low-context (e.g., "leader," "bad guys") prompts. For ML pipelines or business processes with categorical or numeric outcomes that rely on GAI, apply general fairness metrics (e.g., demographic parity, equalized odds, equal opportunity, statistical hypothesis tests), to the pipeline or business outcome where appropriate; Custom, context-specific metrics developed in collaboration with domain experts and affected communities; Measurements of the prevalence of denigration in generated content in deployment (e.g., sub-sampling a fraction of traffic and manually annotating denigrating content).	Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
MS-2.11-003	Identify the classes of individuals, groups, or environmental ecosystems which might be impacted by GAI systems through direct engagement with potentially impacted communities.	Environmental; Harmful Bias and Homogenization
MS-2.11-004	Review, document, and measure sources of bias in GAI training and TEVV data: Differences in distributions of outcomes across and within groups, including intersecting groups; Completeness, representativeness, and balance of data sources; demographic group and subgroup coverage in GAI system training data; Forms of latent systemic bias in images, text, audio, embeddings, or other complex or unstructured data; Input data features that may serve as proxies for demographic group membership (i.e., image metadata, language dialect) or otherwise give rise to emergent bias within GAI systems; The extent to which the digital divide may negatively impact representativeness in GAI system training and TEVV data; Filtering of hate speech or content in GAI system training data; Prevalence of GAI-generated data in GAI system training data.	Harmful Bias and Homogenization

[15] Winogender Schemas is a sample set of paired sentences which differ only by gender of the pronouns used, which can be used to evaluate gender bias in natural language processing coreference resolution systems.

度量 2.11:在映射功能中识别的公平性和偏见得到评估，并记录结果。		
操作 ID	**建议操作**	**GAI 风险**
MS-2.11-001	Schemas[15])来量化生成式人工智能系统输出中的系统性偏见、刻板印象、贬损和仇恨内容； 记录基准的假设和局限性，包括任何实际或可能的训练/测试数据交叉污染，相对于上下文部署环境。	有害偏见与同质化
MS-2.11-002	进行公平性评估以衡量系统性偏见。衡量生成式人工智能系统在不同人口群体和子群体中的表现，涉及服务质量以及任何服务和资源的分配。通过以下方式量化危害：对子群体进行现场测试以确定暴露于表现出有害偏见的生成内容的可能性，使用人工智能红队测试 反事实和低上下文(例如，"领导者"、"坏人")提示。对于机器学习 对于依赖 GAI 且具有分类或数值结果的流水线或业务流程，在适当情况下对流水线或业务结果应用通用公平性度量(例如，人口统计均等、均衡几率、内容机会均等、统计假设检验)；与领域专家和受影响社区合作开发的定制、情境特定度量；在部署中对生成内容中贬损性内容普遍程度的测量(例如，对一部分流量进行子采样并手动标注贬损性内容)。	有害偏见与同质化；危险、暴力或仇恨性
MS-2.11-003	识别可能受到影响的个人、群体或环境生态系统的类别，这些 可能受到 GAI 系统的影响，通过直接接触潜在的 受影响的社区。	环境；有害偏见和 同质化
MS-2.11-004	审查、记录和衡量生成式人工智能训练和TEVV数据中的偏见来源：群体之间和群体内部(包括交叉群体)的结果分布差异；数据源的完整性、代表性和平衡性；生成式人工智能系统训练数据中的人口群体和子群体覆盖范围；图像、文本、音频、嵌入或其他 复杂或非结构化数据中潜在系统性偏见的形式；可能作为有害偏见和同质化人口群体成员身份代理的输入数据特征(即图像元数据、语言方言)或在生成式人工智能系统中以其他方式引起涌现偏见的特征；数字鸿沟可能对生成式人工智能系统训练和TEVV数据的代表性产生负面影响的程度；生成式人工智能系统训练数据中仇恨言论或内容的过滤；生成式人工智能系统训练数据中生成式人工智能生成数据的普遍程度。	

[15] Winogender Schemas是一组配对句子的样本集，仅所用代词的性别不同，可用于评估自然语言处理共指消解系统中的性别偏见。

MS-2.11-005	Assess the proportion of synthetic to non-synthetic training data and verify training data is not overly homogenous or GAI-produced to mitigate concerns of model collapse.	Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, AI Impact Assessment, Affected Individuals and Communities, Domain Experts, End-Users, Operation and Monitoring, TEVV		

MS-2.11-005	评估合成训练数据与非合成训练数据的比例并进行验证 训练数据不应过于同质化或由GAI生成,以缓解以下担忧: 训练数据不应过于同质化或由GAI生成，以缓解以下担忧： 模型崩溃。	有害偏见与同质化
人工智能参与者任务：人工智能部署、人工智能影响评估、受影响的个人和社区、领域专家、最终用户，运行与监控、TEVV		

MEASURE 2.12: Environmental impact and sustainability of AI model training and management activities – as identified in the MAP function – are assessed and documented.

Action ID	Suggested Action	GAI Risks
MS-2.12-001	Assess safety to physical environments when deploying GAI systems.	Dangerous, Violent, or Hateful Content
MS-2.12-002	Document anticipated environmental impacts of model development, maintenance, and deployment in product design decisions.	Environmental
MS-2.12-003	Measure or estimate environmental impacts (e.g., energy and water consumption) for training, fine tuning, and deploying models: Verify tradeoffs between resources used at inference time versus additional resources required at training time.	Environmental
MS-2.12-004	Verify effectiveness of carbon capture or offset programs for GAI training and applications, and address green-washing concerns.	Environmental
AI Actor Tasks: AI Deployment, AI Impact Assessment, Domain Experts, Operation and Monitoring, TEVV		

度量 2.12:在映射功能中识别的人工智能模型训练和管理活动的环境影响和可持续性得到评估和记录。

操作 ID	建议操作	GAI 风险
MS-2.12-001	在部署 GAI 系统时评估对物理环境的安全性。	危险、暴力或仇恨内容
MS-2.12-002	记录预期的环境影响的模型开发，维护以及产品设计决策中的部署。	环境
MS-2.12-003	度量或估算环境影响(例如能源和水消耗)用于训练、微调和部署模型：验证推理时使用的资源与所需额外资源之间的权衡在训练时。	环境
MS-2.12-004	验证有效性的碳捕获或抵消计划用于GAI训练和应用，并回应绿色洗白方面的关切。	环境
人工智能参与者任务：人工智能部署、人工智能影响评估、领域专家、运营与监控、TEVV(测试、评估、验证与确认)		

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MEASURE 2.13: Effectiveness of the employed TEVV metrics and processes in the MEASURE function are evaluated and documented.		
Action ID	**Suggested Action**	**GAI Risks**
MS-2.13-001	Create measurement error models for pre-deployment metrics to demonstrate construct validity for each metric (i.e., does the metric effectively operationalize the desired concept): Measure or estimate, and document, biases or statistical variance in applied metrics or structured human feedback processes; Leverage domain expertise when modeling complex societal constructs such as hateful content.	Confabulation; Information Integrity; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, Operation and Monitoring, TEVV		

MEASURE 3.2: Risk tracking approaches are considered for settings where AI risks are difficult to assess using currently available measurement techniques or where metrics are not yet available.		
Action ID	**Suggested Action**	**GAI Risks**
MS-3.2-001	Establish processes for identifying emergent GAI system risks including consulting with external AI Actors.	Human-AI Configuration; Confabulation
AI Actor Tasks: AI Impact Assessment, Domain Experts, Operation and Monitoring, TEVV		

MEASURE 3.3: Feedback processes for end users and impacted communities to report problems and appeal system outcomes are established and integrated into AI system evaluation metrics.		
Action ID	**Suggested Action**	**GAI Risks**
MS-3.3-001	Conduct impact assessments on how AI-generated content might affect different social, economic, and cultural groups.	Harmful Bias and Homogenization
MS-3.3-002	Conduct studies to understand how end users perceive and interact with GAI content and accompanying content provenance within context of use. Assess whether the content aligns with their expectations and how they may act upon the information presented.	Human-AI Configuration; Information Integrity
MS-3.3-003	Evaluate potential biases and stereotypes that could emerge from the AI-generated content using appropriate methodologies including computational testing methods as well as evaluating structured feedback input.	Harmful Bias and Homogenization

度量 2.13:在度量功能中采用的TEVV指标和流程的有效性得到评估和记录在案。		
操作 ID 建议操作		**GAI 风险**
MS-2.13-001	为部署前指标创建测量误差模型，以证明每个指标的构念效度(即该指标是否有效地操作化了所需概念)：测量或估计并记录应用指标或结构化人工反馈过程中的偏见或统计 应用度量或结构化人工反馈过程中的方差；在建模复杂社会构念（如仇恨性）时利 内容。	虚构；信息 诚信；有害偏见与 同质化
AI 行为者任务：AI 部署、运行与监控、TEVV		

度量 3.2:在难以使用当前可用测量技术评估人工智能风险或指标尚不可用的环境中，考虑风险跟踪方法。		
操作 ID 建议操作		**GAI 风险**
MS-3.2-001	建立识别新兴GAI系统风险的流程，包括 咨询外部人工智能参与者。	人机协同配置； 虚构
人工智能参与者任务：人工智能影响评估、领域专家、运营和监控、TEVV		

度量 3.3:为最终用户和受影响社区建立报告问题和申诉系统结果的反馈流程，并将其整合到人工智能系统评估指标中。		
操作 ID 建议操作		**GAI 风险**
MS-3.3-001	对AI生成内容可能产生的影响开展影响评估，评估其将如何影响 不同的社会、经济和文化群体。	有害偏见与同质化
MS-3.3-002	开展研究以了解最终用户在使用情境中如何感知和交互生成式人工智能内容及随附 内容是否符合他们的期望以及他们可能如何根据所呈现的信息采取行动。	人机协同配置； 信息完整性
MS-3.3-003	评估可能从 AI 中出现的潜在偏见和刻板印象-- 使用适当的方法(包括计算方法)生成内容 测试方法以及评估结构化反馈输入。	有害偏见与同质化

MS-3.3-004	Provide input for training materials about the capabilities and limitations of GAI systems related to digital content transparency for AI Actors, other professionals, and the public about the societal impacts of AI and the role of diverse and inclusive content generation.	Human-AI Configuration; Information Integrity; Harmful Bias and Homogenization
MS-3.3-005	Record and integrate structured feedback about content provenance from operators, users, and potentially impacted communities through the use of methods such as user research studies, focus groups, or community forums. Actively seek feedback on generated content quality and potential biases. Assess the general awareness among end users and impacted communities about the availability of these feedback channels.	Human-AI Configuration; Information Integrity; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, Affected Individuals and Communities, End-Users, Operation and Monitoring, TEVV		

MS-3.3-004	为关于生成式人工智能系统能力和局限性的培训材料提供输入，涉及数字内容透明度 专业人士和公众，关于人工智能的社会影响以及多样化和包容性内容生成的作用。	人机协同配置； 信息完整性；有害偏见 和同质化
MS-3.3-005	通过用户研究、焦点小组或社区论坛等方法，记录并整合来自运营者、用户和潜在受影响社区关于内容来源的结构化反馈。 积极寻求关于生成内容质量和潜在偏见的反馈。评估最终用户和受影响社区对这些反馈渠道可用性的普遍认知。	人机协同配置； 信息完整性；有害偏见 和同质化
人工智能参与者任务：人工智能部署、受影响的个人和社区、最终用户、运营和监控、TEVV		

MEASURE 4.2: Measurement results regarding AI system trustworthiness in deployment context(s) and across the AI lifecycle are informed by input from domain experts and relevant AI Actors to validate whether the system is performing consistently as intended. Results are documented.

Action ID	**Suggested Action**	**GAI Risks**
MS-4.2-001	Conduct adversarial testing at a regular cadence to map and measure GAI risks, including tests to address attempts to deceive or manipulate the application of provenance techniques or other misuses. Identify vulnerabilities and understand potential misuse scenarios and unintended outputs.	Information Integrity; Information Security
MS-4.2-002	Evaluate GAI system performance in real-world scenarios to observe its behavior in practical environments and reveal issues that might not surface in controlled and optimized testing environments.	Human-AI Configuration; Confabulation; Information Security
MS-4.2-003	Implement interpretability and explainability methods to evaluate GAI system decisions and verify alignment with intended purpose.	Information Integrity; Harmful Bias and Homogenization
MS-4.2-004	Monitor and document instances where human operators or other systems override the GAI's decisions. Evaluate these cases to understand if the overrides are linked to issues related to content provenance.	Information Integrity
MS-4.2-005	Verify and document the incorporation of results of structured public feedback exercises into design, implementation, deployment approval (“go”/“no-go” decisions), monitoring, and decommission decisions.	Human-AI Configuration; Information Security
AI Actor Tasks: AI Deployment, Domain Experts, End-Users, Operation and Monitoring, TEVV		

度量 4.2:关于人工智能系统在部署情境中和整个人工智能生命周期中的可信度的测量结果，由领域专家和相关人工智能参与者的输入提供

预期。结果已记录。

操作 ID 建议操作		**GAI 风险**
MS-4.2-001	以固定节奏进行对抗测试，以映射和度量生成式人工智能风险，包括针对试图欺骗或操纵 溯源技术或其他滥用行为。识别漏洞并 了解潜在的滥用场景和意外输出。	信息完整性；信息 安全
MS-4.2-002	评估GAI系统在真实场景中的性能，以观察其 在实际环境中的行为,并揭示可能不会在 在实际环境中的行为，并揭示可能不会在 受控且优化的测试环境。	人机协同配置； 虚构；信息 安全
MS-4.2-003	实施可解释性和可解释性方法以评估GAI系统 决策并验证与预期目的的一致性。	信息完整性；有害偏见 与同质化
MS-4.2-004	监测并记录人类操作员或其他系统出现以下情况的实例 覆盖生成式人工智能决策的测试。评估这些案例以了解覆盖是否与内容来源相关问题有关。	信息完整性
MS-4.2-005	核实并记录结构化公众反馈结果的纳入情况 将演练纳入设计、实施、部署审批(“go”/“no-go”决策)、监控和退役决策中。	人机协同配置；信息安全
人工智能参与者任务：人工智能部署、领域专家、最终用户、运营与监控、TEVV		

MANAGE 1.3: Responses to the AI risks deemed high priority, as identified by the MAP function, are developed, planned, and documented. Risk response options can include mitigating, transferring, avoiding, or accepting.		
Action ID	**Suggested Action**	**GAI Risks**
MG-1.3-001	Document trade-offs, decision processes, and relevant measurement and feedback results for risks that do not surpass organizational risk tolerance, for example, in the context of model release: Consider different approaches for model release, for example, leveraging a staged release approach. Consider release approaches in the context of the model and its projected use cases. Mitigate, transfer, or avoid risks that surpass organizational risk tolerances.	Information Security
MG-1.3-002	Monitor the robustness and effectiveness of risk controls and mitigation plans (e.g., via red-teaming, field testing, participatory engagements, performance assessments, user feedback mechanisms).	Human-AI Configuration
AI Actor Tasks: AI Development, AI Deployment, AI Impact Assessment, Operation and Monitoring		

MANAGE 2.2: Mechanisms are in place and applied to sustain the value of deployed AI systems.		
Action ID	**Suggested Action**	**GAI Risks**
MG-2.2-001	Compare GAI system outputs against pre-defined organization risk tolerance, guidelines, and principles, and review and test AI-generated content against these guidelines.	CBRN Information or Capabilities; Obscene, Degrading, and/or Abusive Content; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content
MG-2.2-002	Document training data sources to trace the origin and provenance of AI-generated content.	Information Integrity
MG-2.2-003	Evaluate feedback loops between GAI system content provenance and human reviewers, and update where needed. Implement real-time monitoring systems to affirm that content provenance protocols remain effective.	Information Integrity
MG-2.2-004	Evaluate GAI content and data for representational biases and employ techniques such as re-sampling, re-ranking, or adversarial training to mitigate biases in the generated content.	Information Security; Harmful Bias and Homogenization
MG-2.2-005	Engage in due diligence to analyze GAI output for harmful content, potential misinformation, and CBRN-related or NCII content.	CBRN Information or Capabilities; Obscene, Degrading, and/or Abusive Content; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content

管理 1.3:针对由映射功能识别出的被视为高优先级的人工智能风险，制定、规划并记录应对措施。风险应对选项可包括缓解、转移、		
操作 ID 建议操作		**GAI 风险**
MG-1.3-001	记录未超出组织风险容忍度的风险的权衡、决策过程以及相关度量和反馈结果，例如在模型发布情境中：考虑不同方法以 模型发布，例如，利用分阶段发布方法。在模型及其预期用例的背景下考虑发布方法。缓解、转移或避免超过组织风险容忍度的风险。	信息安全
MG-1.3-002	监控风险控制和缓解计划的稳健性和有效性 (例如，通过红队测试、现场测试、参与式互动、性能评估) 评估、用户反馈机制)。	人机协同配置
人工智能参与者任务：人工智能开发、人工智能部署、人工智能影响评估、运营与监控		

管理 2.2:已建立并应用相关机制，以维持已部署人工智能系统的价值。		
操作 ID 建议操作		**GAI 风险**
MG-2.2-001	将GAI系统输出与预先定义的组织风险容忍度进行比较， 指南、原则，并对照审查和测试 AI 生成的内容 这些指南。	CBRN信息或能力； 淫秽、有辱人格和/或 滥用内容；有害偏见与 同质化；危险的、 暴力或仇恨内容
MG-2.2-002	记录训练数据来源，以追溯AI的起源和出处-- 生成内容。	信息完整性
MG-2.2-003	评估GAI系统内容来源与人类之间的反馈回路 审查者，并在需要时更新。实施实时监控系统，以确认内容溯源协议持续有效。	信息完整性
MG-2.2-004	评估生成式人工智能内容和数据的表征偏差，并采用 采用重采样、重排序或对抗训练等技术，以减轻生成内容中的偏见。	信息安全；有害偏见 与同质化
MG-2.2-005	进行尽职调查，分析GAI输出中的有害内容、潜在 错误信息，以及与 CBRN 相关或 NCII 内容。	CBRN 信息或能力；淫秽、有辱人格 滥用内容；有害偏见与 同质化；危险、暴力或仇恨内容

MG-2.2-006	Use feedback from internal and external AI Actors, users, individuals, and communities, to assess impact of AI-generated content.	Human-AI Configuration
MG-2.2-007	Use real-time auditing tools where they can be demonstrated to aid in the tracking and validation of the lineage and authenticity of AI-generated data.	Information Integrity
MG-2.2-008	Use structured feedback mechanisms to solicit and capture user input about AI-generated content to detect subtle shifts in quality or alignment with community and societal values.	Human-AI Configuration; Harmful Bias and Homogenization
MG-2.2-009	Consider opportunities to responsibly use synthetic data and other privacy enhancing techniques in GAI development, where appropriate and applicable, match the statistical properties of real-world data without disclosing personally identifiable information or contributing to homogenization.	Data Privacy; Intellectual Property; Information Integrity; Confabulation; Harmful Bias and Homogenization
AI Actor Tasks: AI Deployment, AI Impact Assessment, Governance and Oversight, Operation and Monitoring		

MG-2.2-006	使用来自内部和外部AI行为者、用户、个人以及 社区，以评估人工智能生成内容的影响。	人机协同配置
MG-2.2-007	在可证明有助于追踪和验证人工智能生成数据的谱系与真实性的情况下，使用实时	信息完整性
MG-2.2-008	利用结构化反馈机制来征求并收集用户关于AI-的意见 生成内容，以检测质量或与社区和社会价值观一致性的细微变化。	人机配置；有害偏见与同质化
MG-2.2-009	考虑负责任地使用合成数据及其他隐私保护措施的机会 在生成式人工智能开发中，酌情并在适用情况下采用增强技术， 匹配真实世界数据的统计特性，同时不披露个人可识别信息，也不助长同质化。	数据隐私；知识产权； 信息完整性； 虚构；有害偏见和 同质化
人工智能参与者任务：人工智能部署、人工智能影响评估、治理与监督、运行与监控		

MANAGE 2.3: Procedures are followed to respond to and recover from a previously unknown risk when it is identified.		
Action ID	**Suggested Action**	**GAI Risks**
MG-2.3-001	Develop and update GAI system incident response and recovery plans and procedures to address the following: Review and maintenance of policies and procedures to account for newly encountered uses; Review and maintenance of policies and procedures for detection of unanticipated uses; Verify response and recovery plans account for the GAI system value chain; Verify response and recovery plans are updated for and include necessary details to communicate with downstream GAI system Actors: Points-of-Contact (POC), Contact information, notification format.	Value Chain and Component Integration
AI Actor Tasks: AI Deployment, Operation and Monitoring		

管理 2.3:遵循相关程序，以在识别出先前未知风险时作出响应并从中恢复。		
操作 ID 建议操作		**GAI 风险**
MG-2.3-001	制定并更新GAI系统事件响应和恢复计划与程序，以应对以下事项：审查和维护政策与程序，以考虑新遇到的用途；审查和维护政策与程序，以检测未预见的用途；验证响应 和恢复计划涵盖GAI系统价值链；验证响应和恢复计划已更新，并包含与下游GAI系统参与者沟通所需的必要细节：联系人(POC)、联系信息、通知格式。	价值链与组件 集成
AI 行为者任务：AI 部署、运行与监控		

MANAGE 2.4: Mechanisms are in place and applied, and responsibilities are assigned and understood, to supersede, disengage, or deactivate AI systems that demonstrate performance or outcomes inconsistent with intended use.		
Action ID	**Suggested Action**	**GAI Risks**
MG-2.4-001	Establish and maintain communication plans to inform AI stakeholders as part of the deactivation or disengagement process of a specific GAI system (including for open-source models) or context of use, including reasons, workarounds, user access removal, alternative processes, contact information, etc.	Human-AI Configuration

管理 2.4:已建立并应用相关机制，且已分配并理解相关责任，以取代、脱离或停用表现出与预期用途不一致的性能或结果的人工智能系统。		
操作 ID 建议操作		**GAI 风险**
MG-2.4-001	建立并维护沟通计划，以便在特定GAI系统(包括开源模型)或使用场景的停用或脱离过程中告知人工智能利益相关者，包括原因、变通方案、用户访问权限移除、替代流程、联系信息等。	人机协同配置

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MG-2.4-002	Establish and maintain procedures for escalating GAI system incidents to the organizational risk management authority when specific criteria for deactivation or disengagement is met for a particular context of use or for the GAI system as a whole.	Information Security
MG-2.4-003	Establish and maintain procedures for the remediation of issues which trigger incident response processes for the use of a GAI system, and provide stakeholders timelines associated with the remediation plan.	Information Security
MG-2.4-004	Establish and regularly review specific criteria that warrants the deactivation of GAI systems in accordance with set risk tolerances and appetites.	Information Security
AI Actor Tasks: AI Deployment, Governance and Oversight, Operation and Monitoring		

MG-2.4-002	建立并维护相关程序，以便在特定使用场景或GAI系统整体满足停用或脱离的特定标准时，将GAI系统事件上报至组织风险管理机构。 整体。	信息安全
MG-2.4-003	建立并维护用于修复触发问题的程序 GAI系统使用的事件响应流程，并向利益相关者提供与补救计划相关的时间表。	信息安全
MG-2.4-004	建立并定期审查具体的标准，这些标准证明有必要对停用该 按照既定的风险容忍度和风险偏好，对 GAI 系统进行管理。	信息安全
人工智能参与者任务：人工智能部署、治理与监督、运行与监控		

MANAGE 3.1: AI risks and benefits from third-party resources are regularly monitored, and risk controls are applied and documented.

Action ID	Suggested Action	GAI Risks
MG-3.1-001	Apply organizational risk tolerances and controls (e.g., acquisition and procurement processes; assessing personnel credentials and qualifications, performing background checks; filtering GAI input and outputs, grounding, fine tuning, retrieval-augmented generation) to third-party GAI resources: Apply organizational risk tolerance to the utilization of third-party datasets and other GAI resources; Apply organizational risk tolerances to fine-tuned third-party models; Apply organizational risk tolerance to existing third-party models adapted to a new domain; Reassess risk measurements after fine-tuning third-party GAI models.	Value Chain and Component Integration; Intellectual Property
MG-3.1-002	Test GAI system value chain risks (e.g., data poisoning, malware, other software and hardware vulnerabilities; labor practices; data privacy and localization compliance; geopolitical alignment).	Data Privacy; Information Security; Value Chain and Component Integration; Harmful Bias and Homogenization
MG-3.1-003	Re-assess model risks after fine-tuning or retrieval-augmented generation implementation and for any third-party GAI models deployed for applications and/or use cases that were not evaluated in initial testing.	Value Chain and Component Integration
MG-3.1-004	Take reasonable measures to review training data for CBRN information, and intellectual property, and where appropriate, remove it. Implement reasonable measures to prevent, flag, or take other action in response to outputs that reproduce particular training data (e.g., plagiarized, trademarked, patented, licensed content or trade secret material).	Intellectual Property; CBRN Information or Capabilities

管理 3.1:定期监控来自第三方资源的人工智能风险与收益，并应用和记录风险控制措施。

操作 ID	建议操作	GAI 风险
MG-3.1-001	将组织风险容忍度和控制措施(例如，采购与获取流程；评估人员资质和资格、进行背景调查；过滤GAI输入和输出、基础化、微调、检索增强生成)应用于第三方GAI资源：应用 组织风险容忍度于第三方数据集和其他GAI资源的使用；将组织风险容忍度应用于微调后的第三方模型；将组织风险容忍度应用于适配新领域的现有第三方模型；在微调第三方GAI模型后重新评估风险度量。	价值链与组件集成；知识产权
MG-3.1-002	测试GAI系统价值链风险(例如，数据中毒、恶意软件、其他软件和硬件漏洞；劳动实践；数据隐私和本地化合规；地缘政治一致性)。	数据隐私；信息安全；价值链与组件集成；有害偏见和 同质化
MG-3.1-003	在微调或检索增强生成后重新评估模型风险 实施，以及针对未在初始测试中评估的应用和/或使用场景部署的任何第三方GAI模型	价值链与组件集成
MG-3.1-004	采取合理措施审查训练数据中的CBRN信息以及知识产权，并在适当情况下将其移除 措施，以预防、标记或采取其他行动应对复现特定训练数据的输出(例如，抄袭、商标、专利、许可内容或商业秘密材料)。	知识产权；CBRN 信息或能力

MG-3.1-005	Review various transparency artifacts (e.g., system cards and model cards) for third-party models.	Information Integrity; Information Security; Value Chain and Component Integration
AI Actor Tasks: AI Deployment, Operation and Monitoring, Third-party entities		

MG-3.1-005	审查各种透明度制品(例如，系统卡和模型卡)用于第三方模型。	信息完整性；信息安全；价值链与组件集成
人工智能参与者任务：人工智能部署、运行与监控、第三方实体		

MANAGE 3.2: Pre-trained models which are used for development are monitored as part of AI system regular monitoring and maintenance.

Action ID	Suggested Action	GAI Risks
MG-3.2-001	Apply explainable AI (XAI) techniques (e.g., analysis of embeddings, model compression/distillation, gradient-based attributions, occlusion/term reduction, counterfactual prompts, word clouds) as part of ongoing continuous improvement processes to mitigate risks related to unexplainable GAI systems.	Harmful Bias and Homogenization
MG-3.2-002	Document how pre-trained models have been adapted (e.g., fine-tuned, or retrieval-augmented generation) for the specific generative task, including any data augmentations, parameter adjustments, or other modifications. Access to un-tuned (baseline) models supports debugging the relative influence of the pre-trained weights compared to the fine-tuned model weights or other system updates.	Information Integrity; Data Privacy
MG-3.2-003	Document sources and types of training data and their origins, potential biases present in the data related to the GAI application and its content provenance, architecture, training process of the pre-trained model including information on hyperparameters, training duration, and any fine-tuning or retrieval-augmented generation processes applied.	Information Integrity; Harmful Bias and Homogenization; Intellectual Property
MG-3.2-004	Evaluate user reported problematic content and integrate feedback into system updates.	Human-AI Configuration, Dangerous, Violent, or Hateful Content
MG-3.2-005	Implement content filters to prevent the generation of inappropriate, harmful, false, illegal, or violent content related to the GAI application, including for CSAM and NCII. These filters can be rule-based or leverage additional machine learning models to flag problematic inputs and outputs.	Information Integrity; Harmful Bias and Homogenization; Dangerous, Violent, or Hateful Content; Obscene, Degrading, and/or Abusive Content
MG-3.2-006	Implement real-time monitoring processes for analyzing generated content performance and trustworthiness characteristics related to content provenance to identify deviations from the desired standards and trigger alerts for human intervention.	Information Integrity

管理 3.2:用于开发的预训练模型作为人工智能系统定期监控和维护的一部分受到监控。

操作 ID	建议操作	GAI 风险
MG-3.2-001	应用可解释人工智能(XAI)技术(例如，嵌入分析、模型压缩/蒸馏、基于梯度的归因、反事实提示、词云)，作为持续改进流程的一部分，以减轻与不可解释GAI系统相关	有害偏见与同质化
MG-3.2-002	记录预训练模型如何针对特定生成任务进行调整(例如微调或检索增强生成)，包括任何数据增强、参数调整或其他修改。访问未调优(基线)模型有助于调试预训练权重相对于微调模型权重或其他系统的相对影响更新。	信息完整性；数据隐私
MG-3.2-003	记录训练数据的来源、类型及其出处、数据中存在的与 GAI 应用及其内容溯源相关的偏差；架构、预训练模型的训练过程，包括以下信息：超参数、训练时长以及任何微调或检索增强已应用生成过程。	信息完整性；有害偏见与同质化；知识属性
MG-3.2-004	评估用户报告的有问题内容并整合反馈到系统更新。	人机配置、危险、暴力或仇恨内容
MG-3.2-005	实施内容过滤器，以防止生成与 GAI 应用相关的不当、有害、虚假、非法或暴力内容和 NCII。这些过滤器可以基于规则，或利用额外的机器学习模型来标记有问题的输入	信息完整性；有害偏见与同质化；危险、暴力或仇恨内容；淫秽、有辱人格和/或辱骂性内容
MG-3.2-006	实施实时监控流程，用于分析与内容溯源相关的生成内容性能和可信度特征识别与期望标准的偏差，并触发警报以供人工干预。	信息完整性

MG-3.2-007	Leverage feedback and recommendations from organizational boards or committees related to the deployment of GAI applications and content provenance when using third-party pre-trained models.	Information Integrity; Value Chain and Component Integration
MG-3.2-008	Use human moderation systems where appropriate to review generated content in accordance with human-AI configuration policies established in the Govern function, aligned with socio-cultural norms in the context of use, and for settings where AI models are demonstrated to perform poorly.	Human-AI Configuration
MG-3.2-009	Use organizational risk tolerance to evaluate acceptable risks and performance metrics and decommission or retrain pre-trained models that perform outside of defined limits.	CBRN Information or Capabilities; Confabulation
AI Actor Tasks: AI Deployment, Operation and Monitoring, Third-party entities		

MG-3.2-007	利用组织董事会或 在使用第三方预训练模型时，与 GAI 应用部署和内容溯源相关的委员会。	信息完整性；价值链 和组件集成
MG-3.2-008	在适当情况下使用人工审核系统，按照治理职能中确立的人机协同配置政策审查生成内容， 与使用情境中的社会文化规范保持一致，并适用于已证明 AI 模型表现不佳的环境。	人机协同配置
MG-3.2-009	利用组织风险容忍度来评估可接受的风险和绩效 指标，并停用或重新训练超出规定限值运行的预训练模型。	CBRN信息或能力； 虚构
人工智能参与者任务：人工智能部署、运行与监控、第三方实体		

MANAGE 4.1: Post-deployment AI system monitoring plans are implemented, including mechanisms for capturing and evaluating input from users and other relevant AI Actors, appeal and override, decommissioning, incident response, recovery, and change management.		
Action ID	**Suggested Action**	**GAI Risks**
MG-4.1-001	Collaborate with external researchers, industry experts, and community representatives to maintain awareness of emerging best practices and technologies in measuring and managing identified risks.	Information Integrity; Harmful Bias and Homogenization
MG-4.1-002	Establish, maintain, and evaluate effectiveness of organizational processes and procedures for post-deployment monitoring of GAI systems, particularly for potential confabulation, CBRN, or cyber risks.	CBRN Information or Capabilities; Confabulation; Information Security
MG-4.1-003	Evaluate the use of sentiment analysis to gauge user sentiment regarding GAI content performance and impact, and work in collaboration with AI Actors experienced in user research and experience.	Human-AI Configuration
MG-4.1-004	Implement active learning techniques to identify instances where the model fails or produces unexpected outputs.	Confabulation
MG-4.1-005	Share transparency reports with internal and external stakeholders that detail steps taken to update the GAI system to enhance transparency and accountability.	Human-AI Configuration; Harmful Bias and Homogenization
MG-4.1-006	Track dataset modifications for provenance by monitoring data deletions, rectification requests, and other changes that may impact the verifiability of content origins.	Information Integrity

管理 4.1:实施部署后的人工智能系统监控计划，包括捕获和评估用户及其他相关人工智能参与者输入的机制、申诉与推翻、停用、事件响应、恢复和变更管理。		
操作 ID 建议操作		**GAI 风险**
MG-4.1-001	与外部研究人员、行业专家和社区合作 代表，以持续了解在度量和管 □ □理已识别风险方面的新兴最佳实践和技术。	信息完整性；有害偏见与同质化
MG-4.1-002	建立、维护并评估组织流程的有效性，并 GAI系统部署后监控程序，特别是针对 潜在的虚构、CBRN或网络风险。	CBRN信息或能力； 虚构；信息 安全
MG-4.1-003	评估使用情感分析来衡量用户对GAI的情感 内容性能和影响，并与人工智能行动者协作 在用户研究和体验方面经验丰富。	人机协同配置
MG-4.1-004	实施主动学习技术以识别模型失败的实例 或产生意外输出。	虚构
MG-4.1-005	与内部和外部利益相关者分享透明度报告，详细说明 为提升透明度而采取的更新 GAI 系统的步骤，以及 问责制。	人机配置；有害偏见与同质化
MG-4.1-006	通过监控数据删除来跟踪数据集修改以进行溯源， 更正请求以及其他可能影响可验证性的变更 内容来源。	信息完整性

MG-4.1-007	Verify that AI Actors responsible for monitoring reported issues can effectively evaluate GAI system performance including the application of content provenance data tracking techniques, and promptly escalate issues for response.	Human-AI Configuration; Information Integrity
AI Actor Tasks: AI Deployment, Affected Individuals and Communities, Domain Experts, End-Users, Human Factors, Operation and Monitoring		

MG-4.1-007	核实负责监测已报告问题的 AI 行为者能否有效 评估生成式人工智能系统性能，包括内容来源数据追踪技术的应用，并及时上报问题以	人机协同配置； 信息完整性
人工智能参与者任务：人工智能部署、受影响个人与社区、领域专家、最终用户、人为因素、运营和监控		

MANAGE 4.2: Measurable activities for continual improvements are integrated into AI system updates and include regular engagement with interested parties, including relevant AI Actors.

Action ID	Suggested Action	GAI Risks
MG-4.2-001	Conduct regular monitoring of GAI systems and publish reports detailing the performance, feedback received, and improvements made.	Harmful Bias and Homogenization
MG-4.2-002	Practice and follow incident response plans for addressing the generation of inappropriate or harmful content and adapt processes based on findings to prevent future occurrences. Conduct post-mortem analyses of incidents with relevant AI Actors, to understand the root causes and implement preventive measures.	Human-AI Configuration; Dangerous, Violent, or Hateful Content
MG-4.2-003	Use visualizations or other methods to represent GAI model behavior to ease non-technical stakeholders understanding of GAI system functionality.	Human-AI Configuration
AI Actor Tasks: AI Deployment, AI Design, AI Development, Affected Individuals and Communities, End-Users, Operation and Monitoring, TEVV		

管理 4.2:将持续改进的可度量活动整合到人工智能系统更新中，并包括定期与利益相关方(包括相关人工智能行为者)的互动。

操作 ID	建议操作	GAI 风险
MG-4.2-001	开展定期监测对GAI系统和发布报告详述该性能、收到的反馈以及所做的改进。	有害偏见与同质化
MG-4.2-002	实践并遵循事件响应计划，以处理不当或有害内容的生成，并根据发现调整流程以防止未来再次发生。对事件进行事后分析，并与相关 AI 行为者，以理解根本原因并实施预防性度量。	人机协同配置； 危险、暴力或仇恨性内容
MG-4.2-003	使用可视化或其他方法来表示生成式人工智能模型行为以便于非技术利益相关者对GAI系统功能的理解。	人机协同配置
人工智能参与者任务：人工智能部署、人工智能设计、人工智能开发、受影响个人与社区、最终用户、运营和监测、TEVV		

MANAGE 4.3: Incidents and errors are communicated to relevant AI Actors, including affected communities. Processes for tracking, responding to, and recovering from incidents and errors are followed and documented.

Action ID	Suggested Action	GAI Risks
MG-4.3-001	Conduct after-action assessments for GAI system incidents to verify incident response and recovery processes are followed and effective, including to follow procedures for communicating incidents to relevant AI Actors and where applicable, relevant legal and regulatory bodies.	Information Security
MG-4.3-002	Establish and maintain policies and procedures to record and track GAI system reported errors, near-misses, and negative impacts.	Confabulation; Information Integrity

管理 4.3:事件和错误被传达给相关人工智能参与者，包括受影响社区。跟踪、响应和从事件和错误中恢复的流程得到遵循并记录。

操作 ID	建议操作	GAI 风险
MG-4.3-001	对生成式人工智能系统事件开展事后评估，以验证事件响应和恢复流程得到遵循且有 向相关人工智能参与者以及适用情况下相关法律和监管机构传达事件的程序。	信息安全
MG-4.3-002	建立并维护政策和程序以记录并跟踪生成式人工智能系统报告的错误、未遂事件和负面影响。	虚构；信息完整性

MG-4.3-003	Report GAI incidents in compliance with legal and regulatory requirements (e.g., HIPAA breach reporting, e.g., OCR (2023) or NHTSA (2022) autonomous vehicle crash reporting requirements.	Information Security; Data Privacy
AI Actor Tasks: AI Deployment, Affected Individuals and Communities, Domain Experts, End-Users, Human Factors, Operation and Monitoring		

MG-4.3-003	按照法律法规要求报告 GAI 事件(例如， HIPAA 违规报告,例如 OCR(2023) 或 NHTSA(2022) 自动驾驶汽车 HIPAA 违规报告，例如 OCR(2023) 或 NHTSA(2022) 自动驾驶汽车 崩溃报告要求。	信息安全；数据隐私
人工智能参与者任务：人工智能部署、受影响个人与社区、领域专家、最终用户、人为因素、运营和监控		

Appendix A. Primary GAI Considerations

The following primary considerations were derived as overarching themes from the GAI PWG consultation process. These considerations (Governance, Pre-Deployment Testing, Content Provenance, and Incident Disclosure) are relevant for voluntary use by any organization designing, developing, and using GAI and also inform the Actions to Manage GAI risks. Information included about the primary considerations is not exhaustive, but highlights the most relevant topics derived from the GAI PWG.

Acknowledgments: These considerations could not have been surfaced without the helpful analysis and contributions from the community and NIST staff GAI PWG leads: George Awad, Luca Belli, Harold Booth, Mat Heyman, Yooyoung Lee, Mark Pryzbocki, Reva Schwartz, Martin Stanley, and Kyra Yee.

A.1. Governance

A.1.1. Overview

Like any other technology system, governance principles and techniques can be used to manage risks related to generative AI models, capabilities, and applications. Organizations may choose to apply their existing risk tiering to GAI systems, or they may opt to revise or update AI system risk levels to address these unique GAI risks. This section describes how organizational governance regimes may be re-evaluated and adjusted for GAI contexts. It also addresses third-party considerations for governing across the AI value chain.

A.1.2. Organizational Governance

GAI opportunities, risks and long-term performance characteristics are typically less well-understood than non-generative AI tools and may be perceived and acted upon by humans in ways that vary greatly. Accordingly, GAI may call for different levels of oversight from AI Actors or different human-AI configurations in order to manage their risks effectively. Organizations' use of GAI systems may also warrant additional human review, tracking and documentation, and greater management oversight.

AI technology can produce varied outputs in multiple modalities and present many classes of user interfaces. This leads to a broader set of AI Actors interacting with GAI systems for widely differing applications and contexts of use. These can include data labeling and preparation, development of GAI models, content moderation, code generation and review, text generation and editing, image and video generation, summarization, search, and chat. These activities can take place within organizational settings or in the public domain.

Organizations can restrict AI applications that cause harm, exceed stated risk tolerances, or that conflict with their tolerances or values. Governance tools and protocols that are applied to other types of AI systems can be applied to GAI systems. These plans and actions include:

- Accessibility and reasonable accommodations
- AI actor credentials and qualifications
- Alignment to organizational values
- Auditing and assessment
- Change-management controls
- Commercial use
- Data provenance

附录 A.生成式人工智能主要考虑因素

以下主要考虑因素是从生成式人工智能公开工作组(GAI PWG)咨询过程中提炼出的总体主题。这些考虑因素(治理、部署前测试、内容来源和事件披露)适用于任何设计、开发和使用生成式人工智能的组织自愿使用，并为管理生成式人工智能风险的行动提供参考。所包含的关于主要考虑因素的信息并非详尽无遗，但突出了从生成式人工智能公开工作组中提炼出的最相关主题。

致谢：如果没有社区和 NIST 工作人员生成式人工智能公开工作组负责人的有益分析和贡献，这些考虑因素就无法呈现：George Awad、Luca Belli、Harold Booth、Mat Heyman、Yooyoung Lee、Mark Pryzbocki、Reva Schwartz、Martin Stanley 和 Kyra Yee。

A.1. 治理

A.1.1. 概述

与任何其他技术系统一样，治理原则和技术可用于管理与生成式人工智能模型、能力和应用相关的风险。组织可以选择将其现有的风险分级应用于GAI系统，也可以选择修订或更新人工智能系统风险级别，以应对这些独特的GAI风险。本节描述组织治理制度如何针对GAI情境进行重新评估和调整。它还讨论了在人工智能价值链中进行治理的第三方考量。

A.1.2. 组织治理

生成式人工智能的机遇、风险和长期性能特征通常比非生成式人工智能工具更不为人所理解，并且人类可能以差异很大的方式感知和采取行动。因此，生成式人工智能可能需要人工智能参与者不同程度的监督或不同的人机配置，以有效管理其风险。组织对生成式人工智能系统的使用也可能需要额外的人工审查、跟踪和记录，以及更大的管理监督。

人工智能技术可以以多种模态产生多样化的输出，并呈现多种类别的用户界面。这导致更广泛的人工智能参与者群体在差异极大的应用和使用情境中与GAI系统交互。这些可以包括数据标注和准备、GAI模型开发、内容审核、代码生成和审查、文本生成和编辑、图像和视频生成、摘要、搜索和聊天。这些活动可以在组织环境内或公共领域中进行。

组织可以限制造成伤害、超出既定风险容忍度或与其容忍度或价值观相冲突的人工智能应用。应用于其他类型人工智能系统的治理工具和协议可以应用于生成式人工智能系统。这些计划和行动包括：

- 可访问性与合理性便利措施
- AI 行为者资质与资格
- 与组织价值观保持一致
- 审计与评估
- 变更管理控制措施
- 商业用途
- 数据来源

- Data protection
- Data retention
- Consistency in use of defining key terms
- Decommissioning
- Discouraging anonymous use
- Education
- Impact assessments
- Incident response
- Monitoring
- Opt-outs
- Risk-based controls
- Risk mapping and measurement
- Science-backed TEVV practices
- Secure software development practices
- Stakeholder engagement
- Synthetic content detection and labeling tools and techniques
- Whistleblower protections
- Workforce diversity and interdisciplinary teams

Establishing acceptable use policies and guidance for the use of GAI in formal human-AI teaming settings as well as different levels of human-AI configurations can help to decrease risks arising from misuse, abuse, inappropriate repurpose, and misalignment between systems and users. These practices are just one example of adapting existing governance protocols for GAI contexts.

A.1.3. Third-Party Considerations

Organizations may seek to acquire, embed, incorporate, or use open-source or proprietary third-party GAI models, systems, or generated data for various applications across an enterprise. Use of these GAI tools and inputs has implications for all functions of the organization – including but not limited to acquisition, human resources, legal, compliance, and IT services – regardless of whether they are carried out by employees or third parties. Many of the actions cited above are relevant and options for addressing third-party considerations.

Third party GAI integrations may give rise to increased intellectual property, data privacy, or information security risks, pointing to the need for clear guidelines for transparency and risk management regarding the collection and use of third-party data for model inputs. Organizations may consider varying risk controls for foundation models, fine-tuned models, and embedded tools, enhanced processes for interacting with external GAI technologies or service providers. Organizations can apply standard or existing risk controls and processes to proprietary or open-source GAI technologies, data, and third-party service providers, including acquisition and procurement due diligence, requests for software bills of materials (SBOMs), application of service level agreements (SLAs), and statement on standards for attestation engagement (SSAE) reports to help with third-party transparency and risk management for GAI systems.

A.1.4. Pre-Deployment Testing

Overview

The diverse ways and contexts in which GAI systems may be developed, used, and repurposed complicates risk mapping and pre-deployment measurement efforts. Robust test, evaluation, validation, and verification (TEVV) processes can be iteratively applied – and documented – in early stages of the AI lifecycle and informed by representative AI Actors (see Figure 3 of the AI RMF). Until new and rigorous

- 数据保护
- 数据保留
- 定义关键术语使用的一致性
- 退役
- 劝阻匿名使用
- 教育
- 影响评估
- 事件响应
- 监控
- 退出选项
- 基于风险的控制
- 风险映射与度量
- 基于科学的TEVV实践
- 安全的软件开发实践
- 利益相关方参与
- 合成内容检测与标注工具与技术
- 举报人保护
- 劳动力多样性与跨学科团队

为在正式人机团队环境中使用生成式人工智能以及不同级别的人机配置建立可接受使用政策和指导，有助于降低因误用、滥用、不当再利用以及系统与用户之间不一致而产生的风险。这些实践只是为生成式人工智能情境调整现有治理协议的一个示例。

A.1.3. 第三方考量

组织可能寻求获取、嵌入、纳入或使用开源或专有第三方GAI模型、系统或生成数据，以用于企业范围内的各种应用。使用这些GAI工具和输入对组织的所有职能都有影响--包括但不限于采购、人力资源、法律、合规和IT服务--无论这些活动是由员工还是第三方执行。上述许多行动是相关的，并且是可选项，用于

第三方GAI集成可能引发更高的知识产权、数据隐私或信息安全风险，这表明需要就第三方数据用于模型输入的收集和使用制定明确的透明度和风险管理指南。组织可以考虑对基础模型、微调模型和嵌入式工具采取不同的风险控制措施，增强与外部GAI技术或服务提供商交互的流程。组织可以对专有或开源GAI技术、数据和第三方服务提供商应用标准或现有的风险控制和流程，包括采购和采购尽职调查、软件物料清单(SBOM)请求、服务级别协议(SLA)的应用，以及认证业务准则声明(SSAE)报告，以帮助实现GAI系统的第三方透明度和风险管理。

A.1.4. 部署前测试

概述

生成式人工智能系统可能被开发、使用和再利用的多样方式和情境使风险映射和部署前度量工作变得复杂。稳健的测试、评估、验证与确认(TEVV)流程可以在人工智能生命周期的早期阶段迭代应用并记录，并以代表性人工智能参与者为依据(见 AI RMF 图 3)。在新的严格

early lifecycle TEVV approaches are developed and matured for GAI, organizations may use recommended “pre-deployment testing” practices to measure performance, capabilities, limits, risks, and impacts. This section describes risk measurement and estimation as part of pre-deployment TEVV, and examines the state of play for pre-deployment testing methodologies.

Limitations of Current Pre-deployment Test Approaches

Currently available pre-deployment TEVV processes used for GAI applications may be inadequate, non-systematically applied, or fail to reflect or mismatched to deployment contexts. For example, the anecdotal testing of GAI system capabilities through video games or standardized tests designed for humans (e.g., intelligence tests, professional licensing exams) does not guarantee GAI system validity or reliability in those domains. Similarly, jailbreaking or prompt engineering tests may not systematically assess validity or reliability risks.

Measurement gaps can arise from mismatches between laboratory and real-world settings. Current testing approaches often remain focused on laboratory conditions or restricted to benchmark test datasets and in silico techniques that may not extrapolate well to—or directly assess GAI impacts in real-world conditions. For example, current measurement gaps for GAI make it difficult to precisely estimate its potential ecosystem-level or longitudinal risks and related political, social, and economic impacts. Gaps between benchmarks and real-world use of GAI systems may likely be exacerbated due to prompt sensitivity and broad heterogeneity of contexts of use.

A.1.5. Structured Public Feedback

Structured public feedback can be used to evaluate whether GAI systems are performing as intended and to calibrate and verify traditional measurement methods. Examples of structured feedback include, but are not limited to:

- **Participatory Engagement Methods**: Methods used to solicit feedback from civil society groups, affected communities, and users, including focus groups, small user studies, and surveys.
- **Field Testing**: Methods used to determine how people interact with, consume, use, and make sense of AI-generated information, and subsequent actions and effects, including UX, usability, and other structured, randomized experiments.
- **AI Red-teaming:** A structured testing exercise used to probe an AI system to find flaws and vulnerabilities such as inaccurate, harmful, or discriminatory outputs, often in a controlled environment and in collaboration with system developers.

Information gathered from structured public feedback can inform design, implementation, deployment approval, maintenance, or decommissioning decisions. Results and insights gleaned from these exercises can serve multiple purposes, including improving data quality and preprocessing, bolstering governance decision making, and enhancing system documentation and debugging practices. When implementing feedback activities, organizations should follow human subjects research requirements and best practices such as informed consent and subject compensation.

早期生命周期 TEVV 方法针对生成式人工智能被开发并成熟之前，组织可以使用推荐的“部署前测试”实践来度量性能、能力、局限、风险和影响。本节描述作为部署前 TEVV 一部分的风险度量和估计，并考察部署前测试方法的现状。

当前部署前测试方法的局限性

当前可用于GAI应用的部署前TEVV流程可能不充分、未被系统性地应用，或未能反映部署情境或与部署情境不匹配。例如，通过视频游戏或为人类设计的标准化测试(如智力测试、专业执照考试)对GAI系统能力进行的轶事性测试，并不能保证GAI系统在这些领域中的有效性或可靠性。同样，越狱或提示工程测试可能无法系统地评估有效性或可靠性风险。

度量差距可能源于实验室环境与真实世界环境之间的不匹配。当前的测试方法往往仍聚焦于实验室条件，或局限于基准测试数据集和计算机模拟技术，这些方法可能无法很好地外推到--或直接评估--真实世界条件下的GAI影响。例如，当前GAI的度量差距使得难以精确估计其潜在的生态系统层面或纵向风险以及相关的政治、社会和经济影响。由于提示敏感性和使用情境的广泛异质性，GAI系统的基准测试与真实世界使用之间的差距可能会进一步加剧。

A.1.5. 结构化公众反馈

结构化公众反馈可用于评估生成式人工智能系统是否按预期运行，并校准和验证传统度量方法。结构化反馈的示例包括但不限于：

- **参与式接触方法**：用于征求公民社会团体、受影响社区和用户反馈的方法，包括焦点小组、小型用户研究和调查。
- **现场测试**：用于确定人们如何互动、消费、使用和理解人工智能生成信息以及后续行动和影响的方法，包括用户体验、可用性及其他结构化、随机化实验。
- **人工智能红队测试：**一种结构化测试活动，用于探查人工智能系统以发现缺陷和漏洞，例如不准确、有害或歧视性输出，通常在受控环境中并与系统开发者合作进行。

从结构化公众反馈中收集的信息可以为设计、实施、部署审批、维护或退役决策提供参考。从这些活动中获得的结果和洞见可以服务于多种目的，包括改善数据质量和预处理、加强治理决策以及增强系统文档和调试实践。在实施反馈活动时，组织应遵循人类受试者研究要求和最佳实践，如知情同意和受试者补偿。

Participatory Engagement Methods

On an ad hoc or more structured basis, organizations can design and use a variety of channels to engage external stakeholders in product development or review. Focus groups with select experts can provide feedback on a range of issues. Small user studies can provide feedback from representative groups or populations. Anonymous surveys can be used to poll or gauge reactions to specific features. Participatory engagement methods are often less structured than field testing or red teaming, and are more commonly used in early stages of AI or product development.

Field Testing

Field testing involves structured settings to evaluate risks and impacts and to simulate the conditions under which the GAI system will be deployed. Field style tests can be adapted from a focus on user preferences and experiences towards AI risks and impacts – both negative and positive. When carried out with large groups of users, these tests can provide estimations of the likelihood of risks and impacts in real world interactions.

Organizations may also collect feedback on outcomes, harms, and user experience directly from users in the production environment after a model has been released, in accordance with human subject standards such as informed consent and compensation. Organizations should follow applicable human subjects research requirements, and best practices such as informed consent and subject compensation, when implementing feedback activities.

AI Red-teaming

AI red-teaming is an evolving practice that references exercises often conducted in a controlled environment and in collaboration with AI developers building AI models to identify potential adverse behavior or outcomes of a GAI model or system, how they could occur, and stress test safeguards". AI red-teaming can be performed before or after AI models or systems are made available to the broader public; this section focuses on red-teaming in pre-deployment contexts.

The quality of AI red-teaming outputs is related to the background and expertise of the AI red team itself. Demographically and interdisciplinarily diverse AI red teams can be used to identify flaws in the varying contexts where GAI will be used. For best results, AI red teams should demonstrate domain expertise, and awareness of socio-cultural aspects within the deployment context. AI red-teaming results should be given additional analysis before they are incorporated into organizational governance and decision making, policy and procedural updates, and AI risk management efforts.

Various types of AI red-teaming may be appropriate, depending on the use case:

- General Public: Performed by general users (not necessarily AI or technical experts) who are expected to use the model or interact with its outputs, and who bring their own lived experiences and perspectives to the task of AI red-teaming. These individuals may have been provided instructions and material to complete tasks which may elicit harmful model behaviors. This type of exercise can be more effective with large groups of AI red-teamers.
- Expert: Performed by specialists with expertise in the domain or specific AI red-teaming context of use (e.g., medicine, biotech, cybersecurity).
- Combination: In scenarios when it is difficult to identify and recruit specialists with sufficient domain and contextual expertise, AI red-teaming exercises may leverage both expert and

参与式互动方法

组织可以临时性或更有结构性地设计和利用各种渠道，让外部利益相关者参与产品开发或审查。与选定专家进行的焦点小组可以就一系列问题提供反馈。小型用户研究可以从代表性群体或人群中获得反馈。匿名调查可用于征询或评估对特定功能的反应。参与式互动方法通常不如实地测试或红队测试那样结构化，并且更常用于人工智能或产品开发的早期阶段。

现场测试

现场测试涉及结构化环境，以评估风险和影响，并模拟生成式人工智能系统将部署的条件。现场式测试可以从关注用户偏好和体验调整为关注人工智能风险和影响--包括负面和正面。当与大量用户一起开展时，这些测试可以提供对现实世界交互中风险和影响可能性的估计。

组织还可以在模型发布后，按照知情同意和补偿等人类受试者标准，直接在生产环境中收集用户对结果、伤害和用户体验的反馈。组织在实施反馈活动时应遵循适用的人类受试者研究要求以及知情同意和受试者补偿等最佳实践。

人工智能红队测试

人工智能红队测试是一种不断演进的实践，指的是通常在受控环境中并与构建人工智能模型的人工智能开发者合作开展的演练，以识别生成式人工智能模型或系统的潜在不利行为或结果、其可能发生的方式，并对保障措施进行压力测试。人工智能红队测试可以在人工智能模型或系统向更广泛公众提供之前或之后进行；本节重点关注部署前情境中的红队测试。

AI红队测试产出的质量与AI红队本身的背景和专业知识相关。人口统计学和跨学科多元化的AI红队可用于识别GAI将在各种使用情境中出现的缺陷。为获得最佳结果，AI红队应展示领域专业知识以及对部署情境中社会文化方面的认识。AI红队测试结果在纳入组织治理和决策、政策和程序更新以及AI风险管理努力之前，应进行额外分析。

根据用例的不同，可能适合采用各类AI红队测试：

- 公众：由预期将使用模型或与其输出互动的普通用户(不一定是人工智能或技术专家)执行，他们将自己的生活经验和视角带入人工智能红队测试任务。这些个人可能已获得指示和材料以完成任务，这些任务可能引发有害模型行为。这类演练在大量人工智能红队测试人员参与时可能更有效。
- 专家：由在相关领域或特定人工智能红队测试使用情境(例如医学、生物技术、网络安全)具有专业知识的专家执行。
- 组合：在难以识别和招募具备充分领域与情境专业知识的专家的情况下，人工智能红队演练可以同时利用专家和

general public participants. For example, expert AI red-teamers could modify or verify the prompts written by general public AI red-teamers. These approaches may also expand coverage of the AI risk attack surface.

- Human / AI: Performed by GAI in combination with specialist or non-specialist human teams. GAI-led red-teaming can be more cost effective than human red-teamers alone. Human or GAI-led AI red-teaming may be better suited for eliciting different types of harms.

A.1.6. Content Provenance

Overview

GAI technologies can be leveraged for many applications such as content generation and synthetic data. Some aspects of GAI outputs, such as the production of deepfake content, can challenge our ability to distinguish human-generated content from AI-generated synthetic content. To help manage and mitigate these risks, digital transparency mechanisms like provenance data tracking can trace the origin and history of content. Provenance data tracking and synthetic content detection can help facilitate greater information access about both authentic and synthetic content to users, enabling better knowledge of trustworthiness in AI systems. When combined with other organizational accountability mechanisms, digital content transparency approaches can enable processes to trace negative outcomes back to their source, improve information integrity, and uphold public trust. Provenance data tracking and synthetic content detection mechanisms provide information about the origin and history of content to assist in GAI risk management efforts.

Provenance metadata can include information about GAI model developers or creators of GAI content, date/time of creation, location, modifications, and sources. Metadata can be tracked for text, images, videos, audio, and underlying datasets. The implementation of provenance data tracking techniques can help assess the authenticity, integrity, intellectual property rights, and potential manipulations in digital content. Some well-known techniques for provenance data tracking include digital watermarking, metadata recording, digital fingerprinting, and human authentication, among others.

Provenance Data Tracking Approaches

Provenance data tracking techniques for GAI systems can be used to track the history and origin of data inputs, metadata, and synthetic content. Provenance data tracking records the origin and history for digital content, allowing its authenticity to be determined. It consists of techniques to record metadata as well as overt and covert digital watermarks on content. Data provenance refers to tracking the origin and history of input data through metadata and digital watermarking techniques. Provenance data tracking processes can include and assist AI Actors across the lifecycle who may not have full visibility or control over the various trade-offs and cascading impacts of early-stage model decisions on downstream performance and synthetic outputs. For example, by selecting a watermarking model to prioritize robustness (the durability of a watermark), an AI actor may inadvertently diminish computational complexity (the resources required to implement watermarking). Organizational risk management efforts for enhancing content provenance include:

- Tracking provenance of training data and metadata for GAI systems;
- Documenting provenance data limitations within GAI systems;

普通公众参与者。例如，专家级人工智能红队成员可以修改或验证由普通公众人工智能红队成员编写的提示。这些方法还可能扩大对人工智能风险攻击面的覆盖范围。

- 人类 / 人工智能：由生成式人工智能结合专家或非专家人类团队执行。由生成式人工智能主导的红队测试可能比仅由人类红队成员进行更具成本效益。由人类或生成式人工智能主导的人工智能红队测试可能更适合引发不同类型的危害。

A.1.6. 内容溯源

概述

GAI技术可被用于许多应用，如内容生成和合成数据。GAI产出的某些方面，如深度伪造内容的生成，可能挑战我们区分人类生成内容与AI生成合成内容的能力。为帮助管理和缓解这些风险，数字透明度机制如来源数据追踪可以追溯内容的起源和历史。来源数据追踪和合成内容检测可以帮助促进用户对真实内容和合成内容的更多信息获取，使人们更好地了解AI系统的可信度。当与其他组织问责机制相结合时，数字内容透明度方法可以使流程能够将负面结果追溯至其来源，改善信息完整性，并维护公众信任。来源数据追踪和合成内容检测机制提供关于内容起源和历史的信息，以协助GAI风险管理努力。

来源元数据可以包括关于生成式人工智能模型开发者或生成式人工智能内容创建者、创建日期/时间、位置、修改和来源的信息。元数据可以针对文本、图像、视频、音频和底层数据集进行追踪。来源数据追踪技术的实施有助于评估数字内容的真实性、完整性、知识产权和潜在操纵。一些知名的来源数据追踪技术包括数字水印、元数据记录、数字指纹和人工认证等。

溯源数据追踪方法

生成式人工智能系统的来源数据追踪技术可用于追踪数据输入、元数据和合成内容的历史和来源。来源数据追踪记录数字内容的来源和历史，从而可以确定其真实性。它包括记录元数据以及对内容施加显式和隐式数字水印的技术。数据来源是指通过元数据和数字水印技术追踪输入数据的来源和历史。来源数据追踪流程可以涵盖并协助生命周期中的人工智能参与者，这些参与者可能无法完全了解或控制早期模型决策对下游性能和合成输出的各种权衡和级联影响。例如，通过选择水印模型以优先考虑鲁棒性(水印的持久性)，人工智能参与者可能会无意中降低计算复杂度(实施水印所需的资源)。为增强内容来源而进行的组织风险管理努力包括：

- 跟踪GAI系统训练数据和元数据的来源；
- 记录生成式人工智能系统内溯源数据的局限性；

- Monitoring system capabilities and limitations in deployment through rigorous TEVV processes;
- Evaluating how humans engage, interact with, or adapt to GAI content (especially in decision making tasks informed by GAI content), and how they react to applied provenance techniques such as overt disclosures.

Organizations can document and delineate GAI system objectives and limitations to identify gaps where provenance data may be most useful. For instance, GAI systems used for content creation may require robust watermarking techniques and corresponding detectors to identify the source of content or metadata recording techniques and metadata management tools and repositories to trace content origins and modifications. Further narrowing of GAI task definitions to include provenance data can enable organizations to maximize the utility of provenance data and risk management efforts.

A.1.7. Enhancing Content Provenance through Structured Public Feedback

While indirect feedback methods such as automated error collection systems are useful, they often lack the context and depth that direct input from end users can provide. Organizations can leverage feedback approaches described in the Pre-Deployment Testing section to capture input from external sources such as through AI red-teaming.

Integrating pre- and post-deployment external feedback into the monitoring process for GAI models and corresponding applications can help enhance awareness of performance changes and mitigate potential risks and harms from outputs. There are many ways to capture and make use of user feedback – before and after GAI systems and digital content transparency approaches are deployed – to gain insights about authentication efficacy and vulnerabilities, impacts of adversarial threats on techniques, and unintended consequences resulting from the utilization of content provenance approaches on users and communities. Furthermore, organizations can track and document the provenance of datasets to identify instances in which AI-generated data is a potential root cause of performance issues with the GAI system.

A.1.8. Incident Disclosure

Overview

AI incidents can be defined as an "event, circumstance, or series of events where the development, use, or malfunction of one or more AI systems directly or indirectly contributes to one of the following harms: injury or harm to the health of a person or groups of people (including psychological harms and harms to mental health); disruption of the management and operation of critical infrastructure; violations of human rights or a breach of obligations under applicable law intended to protect fundamental, labor, and intellectual property rights; or harm to property, communities, or the environment." AI incidents can occur in the aggregate (i.e., for systemic discrimination) or acutely (i.e., for one individual).

State of AI Incident Tracking and Disclosure

Formal channels do not currently exist to report and document AI incidents. However, a number of publicly available databases have been created to document their occurrence. These reporting channels make decisions on an ad hoc basis about what kinds of incidents to track. Some, for example, track by amount of media coverage.

- 通过严格的TEVV(测试、评估、验证与确认)流程，监测系统在部署中的能力与局限性；
- 评估人类如何参与、互动或适应生成式人工智能内容(尤其是在由生成式人工智能内容辅助决策的任务中)，以及他们如何对已应用的来源追踪技术(如公开披露)作出反应。

组织可以记录和界定生成式人工智能系统的目标和局限性，以识别来源数据可能最有用的差距。例如，用于内容创建的生成式人工智能系统可能需要鲁棒的水印技术和相应的检测器来识别内容来源，或需要元数据记录技术以及元数据管理工具和存储库来追踪内容来源和修改。进一步细化生成式人工智能任务定义以包含来源数据，可以使组织最大化来源数据和风险管理努力的效用。

A.1.7. 通过结构化公众反馈增强内容来源追踪

尽管自动化错误收集系统等间接反馈方法很有用，但它们往往缺乏最终用户直接输入所能提供的情境和深度。组织可以利用部署前测试部分中描述的反馈方法，从外部来源获取输入，例如通过人工智能红队演练。

将部署前和部署后的外部反馈整合到生成式人工智能模型及相应应用的监控流程中，有助于增强对性能变化的认识，并减轻输出带来的潜在风险和危害。在生成式人工智能系统和数字内容透明度方法部署之前和之后，有许多方法可以捕获和利用用户反馈，以深入了解认证效果和漏洞、对抗性威胁对技术的影响，以及利用内容来源方法对用户和社区产生的意外后果。此外，组织可以追踪和记录数据集的来源，以识别人工智能生成数据是生成式人工智能系统性能问题潜在根本原因的情形。

A.1.8. 事件披露

概述

人工智能事件可以定义为"一个事件、情况或一系列事件，其中一个或多个人工智能系统的开发、使用或故障直接或间接促成以下危害之一：对个人或群体健康的伤害或损害(包括心理伤害和精神健康损害)；关键基础设施管理和运营的中断；侵犯人权或违反旨在保护基本权利、劳动权利和知识产权的适用法律义务；或对财产、社区或环境的损害。"人工智能事件可以以聚合形式发生(即系统性歧视)，也可以以急性形式发生(即针对单个个体)。

人工智能事件追踪与披露现状

目前尚不存在报告和记录人工智能事件的正式渠道。然而，已经创建了一些公开可用的数据库来记录其发生情况。这些报告渠道以临时方式决定跟踪哪些类型的事件。例如，有些渠道按媒体报道量进行跟踪。

Documenting, reporting, and sharing information about GAI incidents can help mitigate and prevent harmful outcomes by assisting relevant AI Actors in tracing impacts to their source. Greater awareness and standardization of GAI incident reporting could promote this transparency and improve GAI risk management across the AI ecosystem.

Documentation and Involvement of AI Actors

AI Actors should be aware of their roles in reporting AI incidents. To better understand previous incidents and implement measures to prevent similar ones in the future, organizations could consider developing guidelines for publicly available incident reporting which include information about AI actor responsibilities. These guidelines would help AI system operators identify GAI incidents across the AI lifecycle and with AI Actors regardless of role. Documentation and review of third-party inputs and plugins for GAI systems is especially important for AI Actors in the context of incident disclosure; LLM inputs and content delivered through these plugins is often distributed, with inconsistent or insufficient access control.

Documentation practices including logging, recording, and analyzing GAI incidents can facilitate smoother sharing of information with relevant AI Actors. Regular information sharing, change management records, version history and metadata can also empower AI Actors responding to and managing AI incidents.

记录、报告和共享有关生成式人工智能事件的信息，可以通过帮助相关人工智能参与者将影响追溯至其来源，来帮助缓解和预防有害结果。提高对生成式人工智能事件报告的认识并实现标准化，可以促进这种透明度，并改善整个人工智能生态系统中的生成式人工智能风险管理。

人工智能行为体的文档记录与参与

人工智能参与者应了解其在报告人工智能事件中的角色。为更好地理解以往事件并采取措施防止未来发生类似事件，组织可考虑制定公开事件报告指南，其中包含有关人工智能参与者责任的信息。这些指南将帮助人工智能系统运营者在整个人工智能生命周期中，以及与不同角色的人工智能参与者一起，识别GAI事件。对于人工智能参与者而言，在事件披露的背景下，记录和审查GAI系统的第三方输入和插件尤为重要；通过插件传递的LLM输入和内容往往是分散的，且访问控制不一致或不充分。

包括记录、登记和分析生成式人工智能事件在内的文档化实践，可以促进与相关人工智能参与者更顺畅地共享信息。定期信息共享、变更管理记录、版本历史和元数据也可以赋能应对和管理人工智能事件的人工智能参与者。

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