Policy Brief

Operationalizing AI Guidance

A Reference Guide for Translating High-Level Goals into Practical Implementation

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Executive Summary

Organizations continue to struggle with successfully integrating artificial intelligence into their operations, leading to cases where the technology fails to support, or even undermines, the organization's mission. Researchers in academia, industry, and civil society have done tremendous work in developing techniques that can assist practitioners in their adoption of AI technology. Yet these contributions can easily be lost in the sea of collective AI efforts. While recent work to synthesize this research in key areas has begun, there remains no comprehensive guide to help practitioners navigate the maze of information. To address this gap, CSET researchers have collated over 1,200 resources from the breadth of academic papers, industry reports, and grey literature with the aim of making AI safety, security, and governance practices more accessible and easier to integrate into an organization's existing processes. Building on CSET's harmonized AI framework, this report collates actionable guidance from these resources into an easy-to-navigate format and connects the information back to core recommended practices, establishing a critical link between high-level principles and practical implementation details. This report aims to answer the core questions that practitioners need to ask to successfully operationalize AI best practices.

What: We identify the key techniques, tools, and practices that organizations should implement in adopting AI systems based on an extensive review of government guidelines, industry reports, academic papers, and the broader set of grey literature.

When: We map these implementation steps across the process of AI adoption, including planning, development, deployment, operation, and improvement.

Where: We provide guidance at all levels of the organization, ranging from organization-wide operations and practices to granular details at the data, model, and system level.

Who: We identify the functional teams within the organization that are most likely involved in carrying out each recommended implementation step.

How: We provide an extensive set of references alongside the implementation steps, identifying valuable resources from the staggering volume of available information.

Why: We link each step in our guide back to the recommendations from the harmonized framework that it serves to implement.

In addressing these key components, this report serves as a practical reference guide that bridges the gap between principles and practice for those adopting AI technology.

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Introduction

Organizations today face mounting pressure to adopt artificial intelligence technology, yet many struggle to successfully integrate AI into their structure and operations such that it supports the organization's mission and furthers its goals [1]. On the one hand, a variety of existing reports provide principles and frameworks intended to inform organizations of **what** they should do when adopting AI systems. On the other, there is an extensive body of industry white papers, academic research, and grey literature that provide details on **how** to implement a specific technique or practice related to AI. While there is value in both high-level abstraction and granular detail, organizations need guidance that aligns the two, mapping out what needs to be done and providing the resources on how to do it [2]. This information can be difficult for organizations to find on their own, crowded out by a deluge of low-quality search results, blog posts, and articles on the internet—a trend that has only worsened with the flood of AI-generated content [3, 4, 5]. Several reports—including the National Institute of Standards and Technology's (NIST) AI Risk Management Framework Playbook, several guides from the Open Worldwide Application Security Project (OWASP) Foundation, and the Partnership on AI's governance toolkit—have begun to address this need, tying together high-level practices with practical implementation details [6, 7, 8, 9]. Yet, each only covers a piece of the overall picture, leaving practitioners without an overarching road map for responsible AI adoption.

This report aims to address that problem by providing an extensive reference guide that (1) covers the range of AI safety, security, and governance practices and (2) ties recommendations for **what** practices organizations should implement to **how** they should do so, including **when**, **where**, **why**, and **by whom**. We build on previous CSET research that condensed the collective knowledge of 52 AI guidance documents into a single harmonized framework [10]. Where that first report lays out a holistic picture of AI best practices, this research provides the link between those high-level recommendations and the detailed reports that illustrate how to implement them. We have waded through the breadth of government and industry reports, academic papers, and grey literature to identify valuable sources that practitioners rely on. Making AI guidance more tangible, this report provides answers to the fundamental questions organizations have when implementing AI best practices:

- **What should I do?** Based on our research, we provide a series of practical implementation steps derived from CSET's harmonized AI framework.
- **When?** We organize these steps according to the stage in the AI adoption life cycle (e.g., planning, development, deployment) in which they occur for easy and logical reference.

- **Where?** We structure the recommendations within each stage according to the level of implementation (e.g., operations, data, model, system) at which these practices occur within the organization.
- **By whom?** We identify the functional teams within the organization that the content is most applicable for, while trying not to assume certain organizational structures or prescribe specific roles and responsibilities.
- **How?** We provide an extensive set of references alongside the implementation steps, identifying valuable resources from the staggering volume of available information.
- **Why?** We map the implementation steps back to the harmonized framework, which represents a synthesis of the recommendations made across 52 reports and the collective expertise of a range of international organizations, government agencies, standards-setting organizations, industry associations, academic institutions, think tanks, and private companies.

Practitioners should use this report as an overarching guide for implementing the wide range of recommended practices necessary to support the responsible adoption of AI systems. The adoption of AI technology affects all aspects of an organization, from its strategy, structure, and operations to its hardware, software, and data. As such, this report provides guidance based on principles from a variety of disciplines. Yet despite their broad impact, AI models and their supporting scaffolding are, at their core, software systems. As a result, many of the recommendations in this guide build on—or draw directly from—existing safety, security, and governance processes that organizations use to manage software systems. While these practices may need to be modified or expanded to address the unique wrinkles that AI models introduce, existing processes and principles should be leveraged by practitioners wherever possible.

Although this report is extensive, it is certainly not comprehensive. The collection of resources concluded in late 2025, and new techniques and methods will continue to be developed. Furthermore, while much of this guidance applies to machine learning (ML) systems broadly, an emphasis is placed on the adoption of generative AI and more advanced frontier models. In addition, the recommendations and resources provided in this report are intended to be use-case and sector agnostic. Organizations should account for the additional nuances specific to their application of AI technology.

We organize this report into four sections. First, we provide some background on the challenges of operationalizing AI best practices and summarize CSET's report on harmonizing AI guidance, which represents the initial step in addressing these challenges. Second, we outline our methodology in developing recommendations and

collating resources. Third, we present the content of the operationalizing guide. Fourth, we close with an assessment of the implications of this work and where future efforts are still needed. Practitioners seeking implementation guidance and resources should feel free to skip directly to the operationalizing guide, which starts on page 18.

Background

The pressure to adopt AI technologies has put many organizations in a challenging position. The purported benefits of AI adoption are high, the need to keep up with competitors is intense, and the risk of AI-enabled threats is growing. The message being received by many organizations is that failing to adopt AI systems risks the organization's reputation, competitive advantage, and security. However, embracing AI technology without the proper policies, procedures, and infrastructure in place to ensure its safety and security presents its own risks that may undermine the intended goals of AI adoption. Despite a myriad of reports, voluntary standards, and proposed best practices for AI systems, there remains a large gap between these recommendations in the abstract and their implementation in practice [11, 12]. The salience of the principle-practice gap has been a common finding across a multitude of studies and reports [1, 2, 13, 14, 15]. The challenge of operationalizing guidance was also a major concern voiced during a workshop hosted by CSET in June 2024 on AI adoption in critical infrastructure [16].

This report represents the second of three phases of research conducted at CSET. This research seeks to reduce the burden of deciphering AI-related guidance currently being shouldered by individual organizations who are seeking to develop or deploy AI technology. The three phases are:

- **Harmonize:** Generate a unified set of recommendations from disparate sources.
- **Operationalize:** Provide steps to implement recommended practices for AI.
- **Tailor:** Apply the guidance to various deployment scenarios and AI use cases.

CSET's recent report entitled "Harmonizing AI Guidance: Distilling Voluntary Standards and Best Practices into a Unified Framework" was the first stage of this work [10]. Now we focus on the second step, operationalizing guidance. In the following sections, we describe how this work relates to the problems organizations face in wrangling existing AI guidance, builds on the previous harmonization report, and identifies future needs in the AI guidance space.

Challenges in Operationalizing AI Guidance

As pressure to adopt AI systems continues to mount, organizations face the daunting challenge of integrating AI technology into their structure, operations, and technical infrastructure. While a variety of voluntary standards and best practices exist to help guide organizations toward this end, implementing proper safety, security, and governance practices remains elusive [1]. As discussed in detail in CSET's recent report

on harmonizing AI guidance, there are five key issues with existing guidance documents that continue to inhibit the successful adoption and integration of AI technology within organizations [10]. First, organizations are inundated with **information overload**. The number of reports and frameworks continues to grow at a prolific rate. Second, these guidance documents come from a wide range of **disparate sources** whose recommendations often overlap and at times conflict with one another. Third, the information contained in these reports is often presented in **inaccessible language** that makes it difficult for organizations to decipher. Fourth, among these documents there are a plethora of high-level objectives identified that organizations are told to achieve, but there is a **lack of implementation details** provided to help guide organizations toward meeting those goals. Fifth, many of these frameworks adopt a **one-size-fits-all** approach, providing a single set of broadly applicable guidance that can frequently be ill-suited for diverse and wide-ranging use cases. For further information on each of these barriers, please refer to the original CSET report on harmonizing AI guidance.

While these challenges stem from the corpus of AI guidance and standards, it is also important to underscore that these issues are compounded by the rapid pace at which large language models (LLMs) and the broader field of artificial intelligence is evolving. As the technology advances, and safety and security practices adapt to keep pace, recommended practices—particularly those that are more granular—become a moving target both for those providing the recommendations and those implementing them. This research does not solve this problem and, as such, acknowledges that this work represents a snapshot of best practices at a specific point in time. That said, AI models are software systems at their core. Many of the established practices and broad principles that have been developed over several decades will continue to apply. These recommendations, like those of other existing guidance documents, will continue to be refined as the technology and state of the art continues to evolve.

CSET Harmonized Framework

To begin addressing these guidance-related barriers, CSET researchers recently developed a harmonized framework for AI development and adoption based on an analysis of over 7,741 recommendations provided across 52 existing guidance documents. This corpus was composed of a variety of frameworks, voluntary standards, and industry best practices that were produced by a range of international bodies, government agencies, standards-setting organizations, industry associations, think tanks, and academic institutions. Using a mix of quantitative and qualitative methods, CSET researchers distilled this collection of knowledge into 258

recommendations, covering 34 topic areas related to governance, safety, security, privacy, and detection and response.

In providing a consolidated, stand-alone, clearly written set of guidance, the harmonized framework helps to address the ongoing challenges related to information overload, disparate sources, and inaccessible language. However, that represents only the first step in removing these guidance-related barriers. This report, representing the second stage of our work, sets out to tackle the fourth identified challenge: the lack of implementation details. This work builds on our previous harmonization efforts, tying concrete actions that an organization can take to the recommendations and objectives contained in CSET framework and, by extension, the broader set of AI guidance that the harmonized framework encapsulates.

Tailoring to Specific Organizational Needs

The recommendations for operationalizing guidance provided in this report are intended to apply broadly to organizations seeking to adopt or deploy AI-based systems for a wide range of use cases. As such, the one-size-fits-all problem remains. The guidance contained in this report will not fully address all of the important aspects of the specific organization, sector, and use case in which the AI system is being deployed. Therefore, use the information provided in this report as a baseline for operationalizing AI safety and security practices. In addition, be sure to assess the nuances of the specific AI use case, identify where this control baseline is insufficient, and seek out further context-specific guidance where available. Some of that guidance may come from future CSET work that plans to tackle various aspects of the one-size-fits-all problem.

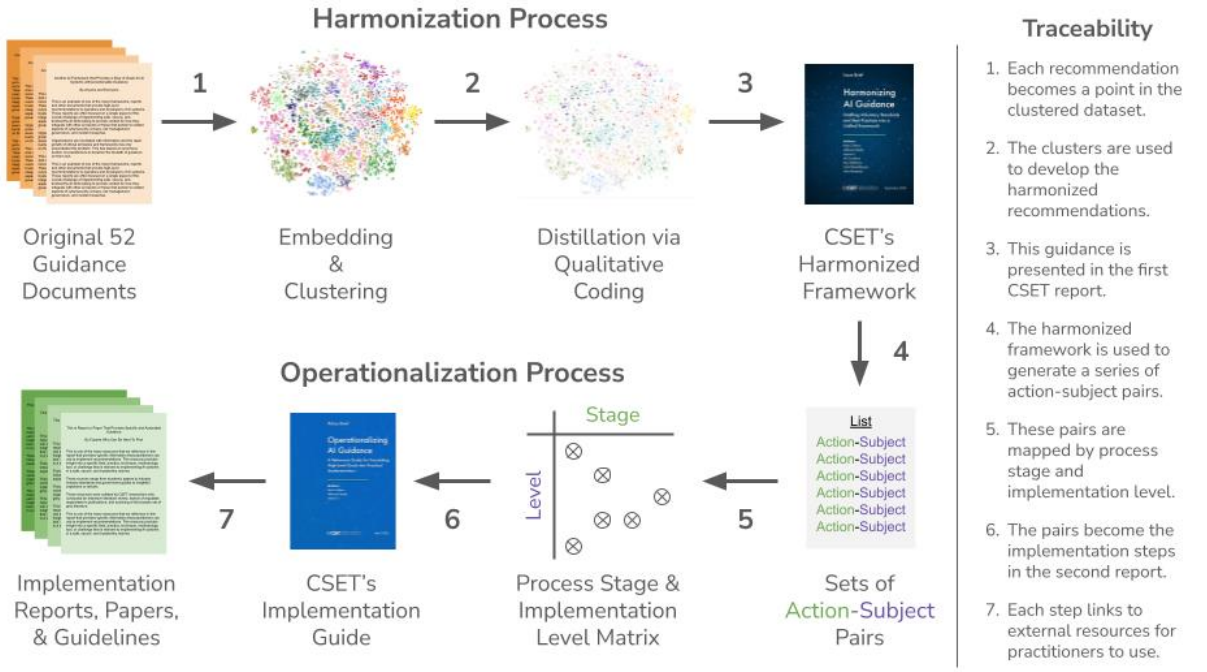
Operationalizing Guidance

The primary aim of this report is to make AI guidance more accessible to organizations by providing a link between the abstract objectives, concepts, and recommendations that make up existing AI guidance and the concrete actions organizations should take to integrate AI systems into their existing policies, practices, and infrastructure. While there are many theoretical approaches for transforming abstract recommendations into concrete practices—often derived from implementation science and applications in the medical field—there is no single agreed-upon process [17]. However, many of these strategies boil down to identifying the fundamental components of the implementation, essentially the questions of who, what, when, where, why, and how [18]. We adopt a generalized version of this approach as follows.

- **What:** We first identify the implementation steps needed for responsible AI adoption by synthesizing the set of *actions* that an organization needs to take and the *subjects* of those actions from CSET's harmonized AI framework [10]. See the Mapping Actions and Subjects section for further details.
- **When:** We then organize these implementation steps by aligning the *actions* with different stages of AI adoption, a process that resembles the software development life cycle (SDLC). See the Stages of AI Adoption section.
- **Where:** In the same vein, we identify the level at which the implementation step occurs based on the *subject*. See the Level of Implementation section.
- **Who:** Next, we assess which functional teams within the organization would be most relevant in implementing these steps. See the Ownership Within the Organization section.
- **How:** For each implementation step, we add more granular recommendations and provide references to external resources for practitioners looking to dive into greater detail.
- **Why:** We provide a link between each implementation step and the recommendations from CSET's harmonized framework. In doing so, we establish a provenance chain from the recommendations in the original 52 reports, to CSET's harmonized framework, to the implementation steps provided in this report, and finally to the breadth of external resources identified alongside our implementation guidance.

We illustrate our end-to-end process of harmonizing and operationalizing guidance in Figure 1. In addition to demonstrating our methodology used across the two CSET reports, this figure shows how the implementation steps and external resources provided in this report trace back to the high-level recommendations from the original 52 guidance documents, as described above.

Figure 1: Overview of the Harmonization and Operationalization Process



Source: CSET.

In the following sections, we describe the process of mapping the harmonized framework into the action-subject pairs used to develop our implementation steps, the stages of AI adoption used to organize the overall structure of this report, the levels of implementation that provide structure within each process stage, and finally an overview of the different functions within the organization and their general responsibilities for AI adoption. Alternatively, you can jump directly to CSET's Guide to Operationalizing AI Systems.

Mapping Actions and Subjects

To identify the key implementation steps that organizations should undertake in their adoption of AI technology, we analyzed the recommendations from the harmonized framework and broke them down into a series of action-subject pairs. To illustrate how this works, take the example of recommendation IT.1 from the harmonized framework, which reads: "Articulate the organization's mission and develop a strategy to achieve its objectives. Align [information technology] IT initiatives and systems with organizational goals."

We break this recommendation down into four action-subject pairs. The first two can be derived from the initial sentence, becoming "articulate mission" and "develop

strategy." We segment the second sentence in much the same way, except that the action is the same for both pairs in this case, leaving us with "align IT initiatives" and "align systems." After applying this methodology to each recommendation, we end up with 814 action-subject pairs. Although that is quite extensive, many of these pairs are closely related or overlap. Through a process of qualitatively grouping similar actions and subjects, we narrow down this set to 232 distinct pairs, each of which corresponds to one of the implementation steps in this report.

Stages of AI Adoption

In analyzing the action-subject pairs, it quickly became apparent that the set of *actions* roughly aligned with the typical stages of the software development life cycle (SDLC). Therefore, we employ a modified version of this process, which we call the AI adoption life cycle. Figure 2 illustrates the process stages and substages that emerged from the analysis.

Figure 2: The Stages of AI Adoption

Source: CSET.

We structure the guidance provided in this report according to the stages and substages of the life cycle diagram. However, it is important to note that while the report is organized sequentially to convey the information in a clear manner, some steps of the process represent ongoing activities, such as operations and monitoring,

and others should likely occur at multiple points throughout the process, such as approval and communication. The stages and substages are described in greater detail below.

- **Review:** The review stage serves as the entry point for the organization in the AI adoption cycle. To begin, the organization should *self-assess* its maturity and readiness to adopt AI technology. At the end of the cycle, the organization should review its policies and procedures to identify areas where it can *improve*. The organization should implement those improvements before continuing the cycle by conducting another self-assessment.
- **Planning:** After conducting a self-assessment, the organization moves into the planning phase. During this stage, the organization should *define* its objectives and requirements for the AI system being adopted, *plan* how the organization will acquire and support the technology, *promote* norms and standards in organizational and system design, *map* how the system will integrate into the organization, and *assess* the potential risks and impacts of adopting the AI system.
- **Implementation:** In the first two steps of the implementation stage, the organization will *acquire* or *develop* the AI system. The extent to which the organization relies on acquisition versus development can vary widely. On one end of the spectrum, an organization could opt to acquire a fully-fledged AI product or service directly from a third party. On the other end, an organization could collect data, train a model, and develop a system using that model all in-house. Many use cases are likely to fall somewhere in the middle, with organizations acquiring some components and developing others themselves. Regardless of where the organization lands on this spectrum, it will need to *control* the access to—and the behavior of—the system and *protect* the system from external threats. Finally, the organization must *test* the performance, capabilities, and vulnerabilities of the system before making a decision whether to *approve* its deployment.
- **Deployment:** During this stage, the organization must first *communicate* relevant information about the system and its development, both internally and externally. Then the organization will *deploy* the AI system, integrating it into the existing infrastructure and operating procedures.
- **Operation:** The operation stage represents the ongoing activities to maintain the proper functioning and performance of the AI system. During this stage the organization should *engage* relevant stakeholders, *manage* the performance of the system over its lifespan, *monitor* for potential threats, and *respond* to issues when they arise.

Level of Implementation

In a similar manner to how the *actions* in the action-subject pairs neatly mapped onto the process stages of the SDLC, the *subjects* presented an inherent structure that corresponded to various implementation levels within the organization. These implementation levels fall roughly under the jurisdiction of various leadership roles within the organization, providing some insight into the actors responsible for operationalization. We describe each of these levels below.

- **Organization:** The organization level consists of the physical and external environment in which the organization operates, the organization's internal structures, and the high-level strategy that governs the adoption of AI technology within the organization. As the broadest level of implementation, these actions generally fall within the purview of the chief executive officer.
- **Operations:** The operations level represents the day-to-day activities of the organization. At this level, implementation focuses on the development of operating procedures and contingency plans, the operation of various organization-wide functions (e.g., legal, compliance), and the fostering of relationships with external stakeholders. Many, but not all, of these responsibilities tend to align with that of the chief operating officer.
- **Workforce:** The workforce level revolves around the organization's personnel. Guidance at this level focuses on fostering and hiring the requisite talent for AI adoption, as well as overseeing the activity of personnel within the organization. In large part, this level corresponds to the duties of the chief human resources officer.
- **Infrastructure:** The infrastructure level consists of the architecture, network, and services that form the information technology backbone of the organization. This level incorporates the broad technical initiatives that will support the organization's adoption and integration of AI systems. Responsibilities at this level generally fall under the chief information officer.
- **Data:** The data level focuses on the collection, processing, and management of data—particularly in the context of data being used to train and fine-tune AI models. We consider this to be a level above the AI model and system, as a single dataset may be used to train multiple models. Depending on the structure of the organization, these activities may be within the scope of the chief data officer or may be rolled up into that of the chief information officer.
- **Model:** The model level consists of the set of activities surrounding the training and testing of the AI model itself. As such, implementation at this level is likely to be the most novel for organizations. Like before, we opt to order the model

above the system, as a single model might be deployed as a part of multiple systems. Ownership at the model level may fall across various roles in the organization. Given the focus on innovation and development, much of the responsibility may fall to the chief technology officer. However, the chief AI officer may take on these duties if an organization decides to establish a new board-level position specifically to oversee the use AI technology within the organization.

- **System:** The system level represents the implementation of the end product—which, for the purposes of this report, is built around an AI model—that users within the organization or customers of the organization will use. As such, implementation at this level focuses around the software scaffolding built around the model and how end users will interact with the system. Responsibility at the system level is likely to vary across organizations, but in many cases will fall to a specific product team under the oversight of a chief product officer.

Ownership Within the Organization

While ownership over implementation can be ascribed broadly by level, in reality responsibility for implementing these practices will not be nearly as neatly defined. Many teams and functional groups throughout the organization will be involved in activities across a range of levels and stages. In addition, we fully acknowledge that organizations, and their org charts, vary widely. As such, we hesitate to be too prescriptive about identifying ownership. However, ignoring the roles and responsibilities for implementing guidance—which many frameworks opt to do—does a disservice to organizations looking for more granular details. Therefore, alongside the implementation guidance provided in this report, we include an indicator of the functional teams (e.g., legal, cybersecurity, research and development) within the organization that are likely to be involved in operationalizing it. We do not attempt to provide more granular distinctions at the level of individual positions or specific teams. We summarize the relevant functional teams and their responsibilities in Table 1 below.

Table 1: Functional Teams and Their Role in Operationalizing AI Guidance

Team	Leadership	Role
Leadership	Chief Executive Officer (CEO)	Defining objectives for AI adoption and making final approval decisions
Strategy	Chief Strategy Officer (CSO)	Establishing a strategy, related policies, and high-level requirements for AI initiatives
Finance	Chief Financial Officer (CFO)	Prioritizing and allocating adequate resources to support AI-related activities
Risk	Chief Risk Officer (CRO)	Assessing and managing the overall risk introduced by the adoption of AI systems
Operations	Chief Operations Officer (COO)	Developing operating procedures for AI systems and overseeing the implementation of AI policies
Workforce	Chief Human Resources Officer (CHRO)	Hiring and retaining requisite talent to responsibly adopt AI technologies
Compliance	Chief Compliance Officer (CCO)	Ensuring the organization meets its AI-related obligations as intended
Responsibility	Chief Responsibility Officer (CRO)	Promoting ethical and responsible AI practices in collaboration with partners
Physical Security	Chief Security Officer (CSO)	Protecting and monitoring the facilities and physical environment of the organization
Communication	Chief Communications Officer (CCO)	Communicating AI practices, decisions, and outcomes internally and externally
Marketing	Chief Marketing Officer (CMO)	Advertising AI products and services transparently and engaging with end users
Supply Chain	Chief Supply Chain Officer (CSCO)	Vetting and coordinating suppliers of AI-related data, models, tools, and services
Cybersecurity	Chief Information Security Officer (CISO)	Protecting AI systems, managing access, and monitoring of security-related events
Privacy	Data Privacy Officer (DPO)	Controlling the use of personal or sensitive data in model training and operation
Trust & Safety	Chief Trust & Safety Officer (CTSO)	Preventing harmful output and behavior of the AI system and assessing AI impacts
Infrastructure	Chief Information Officer	Managing the infrastructure services that support the

Team	Leadership	Role
	(CIO)	operation of the AI system
Data	Chief Data Officer (CDO)	Managing data used to train models and evaluating issues of quality and bias
Innovation	Chief Technology Officer (CTO)	Overseeing the research and development of new AI models and systems
Product	Chief Product Officer (CPO)	Implementing and managing the AI system, from ideation to decommissioning

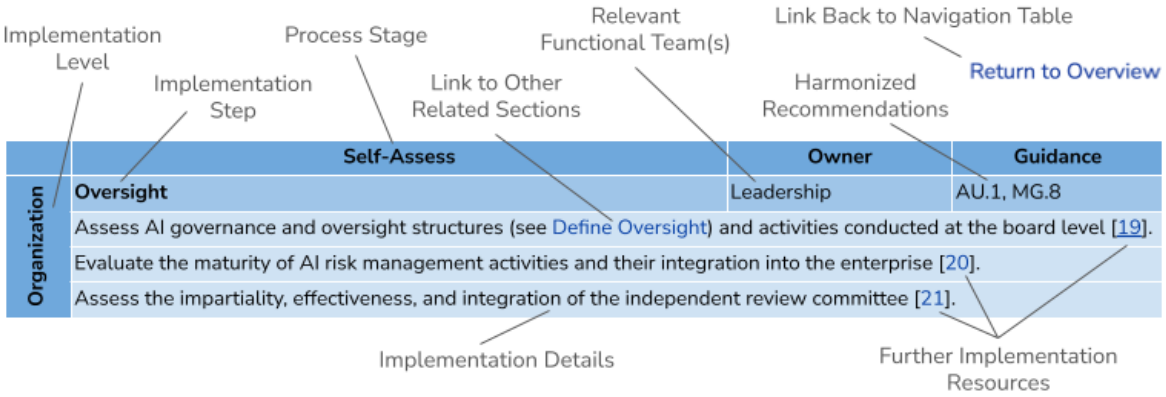
CSET's Guide to Operationalizing AI Systems

In this section, we present an extensive reference guide to aid organizations in operationalizing AI best practices. The guide is based on an extensive review of government frameworks, industry standards and best practices, academic papers, and grey literature sources by CSET researchers to identify practical content that can help organizations translate high-level guidance into implementation steps. We organize our guide into sections that correspond to each stage in the AI adoption process. This starts with a self-assessment of the organization and its readiness to adopt AI technology; proceeds through the planning, development, and operation of the AI system; and concludes with the organization's improvement of its own practices and capabilities. Within each section, we provide the recommendations in a tabular format organized by the level at which they should be implemented, starting with organization as a whole and progressing down to the AI system level.

Since the process of adopting AI technology touches on almost all major aspects of the organization, one of the key challenges in developing this guide was balancing the breadth and depth of the information provided. To strike the right balance, we highlight the most important information related to each implementation step within this report and provide references to more detailed resources for practitioners to dive deeper into specific areas. As such, the citations included alongside each implementation step differ from the references in other reports. Instead of providing evidence to support why we provide a given recommendation, the citations supply direct links to external resources that elaborate further on a specific topic, practice, technique, or tool that can be used to implement the given recommendation.

In addition to these external resources, we identify the relevant functional teams within the organization that will likely be involved and provide references to the recommendations from the harmonized framework that the step helps to implement. In Figure 3, we provide an overview of how this information is presented throughout the guide.

Figure 3: Layout of the Each Implementation Step in This Guide



Source: CSET.

How to Navigate This Guide

The content of this guide is extensive, covering adoption practices across an organization. For many practitioners, only a subset of this information may be applicable. To aid in the identification of relevant content, we provide a complete overview of the guide in Table 2, along with links for quick navigation. Below, we lay out several methods of searching for pertinent information and provide examples of when they might be useful to different types of practitioners.

By process stage: Navigate directly using the links in the first column of Table 2.

- A board member mapping out a vision for the organization's AI adoption
- A CAIO building out the organization's AI capabilities from scratch

By implementation level: Use the links within Table 2 under the relevant column.

- An HR manager looking for guidance on AI workforce development and hiring
- A privacy professional concerned about data practices related to an AI system
- A project lead ensuring their AI system incorporates proper safeguards

By functional team: Search the document using the names defined in Table 1.

- A legal professional assessing the legal ramifications of adopting an AI system
- A risk management specialist identifying and measuring AI-related risks
- A financial officer determining the allocation of resources for AI initiatives

By recommendation: Search by ID used in the harmonized framework (e.g., IT.1, SC.3).

- A compliance officer ensuring practices conform to existing standards

Table 2: Overview of the Topics Covered in CSET's Guide to Operationalizing AI (with links for navigation)

	Organization	Operations	Workforce	Infrastructure	Data	Model	System
Self-Assess	• Strategy • Oversight • Culture	• Practices • Relationships • Resources	• Talent	• Architecture • Innovation • Security & Privacy	• Data Management	• Performance • Test & Evaluation	• Impact & Trust
Define	• Context • Requirements • Objectives • Use Cases • Oversight	• Essential Function • Incidents • Constraints	• Needs	• Classification Scheme	• Legal Basis	• Release Criteria	• Purpose • System Requirements • Metrics
Plan	• Strategy • Policies	• Resource Allocation • Life Cycle • Response	• Staffing & Support	• Integration	• Storage & Retention	• Testing • Release	• Design • Deployment
Promote	• Culture • Responsibility	• Standard Practices • Compliance	• Accountability	• Common Architecture • Least Privilege & Functionality	• Data Minimization	• Safety • Trust • Human Oversight	• Privacy • Security • Ethical & Safe Use
Map	• Stakeholders	• Supply Chain	• Ownership • Approval	• Assets • Data Flows	• Classification • Provenance	• Traceability	• Components
Assess	• Points of Failure • Threats	• Risk • Legality • Ethics • Supply Chain	• Capability	• Platforms	• Data Protection	• Technology Readiness • Trade-Offs	• Impact • Attack Surface
Acquire	• Relationships	• Due Diligence • Contracts	• External Expertise	• Verification	• Consent • Data Collection • Third-Party Datasets	• Third-Party Models	• Third-Party Systems

	Organization	Operations	Workforce	Infrastructure	Data	Model	System
Develop	• Responsible Innovation	• Management Systems	• Diverse Teams	• Logging • Version Control	• Data Quality	• Alignment • Robustness • Transparency • Federated Learning • Privacy Preservation	• Secure Software • Patches
Control	• Physical Environment	• Risk	• Activity	• Identities • Access • Data Flows	• Data Transfers • Classified & Proprietary Data	• Bias • Inputs • Outputs • Synthetic Media	• Action Space • Agency
Protect	• Physical Premises	• Intellectual Property	• Personnel	• Network • Assets • Logs • Backups	• Confidentiality • Integrity	• Weights • Inputs & Outputs • Execution • Resource Utilization	• Availability • Source Code • Users
Test	• Business Continuity	• Incident Response	• Competency	• Controls • Updates • Restoration	• Bias & Skew	• Capabilities • Performance • Fairness	• Security • Safety • Quality • Acceptance • User Interaction
Approve	• Go/No-Go Decision	• Stakeholder Input • Risk Threshold	• Independent Validation	• Integration & Acceptance	• Privacy Assurance	• Release Criteria	• System Review

	Organization	Operations	Workforce	Infrastructure	Data	Model	System
Communicate	• Objectives • Policies	• Practices • Decisions	• Responsibilities	• Controls • Changes	• Data Practices • Data Transparency	• Risks & Limitations	• Test Results
Deploy	• Review Cycle	• Enforcement	• Training & Drills	• Architecture • Inventory & Mappings	• Disclosure	• Release	• Deployment
Engage	• Government • Society • Academia	• Stakeholders	• Personnel	• Service Providers	• Data Subjects	• Collaborative Initiatives	• End Users
Manage	• Situational Awareness	• Relationships	• Personnel Awareness	• Assets • Access • Maintenance • Decommission	• User Control	• Performance	• Vulnerabilities
Monitor	• Context • Physical Environment	• Centralized Analysis • Information Sharing • Third Parties	• Security Operations • Insider Threats	• Access • Data Flows	• Data Quality • Privacy	• Performance • Alignment • Fairness • Inputs & Outputs	• Behavior • Use • Impact
Respond	• Remediation	• Triage • Communication	• Response Team • Alerting	• Containment & Neutralization • Investigation	• Data Breach • Restoration	• Fail-Safes • Restoration	• Resilience Mechanisms • Restoration
Improve	• Strategy	• Procedures • Monitoring • Response • Supply Chain	• Training & Awareness	• Controls	• Data Handling	• Outcomes • Testing	• System Design • User Experience

Self-Assess

The Self-Assess stage represents the entry point into the operational life cycle. Here, the organization should assess its readiness to adopt AI technology [19]. We recommend using an AI maturity model—such as those provided by the General Services Administration, CNA, OWASP, MITRE, and others—to conduct a broad self-assessment [20, 21, 22, 23]. There are also several publicly available self-assessment tools, including those from the U.S. Chief Digital and Artificial Intelligence Office, the Commission Nationale de l'Informatique et des Libertés, Cisco, the European Institute of Innovation and Technology, and Fifth Quadrant [24, 25, 26, 27, 28]. Less mature organizations should start with simpler ML applications and leverage third-party options before attempting to deploy or build more advanced models.

	Self-Assess	Owner	Guidance
Organization	**Strategy**	Strategy	SL.1
	Assess how well the AI strategy (see Plan Strategy) aligns with organizational goals and priorities [29].		
	Evaluate the strategic alignment of organizational initiatives using established models [30, 31, 32, 33].		
	Identify the frequency and regularity with which the AI strategy is reviewed and updated [34].		
	Oversight	Leadership	AU.1, MG.8
	Assess AI governance and oversight structures (see Define Oversight) and activities conducted at the board level [35].		
	Evaluate the maturity of AI risk management activities and their integration into the enterprise [36].		
	Assess the impartiality, effectiveness, and integration of the independent review committee [37].		
	Culture	Leadership, Workforce	SL.5, WF.5, AU.6
	Determine the organization's cultural readiness (see Promote Culture) to adopt new technologies [38].		
	Conduct employee surveys to measure the degree to which AI norms have been embraced [39].		
Operations	**Practices**	Operations	MG.3
	Evaluate the maturity of business process management activities [40]. Assess the organization's AI capabilities and needs [41].		
	Identify whether the organization maintains operating procedures (see Promote Standard Practices) for the use of AI technology [42].		
	Measure internal compliance with organizational policies and procedures [43].		

	Self-Assess	Owner	Guidance
Operations	**Relationships**	Communication, Supply Chain, Leadership	ST.1, SC.1
	Assess the maturity of stakeholder relationship management (see Manage Relationships) within the organization [44].		
	Evaluate the maturity of the organization's supply chain management [45, 46].		
	Assess participation in collaborative AI initiatives such as AI incident reporting, voluntary commitments, and industry forums [47, 48].		
	Resources	Finance	IT.5, IM.6
	Determine whether there are sufficient financial resources for organizational change to the AI system throughout its life cycle [49].		
	Assess the maturity of enterprise resource management activities and systems within the organization [50, 51].		
Workforce	**Talent**	Workforce	WF.1
	Identify existing talent and expertise within the organization that can help to support the adoption of AI technology [52].		
	Assess the AI competencies of existing personnel (see Assess Capability) and identify workforce gaps (see Define Needs).		
	Determine whether the organization's talent acquisition and training resources can adequately address AI talent shortages [53].		
Infrastructure	**Architecture**	Infrastructure	IT.4
	Assess the maturity of the organization's enterprise architecture [54, 55]. Determine how well it can support new AI technologies [56].		
	Determine how well enterprise architecture aligns with and supports business goals, including those specifically for AI adoption [57].		
	Evaluate the maturity of the organization's adoption of zero trust architecture [58].		
	Identify the availability of AI platforms within the organization and potential cloud platforms that could support AI adoption [59].		
	Innovation	Innovation	IT.6, SI.3
	Evaluate the maturity of the software development process and life cycle (see Plan Life Cycle), also known as DevOps [60, 61].		
	Examine the application of software development processes for AI software development, also known as MLOps [62, 63, 64, 65].		
	Determine the maturity of project management activities within the organization [66].		

	Self-Assess	Owner	Guidance
Infrastructure	**Security & Privacy**	Cybersecurity, Privacy	SM.1, PP.2
	Evaluate the maturity of cybersecurity practices within the organization [67, 68].		
	Determine the maturity of the organization's software security and assurance practices [69].		
	Assess the organization's cybersecurity logging and monitoring capabilities [70].		
	Measure the capabilities and maturity of privacy practices within the organization [71, 72, 73].		
Data	**Data Management**	Data	SM.8, TR.5
	Determine the maturity of data governance activities within the organization [74].		
	Assess the capabilities of the organization in identifying and managing bias within datasets and AI models [75].		
Model	**Performance**	Product	PM.2
	Assess quality and performance of AI models used, or being considered for use, within the organization [76].		
	Evaluate the integration of model performance monitoring and alerting into AI operations and oversight [77].		
	Test & Evaluation	Innovation	TE.1
	Determine the maturity of the organization's software testing and evaluation capabilities [78].		
	Evaluate the test and evaluation capabilities for AI models [79].		
	Identify quality assurance processes and evaluate their effectiveness [80].		
System	**Impact & Trust**	Trust & Safety	IM.1, ST.6
	Determine the maturity of AI ethics and related functions within the organization [81, 82, 83].		
	Evaluate the organizational processes for conducting impact assessments of AI systems [84].		
	Assess the procedures within the organization and characteristics of AI systems that support trustworthiness [85].		
	Evaluate the technical methods, analysis, proxy mechanisms, and processes used to establish explainability for AI systems [86].		

Define

The Define stage occurs at the start of the organization's planning for AI adoption. At this stage, the organization should determine its objectives for AI adoption, the requirements of the AI system, and the constraints within the organization that may affect the safe and secure adoption of AI systems. While most of these responsibilities fall to the organization's leadership, input from all levels is needed to adequately inform the definition of the organization's vision for AI adoption.

	Define	Owner	Guidance
Organization	**Context**	Strategy, Legal	IT.2, AU.2, IM.1, RM.1, PP.1, IR.1
	Map out the context in which the organization operates [87, 88]. Assess the external factors relevant to AI adoption [89].		
	Consider using SWOT [90] and PESTLE [91] analysis to assess the internal and external context of the organization.		
	Identify AI regulation and legislation for jurisdictions in which the organization operates [92, 93]. Also identify relevant privacy laws [94].		
	Define the organization's internal and external stakeholders (see Map Stakeholders).		
	Requirements	Leadership, Legal	MG.1, RM.2, ST.1, RM.2
	Conduct regulatory mapping or modeling to link legal obligations to organizational requirements [95, 96].		
	Gather input from internal and external stakeholders to inform the generation of organizational requirements [97].		
	Define the organization's overarching risk appetite and tolerance, as well as that for individual AI systems [98, 99].		
	Objectives	Leadership	IT.1, MG.2, RM.2, RR.1
	Articulate a mission and vision statement for the organization [100, 101].		
	Incorporate stakeholder and business requirements (see Define Requirements) into the strategic goal-setting process [102].		
	Define the objectives and goals of the organization using tools such as balanced scorecards [103] or the SMART framework [104].		
	Determine the organization's AI objectives and align them with organizational goals [105].		

	Define	Owner	Guidance
Organization	**Use Cases**	Strategy, Innovation	IT.1, IT.5, IM.2
	Identify existing challenges and new opportunities within the organization where AI adoption may be impactful [106, 107, 108].		
	Categorize and assess the AI use case [109]. Determine if AI is appropriate for the given challenge or opportunity identified [110].		
	Work with stakeholders and potential end users to validate use cases early on in the development life cycle [111].		
	Oversight	Leadership	SL.2, AU.1, RC.1, MG.8
	Define the board's responsibilities for AI governance [112]. Ensure AI oversight [113] and AI knowledge [114] at the board level.		
	Develop the appropriate level of AI [115] and cybersecurity [116] knowledge among the organization's leadership.		
	Designate ownership of AI among the organization's top-level executives and identify champions throughout the organization [117].		
	Consider creating a new CAIO board-level position [118, 119, 120].		
	Establish independent oversight over AI use within the organization. Consider formalizing an independent review committee [37].		
Operations	**Essential Function**	Leadership, Operations	SM.3, RR.1
	Define the critical business functions within the organization, including any government-defined essential functions [121].		
	Identify the dependencies on which the essential function relies (see Map Supply Chain and Map Assets).		
	Incidents	Cybersecurity, Privacy, Trust & Safety, Operations	IR.3
	Assess the range of potential incidents, including cyber [122, 123], privacy [124], AI [125, 126, 127], and operational [128] incidents.		
	Specify a set of criteria for each incident that, if met, would trigger a planned incident response within the organization [129, 130].		
	Develop an incident priority matrix that maps potential incidents across severity (impact) and priority (urgency) [131].		
	Constraints	Finance, Infrastructure	IT.5, RR.4
	Identify the organization's resource constraints (e.g., physical, human, financial, informational, time) [132].		
	Evaluate the organization's AI resources and constraints related to the AI triad [133] (data, algorithms, compute) and workforce [134].		

	Define	Owner	Guidance
Workforce	**Needs**	Workforce	IM.3, ST.4
	Identify the skills and competencies required to support the organization's adoption of AI technology [135, 136, 137].		
	Determine the AI talent needs of the organization [138, 139] and compare against existing internal expertise (see Self-Assess Talent).		
	Consider the leadership and talent needed to promote a positive culture for AI governance [140].		
	Understand the AI talent market, including the supply [141, 142] demand [143], and gap [144] for AI-related talent.		
Infrastructure	**Classification Scheme**	Infrastructure	IS.1
	Define a data and asset classification scheme that captures relevant security, privacy, and handling information [145].		
	Extend the classification scheme to the AI system, incorporating metrics from existing classification tools and efforts [146, 147].		
	Document the classification scheme and establish a policy that guides its implementation across the organization [148].		
Data	**Legal Basis**	Legal, Privacy	PI.2
	Assess how personal data is being processed within the organization (see Map Data Flows).		
	Identify the lawful basis for each processing activity involving personal data [149, 150].		
	Consider the additional complexity of defining a lawful basis for processing when AI technology is involved [151].		
Model	**Release Criteria**	Innovation	IT.7, TO.2
	Set release criteria that the model and system must meet prior to receiving approval for deployment [152].		
	Identify factors influencing the decision to deploy, or to even pursue developing, a given technology [153].		
	Set risk thresholds for the performance and capabilities of AI models to govern release and response decisions [154, 155, 156].		
System	**Purpose**	Innovation	IT.7, PI.2
	Articulate the specific challenge that the proposed system is intended to address or the benefit that it is intended to provide [157].		
	Define the goals of the system and establish ways to track whether the system is meeting those goals [158].		

	Define	Owner	Guidance
System	**System Requirements**	Innovation, Product	IT.7, IT.8, MG.1, TO.2, IS.1
	Use requirements engineering principles to elicit system requirements from a diverse set of relevant stakeholders [159, 160, 161].		
	Consider the factors and challenges in conducting requirements elicitation for AI systems [162, 163].		
	Identify and resolve tensions that arise between (frequently technical and socio-technical) requirements [164, 165].		
	Metrics	Innovation, Product	PM.1, FS.2, SG.4, TE.6
	Identify metrics to measure the ability of the system to meet requirements (see Define Requirements and Define System Requirements).		
	Define metrics and key performance indicators to track the AI model's performance over time [166, 167, 168].		
	Include measures that capture a wide range of goals such as fairness [169], explainability [170], privacy [171], and sustainability [172].		
	Align performance metrics with the needs of users and the organization's objectives (see Define Objectives) [173].		
	Understand the benefits and limitations of existing AI benchmarks [174, 175, 176].		

Plan

The Plan stage involves the creation of a strategy, policies, and plans to implement the organization's vision for AI adoption as defined in the previous stage. As indicated by the breadth of this report, AI adoption affects almost all aspects of the organization in some way, shape, or form. Therefore, practitioners must not only develop plans for the AI system specifically but also update other plans to account for AI adoption and use within the organization.

	Plan	Owner	Guidance
Organization	**Strategy**	Strategy, Leadership	IT.1, MG.2, RM.2, SL.1, TE.1, PI.1, MO.2, RR.1
	Define a business strategy that articulates the organization's goals and priorities for the development and use of AI technology [177].		
	Align the AI strategy with the organization's overarching mission and goals (see Define Objectives) [29].		
	Ensure that responsible AI initiatives are prioritized as a part of the organization's strategy [178].		
	Policies	Leadership	AU.5, MG.4, MG.6, RC.1, RM.7, SC.5, SI.1, WF.4, AC.1, MS.5, PI.9
	Create an organization-wide policy for AI that guides AI development and deployment within the organization [179, 180, 181].		
	Include a policy on acceptable use of AI within the organization to guide personnel on what activities are allowed and prohibited [182].		
	Establish and enforce an acceptable use policy for internal and external use of the organization's AI tools and services [183].		
	Integrate relevant AI guidelines into other organizational policies such as that for cybersecurity, privacy, data, and risk management [184].		
Operations	**Resource Allocation**	Finance	IT.5, IR.2, WF.3, MG.3, LG.6, DD.1, IM.6
	Plan the allocation of financial, physical, technological, and human resources in alignment with strategic priorities [185].		
	Account for the unique aspects of AI systems, including their high computational intensity and related environmental impact [186].		

	Plan	Owner	Guidance
Operations	**Life Cycle**	Innovation	IT.6
	Establish life cycle stages (similar to the process stages in this report) that account for AI [187, 188] and software [189] development.		
	Build approval processes into the development life cycle, defining where organizational and independent oversight is required [190].		
	Apply software engineering approaches to the development and operation of AI systems [191].		
	Identify AI governance tools across life cycle stages. Note that gaps exist outside of design and development [192].		
	Response	Operations	RC.3, VN.6, ES.5, IR.1, SC.2, RR.2, RR.7, RM.7
	Institute an organization-wide incident response plan that accounts for cybersecurity, privacy, and safety incidents [193, 194, 195].		
	Develop a specific plan for responding to incidents that involve or directly stem from an AI system [196].		
	Conduct a business impact analysis [197] to inform the development of a resilience plan [198] and an IT disaster recovery plan [199].		
	Develop a risk mitigation plan based on the identification and assessment of risks posed by the AI system (see Assess Risk) [200].		
Workforce	**Staffing & Support**	Workforce	DD.1, WF.5, ES.4, SI.3
	Develop a skills-based hiring strategy for acquiring the AI-related talent that the organization needs [201].		
	Conduct workforce planning [202], accounting for the range of technical [203] and soft skills [204, 205] needed to support AI adoption.		
	Plan for the potential displacement of personnel [206] due to the adoption of AI technology [207, 208, 209] in an ethical manner [210].		
	Develop a reskilling program to integrate personnel into the AI-enabled workforce [211, 212], accounting for program limitations [213].		
Infrastructure	**Integration**	Infrastructure	IT.4, SL.4, PP.2, LG.3
	Assess how the AI system aligns with the organization's enterprise architecture (see Promote Common Architecture).		
	Create a plan for how the AI system will integrate into the organization's existing infrastructure [214].		
	Plan how logging and monitoring of the AI system will integrate into the broader organization-wide activities (see Deploy Architecture).		
Data	**Storage & Retention**	Data	IS.1, MG.6, LG.6
	Plan how data used in model training and generated during operation, logging, and monitoring will be stored in a secure manner [215].		
	Determine the capacity requirements for the system's data needs and identify ways of adjusting that capacity as necessary [216].		
	Establish a data retention policy that specifies how long personal data will be stored and how it will be securely disposed of [217, 218].		

	Plan	Owner	Guidance
Model	**Testing**	Innovation	TE.1
	Establish an organization-wide testing strategy for AI systems and their performance [219, 220].		
	Take a multipronged approach to testing that incorporates strategies and paradigms from a variety of disciplines [221].		
	Include AI red teaming in test and evaluation activities [222]. Leverage available red-teaming techniques and tools [223].		
	Release	Innovation	IT.8, IS.9
	Document a set of criteria that the model must meet before being released (see Define Release Criteria).		
	Plan how the model will be released and who will have access [224], taking into account external versus internal deployment [225].		
	If released publicly, determine the degree of model openness and assess the trade-offs in benefits and risks [226, 227, 228, 229].		
System	**Design**	Innovation, Product	IT.7
	Scope the design, and degree of in-house development [230], based on available resources (see Plan Resource Allocation).		
	Develop a plan for developing and managing the system's security, privacy, and supply chain throughout its life cycle [231].		
	Understand the limitations and unresolved challenges in technical AI governance when designing the system [232].		
	Follow software [233] and ML [234] design principles, as well as emerging best practices for AI design [235, 236].		
	Consider the range of additional principles that should be embedded into the system's design (see Promote).		
	Deployment	Innovation, Product	DD.8, IT.8, IT.9
	Document the set of criteria that the system must meet before being deployed (see Define Release Criteria).		
	Develop a strategy for the system's deployment that uses a staged approach, such as blue-green or canary deployments [237].		
	Determine the scope of systems and users that the AI system will be rolled out to at each stage of the deployment [238].		

Promote

The Promote stage serves a twofold purpose. First, it involves the promotion of positive values and practices within the organization. Second, at a more technical level, it includes the promotion of design principles within the infrastructure and systems employed by the organization. As such, at the lower implementation levels this stage corresponds to the design phase of many software development life cycles.

	Promote	Owner	Guidance
Organization	**Culture**	Leadership, Workforce	AU.6, MG.2, SL.5, WF.5
	Take actions that facilitate the development of a positive, risk-aware culture within the organization [239].		
	Develop an organizational culture that promotes the AI adoption [240, 241] and its safe and responsible use [242].		
	Assess factors influencing the organization's cybersecurity culture [243, 244] and develop structures that foster a positive one [245].		
	Build an organizational privacy culture and climate [246, 247]. Identify and support privacy champions within the organization [248].		
	Responsibility	Responsibility, Legal	RC.3 SI.1, SI.3, SI.5, SI.6
	Establish an ethics program within the organization [249, 250]. Consider creating an AI ethics board for independent oversight [251].		
	Understand the challenges that ethics owners within the organization face and work to empower and support them [252].		
	Ensure that the design of AI systems conforms with ethical AI principles [253].		
	Foster an ethical culture [254] and implement due diligence practices to ensure responsible business practices [255].		
	Create confidential mechanisms to report ethical, legal, and safety concerns or violations [256].		
	Account for the environmental impact of AI technology and its relation to the organization's sustainability goals [257, 258].		
Operations	**Standard Practices**	Operations	IT.1, IT.6, MG.1, MG.4, SC.1, LG.1, DD.1, SL.4
	Align practices with strategy (see Plan Strategy) and policies (see Plan Policies).		
	Develop standard practices for AI development and operations that align activities across business functions [259].		
	Apply operations management principles in implementing processes to govern and manage AI activities within the organization [260].		
	Identify key AI-related tasks and develop operating procedures to standardize how they are carried out [261].		

	Promote	Owner	Guidance
Operations	**Compliance**	Compliance	AU.2, AU.4, SC.4, SI.7, MS.8, PI.10, PM.5
	Develop a program to promote compliance with organizational policies (see Plan Policies) and regulation (see Assess Legality) [262].		
	Customize policies to fit the needs of the organization and design them to be realistic and usable by employees [263].		
	Use employee performance feedback as a mechanism to promote compliance with organizational AI policies [264].		
	Work with personnel and business partners to identify and address reasons for noncompliance [265].		
Workforce	**Accountability**	Compliance, Workforce	RC.4, SL.2, WF.4, TO.7
	Collaborate with teams and individual personnel in defining responsibilities (see Map Ownership) and expectations [266].		
	Develop an accountability framework to empower, guide, and track the success of decentralized teams [267, 268].		
	Foster a culture of support and accountability within teams and between managers and direct reports [269, 270, 271].		
Infrastructure	**Common Architecture**	Infrastructure	IT.4, DD.9, DD.10
	Develop a common enterprise architecture across the organization [272], accounting for AI-specific needs [273].		
	Establish a zero trust architecture that verifies all users, devices, and systems when attempting to access resources [274, 275].		
	Compile a common set of controls that systems within the organization should implement [276].		
	Adhere to a common set of security configurations for organizational assets and applications [277].		
	Least Privilege & Functionality	Cybersecurity	AC.2, AC.7, IS.8
	Adhere to the principles of least privilege [278] and least functionality [279] in implementing access control.		
	Apply these principles when specifying access to a given system by personnel or third parties [280].		
	Apply these principles when specifying what a given system can access, which is particularly important for agentic AI [281].		
Data	**Data Minimization**	Data, Privacy	PI.2, PP.6
	Minimize the collection, processing, retention, and transfer of personal or personally identifiable information (PII) [282].		
	Extend the principle of data minimization to the collection of data used for training and fine-tuning AI models [283, 284].		
	Consider trade-offs between minimization and the collection of data to combat bias and monitor use (see Assess Trade-Offs).		

	Promote	Owner	Guidance
Model	**Safety**	Trust & Safety	SI.4, SI.5
	Conduct an early analysis of potential mismatches between needed and actual AI performance that may lead to harm [285].		
	Incorporate safety guardrails into the AI system at the design phase [286].		
	Consider employing a human-centered design approach for AI systems [287].		
	Trust	Trust & Safety	SI.2, IM.3, IM.7
	Establish a meaningful participatory approach to AI design that incorporates stakeholder input and works to build trust [288].		
	Integrate ethical [289] and trustworthy [290] principles into the design of AI systems.		
	Consider employing a value sensitive design approach, adapted for AI, in the requirements gathering and design phase [291].		
	Human Oversight	Trust & Safety	TO.3
	Carefully consider the role that a human will play in the operation of the system, particularly when critical decision-making occurs [292].		
	Design oversight to be human-centric, emphasizing collaboration (AI-in-the-loop) rather than automation (human-in-the-loop) [293].		
	Design AI systems that can identify, measure, and communicate the level of competency or uncertainty in their output [294, 295].		
	Explore the range of human-machine teaming concepts that should be considered as a part of the system's design [296, 297].		
System	**Privacy**	Privacy	DD.1, PP.4, PI.1
	Promote a privacy-by-design approach to system development within the organization [298].		
	Apply established privacy principles to the design of AI systems [299, 300].		
	Security	Cybersecurity	DD.1, DD.3, PP.4, SI.4
	Promote a security-by-design approach to system development within the organization [301].		
	Apply established security principles to the design of AI systems [302], particularly LLM-based [303] and agentic [304] AI systems.		
	Ethical & Safe Use	Trust & Safety	TO.1, ST.6, SI.5
	Design AI systems that promote healthy human-AI interactions and protect a user's mental health [305, 306, 307].		
	Be proactive in designing mechanisms to combat issues of dependence [308], overreliance [309, 310], and emotional attachment [311].		
	Design human-centered interventions targeting the prompting process to promote more responsible and ethical use [312].		

Map

The Map stage captures the activities that provide visibility into the organization and the interconnected web of its external relationships, organizational responsibilities, assets, and data. Maintaining this situational awareness is critical for nearly every other aspect of this guide. Without visibility, it becomes exceedingly difficult—if not impossible—to ensure the proper management, security, and compliance of the organization's operations.

	Map	Owner	Guidance
Organization	**Stakeholders**	Strategy	ST.1, PP.1, IR.1
	Conduct a stakeholder analysis to identify and map the organization's key stakeholders [313, 314].		
	Identify stakeholders directly related to or impacted by the adoption of AI technology [315].		
	Group and prioritize stakeholders using a power-interest matrix, salience model, or similar technique [316, 317]		
	Solicit input from stakeholders throughout the AI adoption process (see Engage Stakeholders).		
Operations	**Supply Chain**	Supply Chain	IT.2, SC.2, RR.3, IV.2
	Conduct a supply chain mapping to identify the external dependencies of the organization [318, 319, 320].		
	Identify potential threats and risks to the AI supply chain [321], in particular those related to data used by AI systems [322].		
	Use the supply chain map to inform the development of a supply chain risk management plan [323].		
Workforce	**Ownership**	Leadership, Operations, Workforce	IT.3, IV.5, RC.1, SL.2, WF.2, IS.9, PP.3, PP.8, PI.1, MO.8, IR.1, IR.2
	Define who owns the AI system, components, model, and associated data within the organization [324].		
	Strategically position AI leaders within the organization's reporting structure and ensure they have the needed authority [325].		
	Map AI-related responsibilities [326, 327] to specific functional units, teams, and individuals (use the mapping in this report as a guide).		
	Delegate responsibilities and authority to individual teams [328] while also providing formal structures to support them [329].		
	Record ownership of organizational assets and related responsibilities in the inventory (see Map Assets).		

	Map	Owner	Guidance
Workforce	**Approval**	Leadership, Operations	IT.6, MG.4, DD.7, DD.8
	Establish a documented approval process and define where in the life cycle approvals are required (see Plan Life Cycle).		
	Map and record the approval workflow (i.e., who is approving, when, in what order) at each stage and for each system component [330].		
Infrastructure	**Assets**	Infrastructure	IV.1, IV.2
	Create a centralized inventory for tracking IT assets. Include the system, components, model, and data in the inventory [331].		
	Use established templates [332] or, preferably, a more advanced asset management systems to track AI-related assets [333].		
	Include relevant metadata about the asset, including provenance (see Map Provenance) and ownership (see Map Ownership).		
	Data Flows	Infrastructure	IV.3, TR.4, SM.7, PP.8
	Conduct a data flow mapping to identify how data moves through the organization, how it is processed, and where it is stored [334, 335].		
	Create a visual representation of the organization's data flows using a data flow diagram [336].		
	Use the data flow mapping to assess privacy risks (see Assess Data Protection) and ensure privacy compliance (see Assess Legality).		
Data	**Classification**	Privacy, Data	IS.1, IV.4
	Systematically classify assets [337] (see Define Classification Scheme) and determine their value in terms of criticality [338].		
	Consider methods to automate the assessment and classification of organizational assets [339].		
	Use the classification and valuation to define the safety, security, and privacy controls required to protect the asset [340].		
	Provenance	Data	FS.5, TR.1, TR.4, IS.7, PI.10
	Trace licenses, creators, uses, and sources to generate standardized documentation regarding dataset lineage [341].		
	Use cryptographic tools such as digital signatures and watermarking to map content and data provenance [342].		
	Replace static reports with interactive provenance visualizations that trace the full AI data life cycle [343].		
Model	**Traceability**	Innovation, Product	TR.2, TR.3, TR.4, TR.6, TR.7
	Embed watermarks using semantic-preserving code transformations so that AI-generated outputs remain traceable [344].		
	Map model traceability using standardized metadata, secure registries, and immutable logs [345].		
	Implement mechanisms to track and record the activity of systems acting autonomously, such as AI agents [346].		

	Map	Owner	Guidance
System	**Components**	Product	IV.1, SC.2, ES.1, TO.6
	Use a bill of materials (BOM) to document system components, including hardware [347], software [348, 349], and AI BOMs [350].		
	Document the AI system and its components, training, evaluation, and intended use through model [351] or use case [352] cards.		
	Consider including information in the system documentation related to the OECD AI classification framework [147].		

Assess

The Assess stage marks the end of the planning phase, before the organization moves on to implementation. This stage involves assessing the plans for the AI system and the organization's capability to implement them safely. It is critical that the organization's leadership review the various assessments below holistically and determine whether it should move forward in adopting the AI system or whether further iteration in the planning phase is required.

	Assess	Owner	Guidance
Organization	**Points of Failure**	Leadership	IM.1
	Identify existing structures and practices that might serve as roadblocks for AI adoption initiatives [353].		
	Understand the technical, and more often social or organizational, reasons why many AI projects fail [354, 355].		
	Incorporate lessons learned from previous AI projects and failures, both internal and external (see Improve) [356].		
	Threats	Cybersecurity	MO.2, DD.2
	Maintain awareness of the cybersecurity threat landscape [357, 358]. Share threat information (see Monitor Information Sharing).		
	Conduct cybersecurity threat assessments to identify potential threat actors [359, 360], leveraging cyber threat intelligence [361].		
	Conduct threat modeling to identify potential vulnerabilities and risks [362, 363, 364, 365], including those specific to AI systems [366].		
	Account for the range of AI-specific attacks, including those related to privacy [367] as well as AI-based attacks [368].		
Operations	**Risk**	Risk	RM.4, RM.5, RM.6, SC.3, IM.7, PM.3, IS.9
	Take a systematic approach to identifying risks [369], including risks [370] and harms [371] specifically related to AI systems [372].		
	Account for AI misuse risks, including chemical, biological [373], radiological and nuclear (CBRN) [374] and cyber [375] risks.		
	Conduct risk assessments [376] using established tools and techniques [377]. Assess the risks stemming from AI adoption [378, 379].		
	Use qualitative and quantitative measures of risk where appropriate [380, 381], accounting for uncertainty [382].		
	Establish a process to prioritize risk [383]. Consider using risk matrices and other prioritization tools to assist in this process [384, 385].		

	Assess	Owner	Guidance
Operations	**Legality**	Legal, Compliance	TO.5
	Assess whether the AI system conforms to applicable laws and regulation (see Define Context), including the EU AI Act [386].		
	Consider the potential liability of the organization for AI-related harms and the applicability of U.S. tort law [387].		
	Evaluate how privacy regulation, such as the General Data Protection Regulation, may impact data use by the AI system [388].		
	Consider applicable antidiscrimination laws [389] and potential civil rights impacts related to the AI adoption and use [390].		
	Ethics	Responsibility, Compliance	TO.5, IM.5, IM.6
	Conduct regular human rights impacts and due diligence assessments of the organization's practices [391].		
	Assess the alignment of the AI system with the organization's mission and ethical principles [253].		
	Implement a multidisciplinary evaluation framework to measure social impacts alongside technical performance [392].		
	Assess ethics through audits that invite third-party evaluation and take into account value sensitive design approaches [393].		
	Supply Chain	Supply Chain	SC.7
	Understand the threats and risks to the organization's supply chain [394] based on the supply chain map (see Map Supply Chain).		
	Conduct a supply chain risk assessment to evaluate risks and dependencies [395, 396], particularly for upstream AI providers.		
	Consider the risks of using open source models, software, or libraries in system development and its future maintenance [397].		
Workforce	**Capability**	Workforce	WF.1, ST.5, DD.1
	Develop or use a maturity grid/model to assess organizational capabilities and how they change over time [398].		
	Assess cybersecurity [399, 400] and AI [401] competencies within the organization's workforce.		
	Determine whether the organization's existing workforce is ready for and can adequately support AI adoption [402].		
Infrastructure	**Platforms**	Infrastructure	DD.3
	Assess the computing needs for AI workloads, which often require specialized hardware for intensive computation [403, 404].		
	Evaluate AI infrastructure options [405], including on-premises [406], cloud [407], and hybrid [408] deployments.		
	Assess the risks [409] and potential security threats [410] of related to the use of cloud computing platforms.		
	Compare the range of AI platform providers and tools if planning on using cloud services or AI-as-a-Service (AIaaS) [59].		

	Assess	Owner	Guidance
Data	**Data Protection**	Cybersecurity, Privacy, Data	PI.7, MS.9
	Use the data mapping (see Map Data Flows) to conduct a data protection [411] and privacy impact assessment [412, 413, 414, 415].		
	Understand the range of privacy harms [416] and the privacy risks that can occur across the AI life cycle [417].		
	Assess the technical and procedural protections available for securing data used by AI systems [418].		
Model	**Technology Readiness**	Innovation	DD.1, IT.2, TO.5
	Assess the maturity of the given AI technology using technology readiness levels [419, 420] applied to AI systems [421].		
	Understand the factors influencing successful AI adoption within organizations [422, 423].		
	Evaluate the maturity of the organization (see Self-Assess) and conduct an AI readiness assessment [424].		
	Trade-Offs	Innovation	IM.7
	Assess the design trade-offs between AI model performance and explainability [425, 426], robustness, and fairness [427].		
	Weigh the benefits of data minimization of sensitive attributes and the limitations when conducting bias assessments [428, 429].		
	Assess the benefits and risks of developing or deploying AI models with dual-use capabilities [430].		
System	**Impact**	Trust & Safety	IM.1, RC.2, SI.3, IT.10, IM.2, IM.5, IM.7, PM.3
	Conduct AI [431, 432, 433, 434] and algorithmic [435] impact assessments, accounting for the system's intended deployment.		
	Assess the impact that the intended AI use case may have on human rights and democratic processes [436, 437, 438].		
	Use established templates for conducting and documenting impact assessments [439, 440, 441].		
	Employ sets of related metrics rather than a single indicator to ensure that assessments capture the system's effects and dynamics [442].		
	Encourage multi-stakeholder participation in assessments across government, academia, civil society, and the private sector [443].		
	Attack Surface	Cybersecurity	DD.2, MO.2, MO.3
	Understand the attack surface [444] of the system, identifying common points of entry or vulnerability in IT [445] and AI [446] systems.		
	Conduct an attack surface analysis to identify high-risk points that will need to be tested and defended [447, 448].		
	Account for vulnerabilities specific to ML [449], generative AI [450], and agentic [451] systems.		
	Take steps to reduce the attack surface by removing unnecessary functionality, code, access points, and system calls [452, 453].		

Acquire

The Acquire stage represents the start of the implementation phase. The degree to which the recommendations in this section apply largely depends on what aspects of the AI system are being developed internally versus acquired from external vendors. The extent of the acquisition can range from the entire system, such as in AIaaS models, down to the data used for model training or open-source libraries used in software development. This section provides guidance that is broadly applicable to all forms of acquisition as well as tailored recommendations for acquiring third-party datasets, models, or AI systems.

	Acquire	Owner	Guidance
Organization	**Relationships**	Leadership, Supply Chain	SC.1, RC.3, AU.6, SI.1, IR.6
	Build relationships with suppliers that enable transparent communication [454] and effective risk management [455].		
	Create a strategy for stakeholder engagement [456] that promotes meaningful participation from AI stakeholders [457, 458]		
	Establish relationships with individuals and organizations in academia [459, 460], civil society [461], and the government [462].		
Operations	**Due Diligence**	Supply Chain, Legal	RC.2, SC.5, TE.4
	Vet potential suppliers using a comprehensive due diligence assessment [463, 464].		
	Quantify the costs, benefits, and risks of doing business with a given supplier as a part of the due diligence process [465].		
	Ensure that suppliers' labor practices are legal and ethical [466], especially for AI-related data annotation and content moderation [467].		
	Select suppliers using a structured evaluation approach, such as multi-criteria decision-making [468].		
	Contracts	Legal, Supply Chain	RC.3, SC.6, VN.2, MS.5
	Closely evaluate the contracts and terms of use involved in the procurement and use of third-party AI models and tools [469, 470].		
	Build key provisions into supplier contracts that address privacy, security, intellectual property, and liability, among others [471, 472].		
Workforce	**External Expertise**	Workforce	ST.4, IM.3, TE.7
	Consider bringing in external AI expertise to augment talent gaps within the organization (see Define Needs).		
	Engage external experts in the AI TEVV and red-teaming processes, particularly when testing for domain-specific capabilities [473].		
	Consider the role that the broader public can play in testing and AI red-teaming activities [474].		

	Acquire	Owner	Guidance
Infrastructure	**Verification**	Supply Chain, Cybersecurity	NS.4, IS.3, ES.4
	Ensure products and services are acquired from trusted and vetted sources only (see Assess Supply Chain, Acquire Due Diligence) [475].		
	Verify the source and integrity of acquired hardware, software, models, data, and other components [476].		
	Take steps to secure the organization's AI supply chain, accounting for the differences between AI and traditional software [477].		
Data	**Consent**	Data, Privacy	FS.5, PP.5, PI.3, PI.4, IS.8
	Obtain informed consent from individuals prior to the collection of personal information and confirm that consent over time [478, 479].		
	Disclose the intended use of collected data, particularly for AI uses [480], and obtain a data processing agreement [481].		
	Provide notice to individuals when their data is being collected [482] and when the policies or use of that data changes [483].		
	Obtain consent from and provide compensation to creative workers whose data is used to train AI models [484, 485].		
	Data Collection	Data	PP.6, PI.2, SG.2
	Determine the appropriate tools and techniques to use for data acquisition, augmentation, and labeling [486].		
	Adhere to the principle of data minimization when collecting and processing personal data (see Promote Data Minimization).		
	Assess ethical, legal, privacy, and data quality issues related to large-scale web scraping used for AI training [487, 488, 489, 490, 491].		
	Scrutinize collected data for potential data poisoning attacks (see Protect Integrity) [492].		
	Third-Party Datasets	Data, Supply Chain	SG.5, SG.2, FS.1
	Assess the various sources of data and the trade-offs in using them for training AI models [493].		
	Follow data supply chain security best practices when acquiring and using third-party data for AI training [494].		
	Weigh the advantages and disadvantages of using synthetic data to train models [495] and the risk of model collapse [496, 497, 498].		

	Acquire	Owner	Guidance
Model	**Third-Party Models**	Innovation, Supply Chain	SG.5, TE.3, TE.4
	Follow relevant public- [499] or private- [500] sector guidance on the strategy and steps to be taken during AI procurement.		
	Scrutinize third-party models for security risks and vulnerabilities that they might introduce (see Map Supply Chain) [501, 502].		
	Assess the challenges in using pretrained models for downstream development [503] and potential dependence on upstream providers.		
	Weigh performance [504], cost [505], documentation [506], transparency [507], and security [508] trade-offs for open models.		
	Determine whether and how the organization will modify the pre-trained model [509]. Assess trade-offs [510] and risks [511].		
System	**Third-Party Systems**	Product, Supply Chain	SG.5, TE.3, TE.4
	Apply a structured approach to procurement and acquisition that includes evaluation and acceptance testing [512].		
	Explore the wide range of AI tools, services, and platforms that are available to identify those that meet the organization's needs [513].		
	Compare different AI offerings [514] and evaluate provider policies for data collection and monitoring. Test models side by side [515].		
	Evaluate potential AI systems against prespecified requirements (see Define System Requirements) in a systemized way [516].		

Develop

The Develop stage complements the previous Acquire stage, covering the development of AI capabilities in-house as opposed to those being acquired from outside sources. While only a handful of companies are likely to be developing their own frontier models from scratch, many are likely to develop their own more specialized models or build on existing, pre-trained models to meet the organization's specific needs. This stage covers the practices and techniques needed for responsible AI development and innovation.

	Develop	Owner	Guidance
Organization	**Responsible Innovation**	Innovation	SI.1, SI.2, SI.3, SI.5, SI.6, IM.3
	Ensure that the organization adheres to responsible innovation practices in its development and adoption of new technology [517].		
	Apply responsible innovation practices to the research and development of AI systems [518, 519].		
	Develop context-specific tools and methods to prioritize fairness, transparency, and accountability in innovation [520].		
Operations	**Management Systems**	Infrastructure	MG.7, IV.4, DD.9, DD.10
	Implement software project management [521] and AI project management [522] best practices.		
	Create a management program to oversee MLOps [523].		
	Establish an asset management system [524, 525] that includes AI- and ML-based assets [333] (see Map Assets and Manage Assets).		
	Develop a dependencies management [526] (see Map Supply Chain) and assurance [527] (see Acquire Due Diligence) program.		
	Put in place common configuration [528] and control [529] management systems (see Promote Common Architecture).		
	Create a risk management function [530] (see Assess Risk and Control Risk), that includes supply chain risk management [531].		
	Develop a vulnerability management program (see Manage Vulnerabilities) [532].		
	Implement change [533] and patch [534] management systems (see Develop Version Control and Develop Patches).		
	Establish an incident [535] and continuity [536] management system (see Respond and Plan Response).		
	Develop a training and awareness program for personnel (see Deploy Training & Drills and Manage Personnel Awareness) [537].		
	Create an overarching situational awareness program within the organization (see Manage Situational Awareness) [538].		

	Develop	Owner	Guidance
Workforce	**Diverse Teams**	Workforce	ST.4
	Build teams that reflect a diversity of backgrounds, knowledge, expertise, and experience [539, 540].		
	Understand the importance of diverse teams for AI development, testing, and operation [541].		
	Develop a recruitment plan to address the scarcity of AI skills, equity gaps in AI talent [542], and lack of diversity on AI teams [543].		
	Facilitate an environment that promotes communication, trust, and psychological safety among individuals on diverse teams [544, 545].		
Infrastructure	**Logging**	Infrastructure	LG.1, LG.2, LG.6, NS.7
	Establish practices to collect, store in a centralized location (see Monitor Centralized Analysis), manage, and protect event logs [546].		
	Prioritize logging within the organization based on the criticality of systems and data sources [547].		
	Determine what events to log, what metadata to capture, and how to store them using standardized log formats [548].		
	Ensure that logs capture the right information to meet transparency [549], auditing, and issue investigation needs [550, 551].		
	Log information and events from AI systems that capture a range of responsible AI metrics, not just model performance [552, 553].		
	Version Control	Infrastructure	MG.7, TR.1, TR.2
	Use a version control system to manage system artifacts, coordinate development, and control changes [554].		
	Apply version control principles to AI and ML workflows to ensure reproducibility in experiments, development, and testing [555].		
Data	**Data Quality**	Data	TR.5, SG.2, IS.4
	Identify the data quality requirements that are important across different stages of AI development [556].		
	Adopt an ML-focused, but model-agnostic, approach to data quality management [557].		
	Employ techniques to assess and improve the quality of data within the organization [558].		
	Treat data as a governance mechanism, managing and improving data across the supply chain to improve AI safety and security [559].		
Model	**Alignment**	Innovation	IT.7, TO.5
	Work with internal and external stakeholders to identify the values, goals, and behaviors with which to align the AI system [560].		
	Align the behavior of the model using forward alignment techniques during training and backward alignment post-training [561].		
	Evaluate the model for deceptive, scheming, or other misaligned behaviors [562].		

	Develop	Owner	Guidance
Model	**Robustness**	Innovation	IM.4, SG.1, SG.2
	Apply robustness techniques to training data, architecture design, model training, and post-processing [563].		
	Include adversarial examples in model training to help make models more robust to adversarial attacks [564].		
	Consider including a consistency alignment training step to improve the robustness of model responses [565].		
	Use robust training frameworks to combat data heterogeneity and Byzantine attacks if using federated learning [566].		
	Employ techniques such as decision-boundary based federated adversarial training for robust federated learning [567].		
	Transparency	Innovation	TO.1, TO.2, TO.6
	Implement mechanisms and employ tools to help provide interpretations of what led models to produce their outputs [568].		
	Incorporate explainability features into the system that support users' understanding the AI model and its output [569].		
	Develop a use-case-centric explainability framework that tailors model response explanations to users and decision contexts [570].		
	Combine model output with symbolic reasoning to improve the transparency of automated decision-making processes [571].		
	Federated Learning	Innovation	PP.7
	Consider federated learning for training ML systems, especially in contexts where data is heterogeneous and unsafe to centralize [572].		
	Use federated learning to share or migrate models securely in cases where local training data is insufficient [573].		
	Acknowledge that federated learning is not a one-step privacy solution and that it may still present security risks [574].		
	Understand the additional risks of and potential attacks on a federated learning system [575].		
	Privacy Preservation	Innovation	PP.7
	Weigh the privacy guarantees provided by differential privacy against utility and performance trade-offs [576].		
	Consider using federated learning (see Develop Federated Learning) to help preserve the privacy of personal data used in training [577].		
	Assess how to minimize the use of sensitive data and features at inference time, while retaining performance [578].		
System	**Secure Software**	Innovation, Product	DD.1, DD.4, VN.2
	Ensure that the organization implements and follows secure software development practices [579].		
	Take steps to mitigate risks in software development, the supply of third-party components, and the build and delivery of software [512]		
	Apply security best practices to the development of AI models and the related code that make up the AI system [580, 581].		

	Develop	Owner	Guidance
System	**Patches**	Innovation, Product	VN.5, ES.8
	Understand the security patch landscape [582] and the challenges in applying patches within an organization [583, 584].		
	Implement a proactive approach to patch management that includes proactive testing, prioritization, and monitoring [585].		
	Consider incorporating automation at various stages in the patch management process [586].		

Control

The Control stage captures the practices and technical solutions to mitigate the risks that may result from the organization's practices, the activity of its personnel, and the operation of its systems. In general, this stage addresses the potential harm stemming from the organization, while the following Protect stage addresses the potential threats to the organization. Not all of these harms necessarily originate from within the organization or result from unintended action; however, many of these risks do.

	Control	Owner	Guidance
Organization	**Physical Environment**	Physical Security	SM.5, SM.6, PS.1, PS.2, PS.3, IA.4, PS.5
	Allocate personnel and security equipment to maintain physical control over the organization's facilities [587].		
	Control physical access to facilities and restricted areas, including the use of photographic, video, and radio-frequency devices [588].		
	Employ controls that help prevent environmental hazards such as fire, water, electrical, and natural disasters [589].		
Operations	**Risk**	Risk	RM.7, RM.8, IM.4, SC.3
	Determine whether the organization will reduce, transfer, avoid, or accept identified risks (see Assess Risk).		
	Implement mitigation strategies to reduce the organization's IT [590] and AI [591, 592] risks.		
	Consider the use of insurance to transfer some of the risk related to AI from the organization to providers [593].		
	Identify opportunities for risk avoidance when adopting new technology [594]. Do not pursue AI if the risks are too great [595, 596].		
	Determine whether to accept risk if it meets defined acceptance criteria [597] and risk tolerance (see Define Requirements).		
Workforce	**Activity**	Workforce	MS.4, MS.5, MS.6, MS.10, NS.2, PS.2
	Screen potential employees and conduct background checks during hiring [598, 599] to reduce the potential of insider threats [600].		
	Establish an internal control system to guide personnel behavior and enforce compliance policies, practices, and laws [601, 602].		
	Employ a separation or segregation of duties policy that prevents full control of a process or asset by any one individual [603].		
	Revoke access, ensure the return of organizational assets, and otherwise mitigate risk during employee separation [604].		

	Control	Owner	Guidance
Infrastructure	**Identities**	Infrastructure	IA.1, IA.3, IA.5, IA.9
	Establish centralized management of identities, credentials, and identity proofing within the organization [605, 606, 607].		
	Enforce a secure password policy and promote the use of password managers [608, 609].		
	Use stronger authentication mechanisms such as multifactor authentication [610] and single sign-on where possible [611].		
	Extend identity management to agentic AI, accounting for the scale, complexity, and dynamic and ephemeral nature of agents [612].		
	Access	Infrastructure, Cybersecurity	DD.5, IA.4, IA.6, IA.7, AC.3, AC.6, AC.7, AC.8, NS.5, MS.6, PP.9, LG.5
	Restrict access of personnel and systems to only what is strictly necessary (see Promote Least Privilege & Functionality) [613].		
	Select and implement an access control model that is appropriate for the organization's maturity, size, and requirements [614, 615].		
	Control what assets personnel have access to, particularly the ability to modify components of the AI system [616].		
	Control what assets the AI system has access to, including what information it can ingest and what actions it can take [617].		
	Data Flows	Infrastructure, Data	SM.7, IA.5, NS.2, NS.3, NS.5, IS.4, MS.2, MS.7, DD.6
	Implement network segmentation (see Protect Network) and enforce access and data flow restrictions across segments [618].		
	Employ controls, such as firewalls [619] and cross-domain solutions [620], at domain boundaries to control the flow of information.		
	Restrict the flow of data across security domains based on its confidentiality classification (see Define Classification Scheme).		
Data	**Data Transfers**	Data	PI.6, PI.9, SM.7, MS.7
	Limit the transfer of personal data outside of the organization to what is strictly necessary (see Promote Data Minimization).		
	Ensure international data transfers comply with relevant privacy legislation [621, 622, 623, 624, 625, 626].		
	Implement controls to prevent the transfer of data via insecure or inappropriate channels that may lead to data leakage [627].		
	Extend these controls to data sent by personnel to commercial AI products via web interface, file upload, and other protocols [628, 629].		

	Control	Owner	Guidance
	Classified & Proprietary Data	Data, Privacy	SM.7, DD.5
	Evaluate the range of proprietary, sensitive, or classified information that employees might send to external AI services [630, 631].		
	Consider that these risks will exist whether the organization provides AI tools or employees use their own personal services [632].		
	Establish policies for acceptable AI use (see Plan Policies) and train employees on responsible use (see Deploy Training & Drills).		
Model	**Bias**	Innovation, Product	FS.1, FS.3, FS.4
	Adopt practices to assess and mitigate issues of equity, diversity, and inclusion related to algorithms and AI use [633, 634].		
	Implement a bias mitigation system that enables dynamic adjustments to model outputs that mitigate bias without retraining [635].		
	Use causal models to detect and correct poorly weighted relationships between sensitive data attributes that lead to bias [636].		
	Implement guardrails to steer model behavior toward unbiased output [637].		
	Inputs	Innovation, Product	IS.4, SG.3, SG.6
	Validate and sanitize inputs to the system [638]. Extend these methods to AI models to handle harmful or malicious input [639].		
	Remove or mask privacy-sensitive information that users provide to AI models [640].		
	Employ controls to prevent injection-based attacks [641], including injection attacks on generative AI models [642, 643, 644].		
	Outputs	Innovation, Product	IS.4
	Selectively prune training data, fine-tune the model, or develop output controls to reduce the likelihood of harmful outputs [645].		
	Build guardrails into the AI system to flag and handle model output that may be inaccurate [646] or harmful [647, 648, 649].		
	Consider that harm may only occur in aggregate or across multiple outputs of the model [650].		
	Synthetic Media	Trust & Safety	FS.5
	Follow best practices in the development, creation, and distribution of AI-generated synthetic media [651].		
	Deploy tools and processes within the organization to identify and protect against the use of deepfakes [652].		
	Apply watermarking techniques to AI-generated media to help identify the content as synthetic [653].		
	Employ content provenance solutions to strengthen the verifiability of non-synthetic media [654].		
	Identify opportunities for using synthetic data in the AI development pipeline [655] and assess the related risks [656].		

	Control	Owner	Guidance
System	**Action Space**	Product, Infrastructure	AC.2, IS.8, ES.3
	Constrain the set of actions that agentic systems can take and require human approval before more high-cost actions are taken [657].		
	Ensure safe exploration of the action space for AI use cases that employ reinforcement learning techniques [658].		
	Agency	Product	TO.3, SG.1
	Consider the potential harms [659, 660] and greater security risks [661, 662] of creating or deploying systems with greater agency.		
	Deploy agentic systems in narrower environments that are more conducive to their limitations [663] and reliability problems [664].		
	Implement technical and nontechnical guardrails to control and monitor the agency with which the system operates [665].		
	Employ human oversight of systems that operate with any degree of autonomy and protect those channels from compromise [666].		
	Extend access, authorization, and delegation controls (see Control Access) to agentic systems [667].		

Protect

The Protect stage captures the practices and technical solutions to mitigate the range of risks to the organization, its personnel, and its systems. In general, this stage addresses the potential threats to the organization, while the preceding Control stage addresses the potential harms stemming from the organization. Not all of these threats necessarily originate from outside the organization or result from purposeful malicious action; however, many of these risks do.

	Protect	Owner	Guidance
Organization	**Physical Premises**	Physical Security	SM.5, PS.4, PS.5
	Implement physical perimeters, external and internal, that are equipped with sensors, alarms, and entry control [668].		
	Consider additional security protections if the organization houses its own computing resources or data centers [669].		
	Employ automated protection mechanisms in electronic systems to ensure physical safety [670].		
Operations	**Intellectual Property**	Legal	MS.8
	Protect intellectual property (IP) when training AI [671, 672]. Ambiguity exists [673], but a recent case indicates limits to fair use [674].		
	Use digital replicas—that is, AI-generated likenesses of people—only with permission [675] and in a legal manner [676, 677, 678].		
	Protect and respect the IP of AI-generated creations [679, 680], particularly where human contributions constitute authorship [681].		
	Protect the organization's AI-based, and AI-assisted [682], IP through legal [683] and technical means (see Protect Weights).		
Workforce	**Personnel**	Workforce, Compliance	RC.2, RC.4, PS.5, MO.8
	Protect the rights and well-being of employees [684], particularly as the organization operates in an increasingly AI-driven world [685].		
	Ensure the organization, and its suppliers, responsibly employ data workers [686, 687] and other contractors or gig workers [688, 689].		
	Help protect the mental health of employees exposed to harmful content, such as AI testers [690] and content moderators [691].		
	Protect employees' privacy and well-being if deploying AI tools internally [692], particularly for surveillance purposes [693, 694, 695].		
	Protect employee data, ensure nondiscrimination, and provide transparency if using AI in hiring or promotion processes [696, 697].		

	Protect	Owner	Guidance
Infrastructure	**Network**	Cybersecurity	NS.1, NS.5, NS.6, IS.2, ES.6, MO.6
	Implement network security best practices [698] and account for shifts in the enterprise IT landscape (cloud, microservices, etc.) [699].		
	Separate the network into segments with different access and security, providing defense-in-depth against intruders [700].		
	Employ intrusion detection and prevention systems at external and internal segment boundaries [701, 702].		
	Deploy honeypot and other network deception and obfuscation techniques to divert attackers and gain insights into their behavior [703].		
	Ensure that edge devices are secured and configured correctly [704].		
	Assets	Cybersecurity	IV.4, SM.2, SM.3, IS.2, ES.5
	Deploy and manage assets with secure configurations and up-to-date software [705], including mobile devices [706] and servers [707].		
	Employ antimalware protections [708] and other preventive security tools and services [709, 710].		
	Implement human-centric protections in addition to technical ones to help address the challenge of human factors in cybersecurity [711].		
	Ensure that personnel understand and follow basic cybersecurity practices to protect their devices [712].		
	Logs	Infrastructure	LG.5, LG.6, LG.7, MG.6
	Protect logging and audit mechanisms from tampering and accidental failures [713].		
	Restrict access to, encrypt, and create redundant backups of log data. Store log data separately from operational systems [714].		
	Backups	Infrastructure	RR.5, RR.7
	Create consistent backups of critical data and systems for restoration in case of a failure of compromise [715, 716].		
	Evaluate on-site, off-site, and cloud storage options for maintaining backups. Retain multiple copies in different locations [717].		
	Maintain and test backups to help protect against ransomware and other data loss events [718].		

	Protect	Owner	Guidance
Data	**Confidentiality**	Privacy, Cybersecurity	IS.2, IS.5, PI.7, PP.7, PP.8
	Defend against common data breach vectors to protect the confidentiality of data [719].		
	Establish safeguards to protect PII and minimize exposure in the case of a data breach [720].		
	Use established post-quantum encryption [721] and key-exchange standards [722] to encrypt data.		
	Remove classified, sensitive, and proprietary information from training datasets and monitor model output for data leakage [723].		
	Protect models against membership inference attacks that can leak information about the underlying training dataset [724, 725].		
	Defend against model inversion attacks that can be used to extract information about the model and its training data [726, 727].		
	Integrity	Cybersecurity	IS.3, ES.3
	Use post-quantum digital signature standards [728, 729] to verify the integrity of data and the identities of senders and receivers [730].		
	Employ integrity-checking mechanisms to validate data, ensure consistency, and detect anomalies [731, 732].		
	Protect the integrity of data used to train and operate AI systems from sourcing to storage to decommissioning [733].		
	Defend against a range of data poisoning attacks that can be used to manipulate AI model behavior [734, 735, 736, 737].		
Model	**Weights**	Cybersecurity	IS.2, IS.5, SM.4
	Conduct a threat assessment and implement a security plan to prevent the theft of model weights [738, 739, 740].		
	Implement protections against unauthorized knowledge distillation and model extraction [741, 742].		
	Consider the risks of model weights leaking through side-channel attacks when deployed on untrusted hardware [743, 744].		
	Consider using trusted execution environments (TEEs) to protect model weights running on untrusted hardware (see Protect Execution).		
	Protect against model poisoning attacks, whether through data poisoning (see Protect Integrity) or direct manipulation [745].		
	Inputs & Outputs	Cybersecurity	SG.3, IS.2, SM.4, MS.3
	Use encryption and secure communication channels to ensure the integrity of model input and output [746].		
	Defend against a wide range of adversarial attacks [747, 748, 749], including model evasion [750, 751] and manipulation [752].		
	Account for multi-turn attacks that can occur across multiple sets of inputs or interactions [753].		
	Consider the risk of exposing model vectors and embeddings [754], as this can leak information about the model and data [755, 756].		
	Defend against side-channel attacks that can be used to reconstruct model input and output [757, 758, 759].		

	Protect	Owner	Guidance
Model	**Execution**	Infrastructure, Cybersecurity	IS.3, ES.4
	Assess security and performance trade-offs [760] of using TEEs to protect model execution on untrusted hardware [761, 762].		
	Stay informed of advances in and limitations of secure computing for GPU [763, 764], NPU [765], TPU [766], and DPU [767] hardware.		
	Protect the model from revealing, or being able to reveal [768], the system prompts guiding the model's behavior [769, 770].		
	Resource Utilization	Infrastructure	NS.6, NS.8, RR.4
	Limit or throttle the volume of requests that any given user can make to the model to prevent resource exhaustion [771].		
	Protect against economic denial of sustainability (EDoS) attacks on cloud computing resources used by the organization [772].		
	Implement protections to identify and mitigate similar resource consumption attacks on AI models [773, 774, 775].		
System	**Availability**	Cybersecurity, Infrastructure	NS.6, RR.4
	Conduct capacity planning [776]. Forecast and allocate computing resources [777, 778]. Dynamically adjust to meet demand [779].		
	Allocate adequate resources to maintain availability and protect against resource-based attacks (see Protect Resource Utilization).		
	Implement defenses against denial of service (DoS) attacks on the organization's networks, services, and public-facing APIs [780].		
	Source Code	Cybersecurity	IS.2, ES.2, ES.3
	Use trusted code repositories to maintain code and implement secure repository practices [781].		
	Employ a version control system (see Develop Version Control) to manage changes and prevent unauthorized modification.		
	Separate secrets (e.g., credentials, keys) from source code, block their inclusion in repositories, and regularly scan code for them [782].		
	Protect access to online repositories from adversaries seeking to steal, poison, or extract credentials from source code [783].		
	Users	Trust & Safety	TO.7, IS.4, FS.4, IM.4
	Design AI as a supplement to—not substitute for—human intelligence [784, 785], interaction [786], learning [787], and work [788, 789].		
	Protect users from developing dependence [790] or overreliance [791] on the organization's AI. Avoid addictive design patterns [792].		
	Be hesitant to develop AI systems with anthropomorphic qualities [793]. If used, address the risk posed to users [794, 795, 796].		
	Acknowledge the potential for severe harm if deploying AI technology in a role that serves as—or could be used as—a replacement for important human-to-human interaction, such as in AI assistants [797], therapists [798, 799], or personal companions [305].		
	Account for the use of the organization's AI tools or services by at-risk populations [800, 801], particularly children [802, 803, 804].		

Test

The Test stage, unsurprisingly, comprises the range of testing procedures that should be carried out to evaluate the organization's practices, competencies, infrastructure, and systems. The results of these tests will help inform the decisions made in the Approve stage. While testing at this point in the adoption life cycle is critical, ongoing testing should occur at regular intervals even once the practices or systems are deployed.

	Test	Owner	Guidance
Organization	**Business Continuity**	Operations	IR.1, RR.5, RR.8
	Use tabletop exercises, or other discussion- or practice-based exercises, to evaluate business continuity plans [805].		
	Use resiliency scoring metrics for measuring and tracking the effectiveness of continuity plans over time [806].		
	Consider using AI models to assist in generating scenarios that stress test the organization's business continuity plans [807].		
Operations	**Incident Response**	Operations, Cybersecurity	RR.3, RR.5, RR.8
	Conduct tabletop exercises to play out and evaluate the organization's response [808].		
	Use external resources to develop incident response tabletop exercises that address a variety of potential incidents [809].		
	Apply a quality assurance approach to testing the readiness of the organization to respond to incidents [810].		
Workforce	**Competency**	Workforce	ST.5
	Implement regular evaluations of employees' AI skills to help identify talent and training gaps [811].		
	Tailor competency evaluations and programs to the demonstrated needs of personnel and the organization (see Define Needs) [812].		
	Use validated instruments to measure and evaluate employee AI literacy [813].		
Infrastructure	**Controls**	Cybersecurity	IS.6, TE.4, PM.3
	Conduct cybersecurity penetration testing and red teaming to evaluate defensive capabilities and identify weaknesses [814].		
	Test the organization's monitoring, alerting, and intrusion-detection systems [815].		
	Follow best practices for testing web- and user-facing protections and controls [816].		

	Test	Owner	Guidance
Infrastructure	**Updates**	Innovation, Product	VN.7, ES.8
	Thoroughly test all updates in a sandboxed environment or virtual machine before releasing them to production [817].		
	Verify the authenticity of patches, evaluate the effectiveness of the solution, and test for compatibility issues before deploying [818].		
	Evaluate the patch management against best practices to help streamline the patching and update process [585].		
	Restoration	Infrastructure	RR.5
	Test the complete process of restoring systems and data from stored backups at a regular interval [819].		
	Evaluate data backups and system snapshots periodically to ensure that they are free from compromise [820].		
Data	**Bias & Skew**	Data	FS.2, TR.5, TO.4
	Understand the many sources of potential bias in the AI life cycle and develop tests to measure their influence [371].		
	Test the system and the data used to train it for issues of bias and skew [821]. Embed fairness testing into data management [822].		
	Evaluate whether the training data reflects the diversity of the populations where the model will be used [823].		
	Improve data quality (see Develop Data Quality) and employ fairness-aware preprocessing techniques to minimize bias [824].		
Model	**Capabilities**	Innovation	SG.4, IM.4, TR.3
	Evaluate the capabilities of AI models using established benchmarks and conduct red teaming to assess dual-use risks [825].		
	Adopt a structured framework for testing model capabilities to systematically identify model strengths and weaknesses [826].		
	Test the reasoning capabilities of models using a diverse set of benchmarks and compare to human performance baselines [827].		
	Evaluate the capabilities of systems that act with agency or autonomy [828]. Use appropriate benchmarks for agentic capabilities [829].		
	Performance	Innovation	TE.3, TE.4, TE.8, IT.10, IM.4
	Test the generalization and robustness of models to ensure reliable performance after deployment [830].		
	Employ methods to verify the performance and reliability of AI systems in realistic settings [831].		
	Evaluate the model and its performance along various metrics of trustworthiness [832].		
	Assess model performance and reliability on real-world tasks and likely downstream use cases [833].		

	Test	Owner	Guidance
Model	**Fairness**	Trust & Safety	FS.2, SI.1
	Test model fairness using multiple quantitative metrics chosen based on the ethical and social context of the model's application [834].		
	Test the systems involved in automated decision-making for issues related to equity, fairness, and discrimination [835].		
	Evaluate real-world outcomes and trade-offs for affected groups, rather than solely relying on parity-based metrics [823].		
	Use statistical-comparison methods to detect bias between human and AI-generated outputs when using synthetic training data [836].		
	Consider using synthetic data with bias to evaluate the model's performance under a range of fairness conditions [837].		
	Test the model's explainability and interpretability—key characteristics that have implications for bias, fairness, and trust [838].		
System	**Security**	Cybersecurity	DD.6, TE.4
	Conduct information security assessments of the system [839] and robust application security testing [840].		
	Ensure that the developer is able to verify that the system meets minimum software security standards [841].		
	Employ fuzzing methods to identify vulnerabilities and system failures [842]. Use automated methods for root cause investigation [843].		
	Evaluate how the AI system performs against adversarial attacks [844] and other attacks specific to AI/ML systems [8].		
	Conduct red-teaming exercises to assess the security risks of the AI system [845], particularly for agentic AI systems [846].		
	Safety	Trust & Safety	TO.4, TE.8
	Conduct model and contextual safety evaluations to measure potential safety risks [847].		
	Use a life-cycle-wide evaluation framework that evaluates model and system components for safety [848].		
	Measure model safety against established benchmarks and track performance over time [849].		
	Evaluate the safety of the AI system in the context in which it will be deployed and operate, rather than just the model in isolation [850].		
	Consider using automated tools to generate and expand the scope of test cases and test data [851].		
	Quality	Product	IT.8, DD.7
	Identify key assessment metrics for measuring the quality of software and systems [852].		
	Conduct criteria-based assessments to evaluate whether the system meets requirements (see Define System Requirements) [853].		
	Evaluate the system using quality assurance and validation techniques specific to AI systems [854, 855, 856].		

	Test	Owner	Guidance
System	**Acceptance**	Infrastructure, Product	TE.2, TE.7
	Use risk acceptance criteria to structure AI-specific safety cases for acceptance testing [857].		
	Conduct a range of acceptance tests to ensure the system meets safety, security, compliance, and regulatory requirements [858].		
	Explore automated acceptance testing in contexts that do not rely on user input (i.e., not beta testing) [859].		
	Conduct separate user acceptance testing to ensure the system meets end user requirements [860].		
	User Interaction	Product	ST.6
	Employ human-centered evaluations that involve real end users and assess interactions across high- and low-stakes activities [861].		
	Conduct interactive evaluations to capture how AI systems affect users over sustained use [862].		
	Assess whether AI interactions disproportionately affect certain groups of users [863], particularly those that are vulnerable [864].		
	Evaluate the potential influence that the AI system will have on human decision-making and determine if appropriate [865].		
	Evaluate how users can purposefully misuse the AI system and assess the likelihood of that misuse [866].		
	Employ metrics that capture how operators interact with AI systems when deployed in human-machine teaming situations [867].		

Approve

The Approve stage represents the end of the implementation phase. This section covers the decision of whether to proceed with deployment and the inputs that should be assessed in making that decision. Although this stage in the adoption life cycle represents the most important decision-making point, review and approval should also occur at multiple, predefined points throughout this process. This should include, at minimum, an approval step between the planning and implementation phases.

	Approve	Owner	Guidance
Organization	**Go/No-Go Decision**	Leadership	IT.8, RM.3
	Incorporate inputs, such as test results and readiness criteria, from all relevant teams when making high-level approval decisions [868].		
	Prioritize decision criteria (e.g., user acceptance, performance) in alignment with the organization's goals (see Define Objectives) [869].		
	Construct processes that enable decision-makers to change or abandon previously chosen courses of action [870].		
Operations	**Stakeholder Input**	Communication	ST.3, ST.4
	Gather insights from identified stakeholders (see Map Stakeholders) at key stages throughout the adoption life cycle [871].		
	Create organizational incentives to gather stakeholder input and incorporate it into approval decisions [872].		
	Determine the goal of the stakeholder input process and the extent to which stakeholder input will affect approval decisions [873].		
	Risk Threshold	Risk	PM.2, RM.3
	Determine whether the system exceeds the organization's risk tolerance (see Define Requirements) based on testing results.		
	Consider using prespecified "if-then" commitments to govern decisions on AI risk and how systems will be deployed [874].		
Workforce	**Independent Validation**	Workforce	DD.6, TE.7
	Ensure that the system and testing results are reviewed by the independent review committee (see Define Oversight).		
	Engage external and third-party auditors to review AI models and systems that have been developed in-house [875].		
	Seek out external subject matter experts to support internal AI auditing efforts [876].		

	Approve	Owner	Guidance
Infrastructure	**Integration & Acceptance**	Infrastructure	TE.1, DD.10
	Review and approve the results of system integration and user acceptance testing (see Test Acceptance).		
	Address potential adoption hurdles and factors affecting user acceptance of new IT [877] and AI [878, 879] technology.		
	Foster communities of practice around AI use within the organization and create a center of excellence to help obtain user buy-in [880].		
Data	**Privacy Assurance**	Data	PI.1, PI.10
	Ensure the organization has obtained informed consent for any personal data processed by the system (see Acquire Consent).		
	Establish an assurance mechanism to review that data processing by the system aligns with the organization's privacy policy [881].		
Model	**Release Criteria**	Product	IT.8, DD.10
	Determine whether the model meets the requirements specified in the release criteria (See Define Release Criteria).		
	Assess the model against general AI release-readiness checklists [882].		
	Understand that AI evaluations have limits [883, 884] and that unanticipated risks or emergent capabilities can occur [885, 886].		
System	**System Review**	Product	IT.6, DD.7, PM.2, SG.4, TE.5
	Require the developers of the system to demonstrate that the implementation meets requirements (see Define System Requirements).		
	Establish standard peer reviews of the model, software, and system by individuals external to the development team [887].		
	Conduct internal auditing of the AI system throughout the development life cycle to produce an overall audit report [888].		
	Conduct a management review of the system, including a review of the test results [889].		

Communicate

The Communicate stage marks the start of the deployment phase. This stage involves both the documentation and communication of organizational policies, practices, and technical systems. As part of this stage, the organization must determine what information remains for internal use and what information or data is shared with external audiences or published publicly, balancing the need for transparency with the privacy and security risks.

	Communicate	Owner	Guidance
Organization	**Objectives**	Leadership	SM.1, MG.2, AU.7, IM.2
	Engage with personnel to build internal support for the organization's mission and objectives (see Define Objectives) [890].		
	Be transparent internally about how the goals for AI adoption align with the overarching mission of the organization [518].		
	Present the organization's AI strategy and its objective for AI adoption to stakeholders and work to attain buy-in [891].		
	Policies	Leadership, Communication	AU.7, MG.4, MG.5, RC.1, SL.1, WF.4, SM.1, PP.5
	Describe organizational policies clearly in public- or employee-facing documentation and update these documents regularly [892].		
	Use organizational policies, and their communication, as tools to frame values and shape organizational identity [893].		
	Solicit continuous input and feedback (see Engage Stakeholders, Engage Personnel) on policies and where they can be improved [894].		
Operations	**Practices**	Operations	AU.7, MG.4, MG.5, RC.1, RC.5, ST.2, PP.5, PI.3
	Document procedures to standardize practices and facilitate their communication across the organization [895].		
	Communicate to personnel and stakeholders how the organization's policies and practices relate to its AI strategy [896].		
	Decisions	Leadership, Operations	MG.5, IS.7, PI.10
	Document and communicate the reasoning behind the decisions that the organization makes [897].		
	Assess how AI systems may influence organizational decision-making [898] and provide guidance on how to calibrate AI input [899].		
	Develop practices and processes for clearly explaining decisions made with or by AI systems [900].		

	Communicate	Owner	Guidance
Workforce	**Responsibilities**	Workforce, Communication	IV.5, RM.3, WF.4, SM.1, PP.3
	Communicate roles and responsibilities to personnel for the development, management, and oversight of the AI system [901].		
	Establish clear roles and communication channels between business and analytics (or technical) teams in developing new products [902].		
Infrastructure	**Controls**	Cybersecurity	TO.4, DD.10, RM.10
	Use transparency around internal safety and security efforts to build trust with external stakeholders [903].		
	Balance transparency with the potential of information disclosed about controls and safeguards being used by attackers [904].		
	Where applicable, notify users of acceptable use policies and how they will be enforced (e.g., denials, account bans) [183].		
	Changes	Product, Cybersecurity	VN.1, TR.1, TR.2
	Communicate changes to models, as they can be difficult to detect in downstream uses while also having important impacts [905].		
	Provide end users with clear and informative alerts when updates or security patches for the system are available or implemented [906].		
	Disclose AI-related vulnerabilities and risks to downstream parties once identified and when mitigations have been implemented [907].		
Data	**Data Practices**	Data, Privacy	TR.3, PP.5, PI.3, PI.9, PI.10
	Provide clear, easy-to-read documentation of the organization's data and privacy practices in a publicly posted privacy policy [908].		
	Disclose data protection practices to stakeholders through interactive interfaces for increased accessibility and usability [909].		
	Document and communicate data practices for, or involving the use of, AI systems [910].		
	Data Transparency	Data	FS.3, PP.5
	Clearly document the use of upstream datasets in model training where possible [911].		
	Publish a training data declaration to provide transparency around the data used to train or fine-tune the AI model [912, 913].		
	Provide ample documentation—and account for privacy risks—if providing open datasets for public use [914].		
Model	**Risks & Limitations**	Risk, Communication	TO.1, IM.5, FS.3, RC.5, RM.10
	Communicate known risks to stakeholders and interested parties [915]. Consider publishing an organizational risk profile [916].		
	Document the model and its development to provide transparency around its risks, capabilities, and limitations [917, 918].		
	Publish a pre-deployment AI risk disclosure to inform downstream use of the model [919].		
	Maintain and publish up-to-date safety-critical information related to the model [920]. Regularly publish transparency reports [921].		

	Communicate	Owner	Guidance
System	**Test Results**	Innovation, Product, Communication	TE.3, TE.6, TR.3, TR.6, SG.4, RM.10
	Document the process, activities, and results of testing to enable comparison across models and organizations [922, 923].		
	Communicate test results to the development team and ensure that actions are taken to rectify issues identified during testing [924].		
	Publish test results—to the extent that doing so does not compromise the safety or security of the system—publicly to build trust [925].		

Deploy

The Deploy stage consists of the release of the AI model or deployment of the AI system, internally or publicly. This process includes the integration of the system into existing infrastructure, training personnel to support it, and adding system support functions to the organization's day-to-day operations.

	Deploy	Owner	Guidance
Organization	**Review Cycle**	Leadership, Compliance	SL.3, MG.8, AU.3
	Integrate the deployed system and related procedures into the regular management review cycle within the organization [926].		
	Apply a continuous improvement strategy focusing on incremental change and improvement to the system and processes [927, 928].		
	Conduct regular audits of the AI system including related data, controls, risk mitigations, and operating procedures [929, 930, 931].		
Operations	**Enforcement**	Compliance, Workforce	AU.4, SL.1, WF.4, SM.1, DD.10, AC.8, MS.5, MS.7
	Understand the various factors that influence compliance with organizational safety and security policies [932, 933].		
	Evaluate the range of internal compliance strategies and tactics to determine the approach that best suits the organization [934, 935].		
	Assess potential harms to employees before deploying surveillance tools [694, 936], and be transparent about their use [937].		
Workforce	**Training & Drills**	Workforce	SC.4, SI.3, WF.1, IA.8, ES.5, IR.1, IR.2, RR.8, TO.1
	Provide training to aid personnel in improving their AI skills [938] and help meet organizational talent needs (see Define Needs).		
	Consider deploying a rapid occupational training program based on an existing model to develop more advanced AI talent [939].		
	Collaborate with external partners [940] and scale up internal programs [941, 942, 943] to further the availability of AI training.		
	Conduct tabletop exercises [944] and drills [945, 946, 947] to improve personnel's response capabilities and to test response plans.		
Infrastructure	**Architecture**	Infrastructure	IT.4, MO.7, LG.1
	Develop an enterprise integration architecture to ensure the interoperability across the organization's IT infrastructure [948].		
	Conduct early integration planning, compatibility specification, and integration testing to facilitate system deployment [949].		
	Integrate the system [950] and its associated data and events [951] (i.e., for logging and monitoring) into the enterprise architecture.		

	Deploy	Owner	Guidance
Infrastructure	**Inventory & Mappings**	Infrastructure	IV.1, IV.2, IV.3, SM.8
	Add the system and its components to the asset inventory (see Map Assets).		
	Update the data flow mapping to include the new system and how it consumes, produces, and processes data (see Map Data Flows).		
	Employ tools to facilitate the automatic detection of IT assets and the automated updating of inventory and mappings [952, 953].		
Data	**Disclosure**	Privacy, Legal	PI.9, IS.9
	Do not disclose or transfer personal data without consent (see Control Data Transfers).		
	Use differential privacy techniques to provide transparency around datasets and models while managing privacy risks [954, 955].		
	Understand that public datasets containing personal data present privacy risks [956], even if anonymization steps are taken [957].		
	Review the legal and privacy implications of disclosing information about, or the weights of, a model trained on personal data [958, 959].		
Model	**Release**	Product, Infrastructure	IT.9, DD.8, IS.9
	Ensure the model meets the prespecified requirements for release (see Define Release Criteria).		
	Implement the organization's release plan (see Plan Release), making adjustments based on testing results as necessary.		
	Determine the appropriate transparency and due diligence needed based on the type of model and degree of openness [960].		
System	**Deployment**	Product, Infrastructure	IT.9, DD.8, IS.9
	Ensure the system meets the prespecified requirements for deployment (see Define Release Criteria).		
	Implement the organization's staged deployment plan (see Plan Deployment), making adjustments based on testing results as necessary.		
	Adopt a continuous integration strategy that uses automated builds and deployment to facilitate frequent system updates [961].		
	Employ secure automated deployment methods, such as through an infrastructure as code approach [962].		
	Follow established guidelines to ensure the secure deployment of AI systems [963].		

Engage

The Engage stage represents the transition from the deployment phase into operations. Important throughout the adoption life cycle, this stage focuses on the organization's engagement with internal and external stakeholders. By engaging in these collaborative efforts, the organization helps to support a safer and more trustworthy AI ecosystem, build trust with its stakeholders, and identify potential issues when they arise.

	Engage	Owner	Guidance
Organization	**Government**	Leadership	SI.5, SI.7
	Support international collaboration efforts on AI risk management and governance [964, 965].		
	Ensure responsible use of the organization's AI systems if deployed for military applications [966, 967, 968].		
	Contribute to public AI information sharing [969], transparency and accountability [970], and incident disclosure [971, 972] initiatives.		
	Society	Responsibility	SI.1, SI.3
	Determine whom within civil society and the public the organization should engage with on the responsible use of AI systems [973].		
	Assess the range of public engagement mechanisms and select those best suited to reach the intended stakeholders [974].		
	Commit to responsible AI principles or other similar guidance and publicly publish those commitments [975].		
	Develop technology designed to promote rather than subvert social and civic processes [976].		
	Academia	Innovation, Cybersecurity	SI.1, SI.4, SI.5, VN.1
	Assess the opportunities and challenges in collaborating with academic institutions on AI research [459].		
	Enable structured access to AI models for researchers to help further the state of AI safety and security research [977].		
	Establish bug bounty programs to incentivize researchers to identify potential vulnerabilities or safety issues [978].		

	Engage	Owner	Guidance
Operations	**Stakeholders**	Communication, Marketing	SI.4, RC.2, ST.1, ST.3, ST.4, PP.10
	Maintain awareness of the sentiment and opinion of the general public on issues pertaining to AI technology and use [979, 980].		
	Engage with and gather input from a wide range of diverse stakeholders throughout the AI adoption life cycle [981].		
	Include secondary stakeholders, such as data contributors and affected communities, in engagement activities [982].		
	Work with stakeholders to proactively address concerns and provide mechanisms for transparency and redress [983].		
	Manage the expectations that stakeholders have related to AI adoption and provide mechanisms to collect feedback [984].		
Workforce	**Personnel**	Workforce	RC.4, IR.3, VN.1
	Include personnel in the process of AI adoption and provide opportunities for them to share and deliberate on how AI is used [985].		
	Make confidential issue reporting [986] and whistleblowing [987] mechanisms readily and meaningfully available to employees.		
	Help personnel develop basic generative AI competencies, including how to appropriately use AI and identify synthetic media [988].		
	Support personnel in adopting AI tools and work to strategically integrate AI initiatives in ways that advance their work [989].		
Infrastructure	**Service Providers**	Supply Chain	IM.2
	Work with service providers to mitigate security risks to the organization and collaborate on security incidents [990].		
	Engage service providers in the development of organizational AI supply chain risk management models [991].		
	Map out dependency networks (see Map Supply Chain) and engage service providers in conversations around accountability [992].		
Data	**Data Subjects**	Privacy, Data	PI.4, PI.5, PP.10
	Be transparent and public about how users' data is collected and used (see Communicate Data Practices).		
	Create channels for data subjects to request more information and lodge grievances [993, 994].		
	Provide mechanisms for individuals to object to [995] and opt out [996] of the collection and processing of their personal data.		
	Incorporate contestability into AI and algorithmic design [997]. Provide mechanisms to contest automated decision-making [998].		

	Engage	Owner	Guidance
Model	**Collaborative Initiatives**	Innovation, Cybersecurity	SI.4, SI.7, MO.5
	Participate in information sharing (see Monitor Information Sharing) and incident reporting (see Respond Communication) initiatives.		
	Contribute to collaborative AI governance and standards-setting programs [999].		
	Consider participating in regional or sector-specific cybersecurity mutual assistance programs, where available [1000, 1001].		
	Consider federated learning collaborations that enable institutions to jointly train systems while preserving privacy [1002].		
System	**End Users**	Product, Communication	SI.2
	Assess the factors influencing AI acceptance and take steps to address potential hurdles in adoption by users [878].		
	Provide end users with information on how to effectively use the AI system and training on its appropriate application [1003].		
	Establish clear mechanisms for users to provide feedback, report issues, and engage in auditing the AI system [1004, 1005].		
	Work with end users to calibrate an appropriate level of trust in the output of AI systems and combat automation bias [1006, 1007].		

Manage

The Manage stage represents the day-to-day operations of the organization. This includes activities to support the continued function, safety, and security of the organization's infrastructure and systems. This stage coincides with the monitoring efforts described in the following stage, as both of these operations represent ongoing activities.

	Manage	Owner	Guidance
Organization	**Situational Awareness**	Leadership	RC.1, MG.5, PM.5, MO.5
	Identify the information needs of the organization's leadership in order to maintain awareness of the organization's operations [1008].		
	Prioritize the sources of information needed for situational awareness, including threat intelligence and vulnerability assessment [1009].		
	Implement a program for collecting, synthesizing, and distributing actionable information (see Develop Management Systems) [1010].		
Operations	**Relationships**	Supply Chain	SC.1, RC.3
	Build relationships with stakeholders (see Engage Stakeholders) and develop relationship management practices [1011, 1012].		
	Implement supply chain management practices to cultivate and maintain relationships with suppliers and customers [1013].		
	Communicate information about the organization's adoption and use of AI systems to both internal and external stakeholders [1014].		
Workforce	**Personnel Awareness**	Workforce, Cybersecurity, Trust & Safety	WF.1, SC.4, FS.5, TO.1
	Provide cybersecurity training and awareness to all personnel within the organization [1015].		
	Disclose to employees what information is collected about them and their activity as part of enterprise security practices [1016].		
	Work with personnel to develop their AI literacy, including awareness of AI capabilities and limitations [1017, 1018, 1019].		
	Ensure that personnel are aware of the risks of synthetic media and its use in social engineering and misinformation [1020, 1021].		
	Provide situational awareness and information sharing mechanisms to support personnel working in human-machine teams [1022].		
Infrastructure	**Assets**	Infrastructure	NS.1, IV.4, SM.4, ES.1, IT.10
	Keep the asset inventory (see Map Assets) up-to-date and ensure all AI-related assets are accurately recorded [1023, 1024].		
	Schedule regular assurance checks and audits of the organization's AI inventory [527].		
	Employ asset management best practices (see Develop Management Systems) to maintain IT assets over their lifetime.		

	Manage	Owner	Guidance
Infrastructure	**Access**	Cybersecurity	SM.6, AC.3, AC.4, AC.5, AC.6, AC.8, AC.9, IA.2, IA.8
	Implement mechanisms to encourage regular review of user access and access updates when needs or roles change [1025].		
	Maintain access logs in accordance with organizational policies and legal requirements (see Monitor Access) [1026].		
	Deconflict access management policies made or implemented by multiple teams or stakeholders [1027].		
	Maintenance	Infrastructure	IM.8, ES.7, ES.8
	Keep a regular maintenance schedule in accordance with a severity or prioritization system [1028].		
	Consider using predictive maintenance to enhance the resilience and availability of systems [1029].		
	Consider maintenance approaches that balance security, risk management, cost, and efficiency [1030].		
	Decommission	Infrastructure	NS.8, MG.6, MS.1, PI.2
	Decommission assets and revoke permissions once they are no longer needed [524].		
	Employ a consistent process for decommissioning assets that accounts for dependencies and stakeholder communication [1031].		
	Update inventories once assets are decommissioned and monitor for unforeseen impacts resulting from decommissioning [1032].		
Data	**User Control**	Privacy, Data	PI.4, PI.5
	Provide mechanisms for users to view data that the organization has collected about them and how it has been processed [1033].		
	Respond to data subject access requests from users, or entities operating on their behalf, in a timely manner [1034].		
	Honor and comply with user requests to modify or delete personal data [1035]. Respect an individual's right to be forgotten [1036].		
	Comply with data control requirements (see Assess Legality) of the jurisdictions in which personal data is collected or processed [1037].		
Model	**Performance**	Product	PM.5, IT.10
	Review model performance (see Monitor Performance) and assess whether recalibrating, refitting, or retraining is needed [1038].		
	Use techniques such as unlearning [1039], fine-tuning [1040], or model editing [1041] to correct and align model behavior.		
	Consider techniques and strategies to automate model corrections [1042].		
	Detect and manage issues of data and model drift that can reduce the performance of model inference [1043].		

	Manage	Owner	Guidance
System	**Vulnerabilities**	Cybersecurity, Product	VN.3, VN.4, VN.5, VN.6
	Implement a standard process managing vulnerabilities in organizational and third-party assets [1044].		
	Maintain awareness of known risks and vulnerabilities [1045], including those specifically related to AI systems [47, 1046, 1047].		
	Identify vulnerabilities via scanning [1048], testing (see Test Security), and information sharing (see Monitor Information Sharing).		
	Investigate, triage, and remediate detected vulnerabilities in a systematic way, prioritizing the most critical first [1049, 1050].		
	Mitigate the risk of vulnerabilities that have not been, or cannot, be patched [1051]. AI systems inherently present these risks [1052].		
	Communicate and share information about vulnerabilities, including those found in AI systems [1053].		

Monitor

The Monitor stage covers the range of ongoing activities intended to detect issues as they arise. These issues include a range of safety, security, privacy, compliance, and performance problems. These activities, like those of the previous Manage stage, make up the ongoing operations of the organization. When an issue is detected, that triggers the Respond stage, which is described in the next section.

	Monitor	Owner	Guidance
Organization	**Context**	Legal	AU.2
	Monitor the evolving legal and regulatory landscape as it pertains to AI to identify changes that impact the organization [1054, 1055].		
	Understand the legal and regulatory context governing which activities or events can be monitored and logged [546].		
	Establish an authority who can respond to requests for information from law enforcement or other external stakeholders [1056].		
	Physical Environment	Physical Security	PS.6, PS.3, MO.6, SM.6
	Monitor physical access to the organization's facilities and centralize physical security functions within an internal security office [587].		
	Coordinate regular security risk assessments to assess priorities and avoid duplication of efforts [1057].		
	Monitor the physical environment to detect and prevent environmental hazards and safety incidents [1058].		
Operations	**Centralized Analysis**	Operations, Cybersecurity	MO.1, MO.3, MO.7, IR.8, LG.3, VN.4
	Establish a security information and event management platform for centralized event and log analysis [1059].		
	Prioritize what information and logs are included in the centralized analysis repository [1060].		
	Conduct ongoing vulnerability and security log analysis to detect potential security events [1061].		
	Enhance analysis capabilities by using predictive analytics and AI/ML techniques [1062].		

	Monitor	Owner	Guidance
Operations	**Information Sharing**	Cybersecurity	MO.2, MO.5, IR.6, VN.1, VN.4, IR.3, IR.6, ES.5, IS.5
	Collect, analyze, and share cyber threat intelligence to inform security decisions and maintain a proactive security posture [1063, 1064].		
	Participate in cybersecurity information sharing initiatives to receive and provide rapid information about emerging attacks [1065].		
	Consider joining the organization's sector-specific information sharing and analysis center or organization [1066].		
	Report incidents and near misses through established incident reporting channels [1067].		
	Third Parties	Supply Chain, Cybersecurity	AU.5, SC.7, PS.2
	Monitor third-party access [1068] to the organization's systems and facilities and their activity while having access [1069].		
	Monitor suppliers to ensure their continued compliance and that they uphold service level agreements [1070, 1071].		
	Establish mechanisms to share pertinent information with third-party suppliers [1072, 1073].		
	Use predictive analytics to improve the monitoring and identification of supply chain threats [1074].		
Workforce	**Security Operations**	Cybersecurity	MO.1, MO.8
	Establish a security operations center or similar team to monitor and analyze potential incidents across the organization [1075].		
	Identify and employ personnel with institutional knowledge and subject matter expertise in various monitoring domains [1076].		
	Ensure that personnel with monitoring responsibilities are placed in the correct teams and under the proper reporting structure [1077].		
	Insider Threats	Physical Security, Cybersecurity	MO.6, AC.9, LG.4
	Understand the indicators of insider threats and establish mechanisms to systematically measure them [1078].		
	Monitor personnel activity and access patterns to identify potential insider threats [1079, 1080, 1081].		
Infrastructure	**Access**	Cybersecurity	MO.4, LG.2, SM.6, IA.6, AC.9
	Validate access patterns against established access control rules to identify violations and anomalies (see Control Access).		
	Monitor users' interactions with the organization's systems and data through access control logs and similar audit mechanisms [1082].		
	Perform periodic reviews of access control policies. Update account permissions in accordance with least privilege principles [1083].		

	Monitor	Owner	Guidance
Infrastructure	**Data Flows**	Infrastructure, Cybersecurity	MO.4, IS.5, LG.2
	Monitor the organization's networks and log events that capture cybersecurity-relevant information for analysis [547, 1084].		
	Employ anomaly detection techniques to identify unusual and suspicious activity on the organization's networks [1085].		
	Set appropriate thresholds for anomaly detection and recalibrate regularly [1086]. Consider using adaptive dynamic thresholds [1087].		
	Monitor for indicators of network compromise [1088]. Update the set of known indicators in a regular or automated fashion [1089].		
Data	**Data Quality**	Data	TR.5
	Determine appropriate indicators of data quality and employ metrics to measure them over time [558, 1090, 856].		
	Implement a data management pipeline that enables continuous monitoring to assess and detect data quality issues [1091].		
	Privacy	Privacy, Data	PI.7, PI.8
	Monitor network traffic, transfers, and access logs to detect potential data breaches or unintended data exposure [1092].		
	Employ continuous privacy monitoring at the organization, business-process, and information-system level [1093].		
	Ensure that monitoring and logging comply with privacy and data retention best practices [1094].		
Model	**Performance**	Product	PM.1, PM.2, TO.4, SG.4
	Select metrics (see Define Metrics) and appropriate benchmarks to track model performance over time [1095].		
	Design a continuous monitoring strategy that tracks outcomes across different subgroups and environments [1096].		
	Employ automated methods of tracking and identifying model drift [1097].		
	Monitor for performance anomalies and use collected data to identify bottlenecks in system processing [1098].		
	Develop a post-deployment performance baseline and monitor for substantial deviations [1099].		
	Alignment	Product	PM.2
	Log and monitor AI model alignment and set thresholds for misalignment where appropriate and feasible [1100].		
	Adopt or create scoring metrics for model alignment that are tailored to the organization's specific use case [1101].		
	Consider integrating self-monitoring mechanisms into a model's chain-of-thought reasoning process [1102].		

	Monitor	Owner	Guidance
Model	**Fairness**	Trust & Safety	FS.2, FS.4, TO.4
	Establish metrics to continuously monitor issues of bias and fairness [1103].		
	Implement run-time monitoring for certain fairness metrics that may differ between development and deployment contexts [1104].		
	Consider how different methods for evaluating fairness may lead to different outcomes or may be inappropriate in given contexts [1105].		
	Inputs & Outputs	Product	SG.3, IS.4
	Monitor model inputs and outputs for unanticipated issues or bypassed safeguards (see Control Inputs and Control Outputs).		
	Monitor the relationship between inputs and outputs to detect malicious attacks on AI models [1106].		
	Account for harm [1107] and malicious use [1108] that can occur across multiple interactions or be distributed across multiple accounts.		
System	**Behavior**	Product	PM.2, SG.4, SG.6, LG.5
	Establish a baseline of the system's normal operating behavior to aid in the identification of anomalous behavior [1109].		
	Review and update the baseline for system behavior and the safety and security thresholds used to trigger a response [1110].		
	Consider using adaptive thresholds for anomaly detection in complex systems and environments [1111, 1112].		
	Implement methods to facilitate real-time failure detection for systems that are operating with some level of autonomy [1113].		
	Use	Trust & Safety	AU.5, TO.4, LG.5
	Establish criteria for acceptable system use or indicators of misuse. Monitor these metrics to flag potential misuse [1114].		
	Consider the use of user and entity behavior analytics to detect anomalous user behavior [1115].		
	Identify cases when the AI system is used for purposes other than what it was intended for that may lead to harm [1116].		
	Impact	Trust & Safety	IM.2, IM.8
	Identify relevant impact metrics and design mechanisms to monitor them over time [444].		
	Measure negative downstream impacts of AI systems including societal [1117], environmental [1118], and health [1119] impacts.		
	Account for attritional harms from AI that develop gradually over time and can be harder to identify and measure [1120].		
	Measure and promote positive downstream impacts of AI [1121].		

Respond

The Respond stage is unique, as its occurrence is contingent on a potential issue being detected during the course of the organization's ongoing monitoring operations. The guidance in this stage reflects general incident response practices and the nuances in responding to issues involving or stemming from AI systems.

	Respond	Owner	Guidance
Organization	**Remediation**	Legal	RC.4, RC.6, TO.7
	Identify the individuals and stakeholders that were impacted as a result of the indecent, adverse event, or other harm [1122].		
	Provide for or cooperate in remediation efforts and comply with any judicial remediation decisions [1123, 1124].		
	Ensure that the organization provides meaningful redress for AI harms and works to translate those efforts into systemic change [1125].		
Operations	**Triage**	Operations	IR.3, IR.4
	Develop an incident severity scale, rubric, or classification framework to aid in the triage of potential incidents [1126, 1127].		
	Map alerting and monitoring systems to the incident severity scale (see Monitor Centralized Analysis).		
	Employ automated tools to support human security analysts in triaging the often overwhelming number of alerts [1128, 1129].		
	Provide decision support to aid response teams in balancing individual event triage and broader operational awareness [1130].		
	Communication	Communication	IR.1, IR.6, MO.5, IR.7, RR.3, PS.5, PI.8
	Support crisis management activities by communicating incident information, status, and strategic decisions to stakeholders [1131].		
	Designate responsibilities and coordinate response activities among all parties involved in responding to the incident [1132].		
	Recognize that insider events can present additional challenges that require a specialized approach to communications [1133].		
	Report cybersecurity incidents in accordance with legal requirements [1134]. Report AI incidents as channels are created [1135, 1136].		
	Communicate information about the incident and its response to stakeholders post-incident and work to repair public relations [1137].		
	Document information about the incident, response activities, and evidence collected during the investigation [1138].		

	Respond	Owner	Guidance
Workforce	**Response Team**	Workforce	IR.1, IR.2, MO.8
	Define a core response team [1139] and a broader set of personnel that can be pulled in to provide specific expertise [1140].		
	Ensure the broader response team includes personnel with AI expertise and upskill the entire team on AI-related incidents [1141].		
	Foster adaption, collective problem-solving, communication, trust, and shared knowledge among response team members [1142].		
	Provide adequate guidance and empower response team members to make critical decisions related to incident response [1143].		
	Support the incident response team and take steps to address issues of burnout that can be high among response staff [1144].		
	Alerting	Communication	MO.1, MO.8, IR.2
	Establish a rotation of personnel for incident monitoring and on-call staff to alert in case of emergencies [1145].		
	Create incentives for employees to report anomalies, alerts, or suspicious events. Do not unnecessarily punish false alarms [1146].		
	Establish multiple communications channels to rapidly alert relevant personnel of incidents when they arise [1147].		
Infrastructure	**Containment & Neutralization**	Operations, Infrastructure	IR.4, RR.9, MO.3, MO.6, IR.2
	Employ segmented and compartmentalized security domains to quickly lock down systems and contain security threats [1148].		
	Consider employing automated and AI-based incident detection and response mechanisms for more rapid containment [1149].		
	Respond to AI incidents quickly, applying deployment corrections to address dangerous capabilities, behavior, or misuse [1150].		
	Neutralize and remove the source of the incident once contained [1151].		
	Investigation	Operations, Cybersecurity	IR.5, IR.8, PI.8
	Initiate a computer forensics investigation to identify the cause of the incident, the scope of impact, and potential attribution [1152, 1153].		
	Identify aspects of AI systems that may require AI-specific digital forensic analysis [1154] or an agent-specific analysis [1155].		
	Consider the use of ML and AI technologies to augment digital forensics teams [1156].		
	Conduct backward analysis to identify if similar undetected issues occurred or similar vulnerabilities remain [1157].		
	Cooperate with government investigations when significant cyber incidents (e.g., widespread or critical outages) occur [1158].		

	Respond	Owner	Guidance
Data	**Data Breach**	Privacy, Cybersecurity	PI.8
	Follow response checklists [1159] when responding to data breaches, including specific guides for ransomware [1160] incidents.		
	Comply with legal obligations regarding notification about data breaches involving personal data [1161].		
	Investigate cases where data breaches involve AI systems, including where shadow AI use by employees caused the breach [1162].		
	Restoration	Data	RR.9
	Validate backup integrity and ensure recoverability before attempting to restore data [1163, 1164].		
	Use forensic recovery tools and techniques in cases where backups are missing, partially corrupted, or insufficient [1165, 1166].		
Model	**Fail-Safes**	Product	SG.1
	Develop fail-safes such that the AI system is able to revert to safe states when encountering various failure modes [1167].		
	Employ human-in-the-loop mechanisms for AI systems [1168] and defer to human oversight when issues or failures occur [1169].		
	Understand the conditions where various forms of human oversight and control over AI is possible and where it is limited [1170].		
	Restoration	Product	RR.9, SG.3, SG.6, PM.4
	Investigate and address issues of corruption [1171] or compromise [1172, 1173] in models and backups before restoration.		
	Implement pipelines that capture snapshots of model states to facilitate rapid restoration after an incident occurs [1174].		
System	**Resilience Mechanisms**	Product	RR.6, SG.1
	Implement checkpoints to save operational state and mechanisms to roll back to that state in the case of failures [1175].		
	Consider employing hardware, software, data, network, infrastructure, and utility redundancy [1176].		
	Employ failover, load balancing, and redundancy to ensure the high availability of critical systems [1177].		
	Ensure that the system can be safely and promptly shut down when needed, particularly if AI based [1178].		
	Restoration	Product	RR.9
	Perform walk-throughs of system and data restoration procedures with key employees and stakeholders pre-incident [1179].		
	Triage system functions and prioritize restoring the most important functionality first, especially in safety-critical contexts [1180].		
	Verify the integrity of systems and ensure that they are restored to a safe state before resuming operations [1181].		

Improve

The Improve stage represents the transition from normal operations back to the review phase in which the organization started. This stage should be triggered at defined intervals, after an incident occurs and the related response completes, and before the organization sets out to adopt additional or more advanced AI systems. At this stage, the organization should review its practices to identify and implement improvements—incorporating lessons learned from the previous adoption cycle and from any incidents that have arisen. Improvements that require major changes to the AI system may warrant starting the cycle from the self-assessment stage once more.

	Improve	Owner	Guidance
Organization	**Strategy**	Leadership	MG.4, MG.8, SL.3, SM.1, TO.5, AU.2
	Conduct an honest and open business strategy review to determine whether and how the strategy should change [34].		
	Identify gaps in knowledge and awareness that can be addressed across the organization in order to better inform strategy [1182].		
	Prioritize an organizational strategy that integrates crisis management [1183] and builds resilience against future incidents [1184].		
Operations	**Procedures**	Operations	MG.4, MG.8, Sl.3, RM.9, AU.4
	Conduct regular audits of the management system and IT processes to identify improvements [1185].		
	Collaborate with personnel to generate process improvement ideas [1186].		
	Assess whether resource utilization and allocation are appropriate and whether improvements can be made [53].		
	Learn strategically from incidents and near misses, incorporating lessons learned to update policies and procedures [1187].		
	Monitoring	Operations	IM.8, MO.4, MO.5
	Conduct a post-incident review to refine monitoring systems and evaluate whether existing processes are sufficient [1188].		
	Update organizational knowledge and personnel awareness after incidents occur to improve future detection [1189].		
	Response	Operations	PM.4, IR.5, IR.9, RR.2
	Review past incidents and response activities to identify lessons learned [1190].		
	Update the incident response plan (see Plan Response) based on the lessons learned from previous incidents [1191].		

	Improve	Owner	Guidance
Operations	**Supply Chain**	Supply Chain	SC.6, SC.7
	Establish metrics to track the performance of the organization's supply chain management [1192].		
	Conduct regular audits of the supply chain and supplier practices [1193].		
	Engage employees [1194] and customers [1195] to identify improvements along the organization's supply chain.		
Workforce	**Training & Awareness**	Workforce	WF.1, ST.5, SC.4
	Review and evaluate the effectiveness of the organization's performance management system [1196].		
	Evaluate the effectiveness of training programs [1197] and cybersecurity awareness initiatives [1198].		
	Reassess talent gaps (see Define Needs) and adapt training programs to address them, as necessary [1199].		
Infrastructure	**Controls**	Cybersecurity	IS.6, IR.9, RM.8, ST.3
	Identify root causes of incidents and update controls to prevent or mitigate future occurrences [1200, 1201].		
	Align control improvement plans with threat intelligence, frameworks, and other resources that impact organizational strategy [1202].		
	Collect metrics for access control performance and use them to improve access control across the organization's systems [1203].		
	Conduct regular audits of the organization's cybersecurity program, controls, and protections [1204, 1205].		
Data	**Data Handling**	Data, Privacy	PP.2
	Conduct data audits on a regular basis to review the organization's data management practices [1206].		
	Improve data governance capabilities to enhance the development of future systems and promote trustworthiness [1207].		
	Investigate cases where data has been mishandled or accidentally exposed and work to ensure that it does not occur again [1208, 1209].		
Model	**Outcomes**	Product, Cybersecurity	PM.5, TO.5
	Assess and correct the alignment of the AI model with human values and organizational goals on a regular basis [1210].		
	Review the decision-making and improve the accountability of AI systems [1211] and human-AI teams [1212].		
	Update model guardrails and broader risk controls (see Control Risk) after an incident to prevent similar issues in the future [1213].		

	Improve	Owner	Guidance
Model	**Testing**	Innovation	SG.4, TE.5, PM.3, IM.8
	Stay up-to-date with test and evaluation best practices, as these continue to evolve for AI systems [1214].		
	Continue to conduct testing of the AI model and system throughout its life cycle, not just at the end of model development [1215].		
	Review and improve on the technical, procedural, and organizational aspects of software system testing [1216].		
System	**System Design**	Product, Innovation	PM.5
	Analyze system failures to identify improvements and inform the requirements and design of future systems [1217].		
	Conduct a postmortem analysis of the system once in production to identify improvement for future projects [1218].		
	Apply a continuous improvement approach to the organization's software and systems [1219].		
	User Experience	Product	IR.9, SI.2
	Incorporate feedback from users (see Engage End Users) on their experience to identify system improvements [1220, 1221].		
	Assess usability [1222] and user experience [1223] to identify improvements to the AI system [1224].		
	Promote widespread and equitable access to the organization's AI tools and services [1225].		

Conclusion

In this report, we provide an extensive reference guide to support practitioners in operationalizing AI best practices within their organizations. In doing so, we help to answer the core questions required for implementation: who (the business function responsible), what (the implementation step with its detailed recommendations), when (at which stage in the adoption life cycle), where (at what implementation level within the organization), why (which recommendation from the harmonized framework does it implement), and how (the external resources). Altogether, this guide identifies 238 implementation steps, 817 detailed recommendations, and 1,225 external resources to support operationalization. As a whole, this guide represents a comprehensive picture of AI adoption, but for many practitioners only a subset of this information will be immediately relevant. As such, we present this guide in a structured manner to enable practitioners to easily identify implementation steps that are pertinent to their use case, and we provide mechanisms for quick navigation across the report.

This report represents the second step in addressing the challenges organizations face in implementing AI guidance. Building on CSET's initial research that harmonized AI guidance into a single unified framework, this work provides practical steps to implement that harmonized guidance [10]. In doing so, we help to address the lack of implementation details that are common in AI guidance documents and frameworks. To aid practitioners further, future research is needed to tailor these recommended practices to the unique aspects of various AI use cases, sectors, and types of organizations.

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