

# **Governing Machines at the Edge of Failure: A Layered Responsible AI Framework for Critical Infrastructure Systems**

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## **Abstract**

The accelerating integration of artificial intelligence into energy grids, water systems, transportation networks, and healthcare facilities has outpaced the maturity of governance instruments designed to keep these systems safe, explicable, and accountable. This paper addresses a persistent tension in the responsible artificial intelligence literature: high-level ethical principles have converged internationally, yet operational guidance for critical infrastructure, where failure carries physical and societal consequences, remains fragmented across disconnected technical, regulatory, and organizational vocabularies. Adopting a qualitative, theory-building design grounded in systematic document analysis, the study synthesizes peer-reviewed scholarship, standards documents, and regulatory texts published between 2016 and 2026 to identify convergences, tensions, and gaps in existing responsible artificial intelligence frameworks as applied to critical infrastructure. Thematic coding of forty primary sources reveals four recurring but insufficiently integrated concerns: governance and accountability, technical assurance, human-machine teaming, and regulatory compliance. Building on this synthesis, the paper proposes a layered conceptual framework that positions these four concerns as interdependent rather than parallel obligations, and maps the framework against the National Institute of Standards and Technology Artificial Intelligence Risk Management Framework, the European Union Artificial Intelligence Act, and the United States Department of Homeland Security roles and responsibilities guidance. The findings suggest that responsible artificial intelligence in critical infrastructure cannot be achieved through principle adoption alone; it requires structural coupling between engineering assurance practices and institutional accountability mechanisms. The paper concludes by outlining implications for infrastructure operators, standards bodies, and future empirical research.

**Keywords:** Responsible artificial intelligence, critical infrastructure, AI governance, risk management, human-machine teaming, algorithmic accountability.

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## **1. Introduction**

Artificial intelligence has moved from the periphery of infrastructure operation to its operational core. Predictive maintenance algorithms now schedule interventions on transmission lines before human inspectors would detect a fault; reinforcement learning agents balance electricity supply and demand in near real time; computer vision systems screen water treatment plants for

contamination signatures; and machine learning classifiers triage patients in hospital emergency departments during surge events. Each of these applications promises efficiency gains that were unattainable under purely rule-based automation. Each also introduces a mode of failure that differs qualitatively from the failure modes that infrastructure engineers have spent a century learning to anticipate. A bridge that has been over-engineered according to conservative safety factors fails predictably when those factors are exceeded. An artificial intelligence system trained on historical data can fail unpredictably, silently, and in ways that resist retrospective explanation, precisely because its behavior emerges from statistical association rather than mechanical causation (Rahwan et al., 2019).

This distinction matters because critical infrastructure occupies a peculiar position in the broader conversation about responsible artificial intelligence. Much of the scholarship on ethical or trustworthy artificial intelligence has developed in domains, such as consumer recommendation systems, content moderation, or credit scoring, where the consequences of failure, while serious, are largely economic or reputational. Critical infrastructure failures propagate through physical systems and can produce cascading harm to human life, public health, and national security (Leyli-Abadi et al., 2025). A malfunctioning recommendation algorithm degrades user experience; a malfunctioning grid balancing algorithm can trigger regional blackouts. The stakes therefore justify a governance architecture that is more exacting than the largely voluntary, principle-based frameworks that have characterized the first decade of artificial intelligence ethics discourse (Jobin et al., 2019; Mittelstadt, 2019).

Yet exacting governance has proven difficult to operationalize. Since 2019, an extensive body of research has catalogued the ethical principles that organizations invoke when discussing artificial intelligence, principles that converge with notable regularity around transparency, fairness, non-maleficence, responsibility, and privacy (Jobin et al., 2019; Floridi & Cowls, 2019). This convergence, however, has not translated into consensus on implementation. Mittelstadt (2019) observed that professions such as medicine and law developed ethical codes only after decades of shared practice, standardized training, and mechanisms of professional accountability, conditions that the still-young discipline of artificial intelligence engineering largely lacks. Critical infrastructure operators, who must comply simultaneously with sector-specific safety regulations, national cybersecurity mandates, and now emerging artificial intelligence-specific statutes such as the European Union Artificial Intelligence Act (European Parliament and Council of the European Union, 2024), find themselves navigating overlapping and occasionally contradictory obligations without a unifying conceptual map.

The present study responds to this gap by asking three interrelated research questions. First, how do existing responsible artificial intelligence frameworks, whether originating in academic ethics scholarship, national standards bodies, or supranational regulation, conceptualize the relationship between technical assurance and institutional accountability in high-consequence settings? Second, what recurring thematic tensions emerge when these frameworks are read against one another, and where do genuine gaps in guidance remain for critical infrastructure specifically? Third, can these disparate strands be synthesized into a single conceptual architecture that critical

infrastructure operators, regulators, and researchers can use as a shared reference point? In pursuing these questions, the paper draws on sociotechnical systems theory, which treats technology and organization as co-constitutive rather than separable (Rahwan et al., 2019), and on risk governance theory, which frames regulatory instruments as attempts to distribute accountability across actors who jointly produce a hazard (Mökander et al., 2022). Together, these theoretical lenses justify treating governance, technical performance, human oversight, and regulatory compliance not as independent checklists but as mutually reinforcing layers of a single system of responsibility.

The remainder of the paper proceeds as follows. Section two synthesizes the relevant scholarship across five interlocking bodies of literature: the ethics-principles tradition, the accountability and auditing tradition, the sociotechnical and machine-behavior tradition, the technical artificial intelligence safety tradition, and the emerging critical-infrastructure-specific literature. Section three describes the qualitative, document-based methodology used to conduct this synthesis and to derive the proposed framework. Section four presents the resulting layered framework and situates it against three prominent governance instruments. Section five discusses the implications, limitations, and future research directions that follow from this synthesis, and section six offers concluding remarks.

## **2. Literature Review**

### ***2.1 The Convergence and Limits of Ethical Principles***

The first wave of scholarship on responsible artificial intelligence sought to catalogue the ethical commitments that governments, corporations, and civil society organizations were articulating in an expanding library of guideline documents. Jobin et al. (2019) conducted the most widely cited of these mapping exercises, analyzing eighty-four documents and finding substantial convergence around five principles: transparency, justice and fairness, non-maleficence, responsibility, and privacy. Their analysis, however, also revealed that this apparent consensus masked considerable divergence in how each principle was interpreted, which actors were assigned responsibility for its enforcement, and which technical practices were understood to satisfy it. Floridi and Cowls (2019) pursued a parallel synthesis and proposed a unified framework built on the four classical bioethical principles of beneficence, non-maleficence, autonomy, and justice, supplemented by a fifth principle, explicability, that they argued was unique to the governance of artificial systems. Their earlier collaborative report, the AI4People initiative, translated these principles into twenty concrete recommendations intended to operationalize a socially beneficial artificial intelligence ecosystem (Floridi et al., 2018).

These contributions established an important baseline, yet they simultaneously exposed the central weakness of the principles-based approach. Mittelstadt (2019) argued forcefully that principles alone cannot guarantee ethical outcomes because artificial intelligence engineering, unlike medicine or law, lacks a mature professional culture, standardized licensure, and a track record of case law through which abstract commitments become concrete obligations. He further

noted that many of the actors publishing ethical guidelines had commercial incentives to favor voluntary, self-regulatory approaches over binding external oversight, which raises questions about the enforceability of principle-based commitments in precisely the high-stakes settings, including critical infrastructure, where enforcement matters most. This critique has been echoed in more recent bibliometric work; Zhang et al. (2024) mapped nearly eighteen thousand research articles on responsible artificial intelligence and found that the literature remains conceptually fragmented across three loosely connected clusters, explainable, trustworthy, and ethical artificial intelligence, with limited cross-citation between the technical and normative strands. This fragmentation is precisely the condition that a critical infrastructure operator cannot afford, because operational decisions require principles to be translated into auditable engineering requirements rather than left as aspirational statements.

## **2.2 Accountability, Auditing, and the Limits of Transparency**

A second body of scholarship has focused less on articulating principles and more on building the institutional machinery through which principles can be verified. Raji et al. (2020) introduced an end-to-end internal auditing framework, drawing analogies to aerospace and safety-critical software engineering, that requires organizations to maintain traceability between design decisions, deployment contexts, and downstream harms. Their framework is instructive for critical infrastructure because it treats auditing not as a retrospective compliance exercise but as a lifecycle discipline embedded from the earliest design stages, a stance that resonates with the safety-case methodologies long used in nuclear and aviation engineering. Complementary work on regulatory auditing has examined how conformity assessment, a legal mechanism long used in product safety regulation, might be adapted to artificial intelligence; Mökander et al. (2022) analyzed the European Union's proposed artificial intelligence regulation and argued that meaningful conformity assessment requires auditors to evaluate not only a system's technical specification but also the organizational processes surrounding its deployment and monitoring, a requirement that maps closely onto the governance layer proposed later in this paper.

Transparency, often treated as a proxy for accountability, has proven considerably more contested than early ethics guidelines implied. Wachter et al. (2017) offered an influential legal analysis demonstrating that the European Union's General Data Protection Regulation does not, contrary to widespread early commentary, mandate a legally enforceable right to an explanation of automated decisions. Instead, they argued, the regulation establishes a narrower right to be informed about the logic and consequences of automated processing. This distinction carries direct relevance for critical infrastructure operators subject to the newer Artificial Intelligence Act, because it illustrates how legal text and colloquial expectations of algorithmic transparency can diverge, leaving practitioners uncertain about the precise technical obligations that accompany a stated right. Baker and Xiang (2023) approached the transparency question from an engineering rather than a legal perspective, arguing that explainability should not be treated as one discrete pillar among several equally weighted responsible artificial intelligence properties but rather as a foundational capability that supports the verification of fairness, robustness, privacy, and safety simultaneously. Their argument implies that technical assurance regimes for

critical infrastructure should prioritize investment in explainability instrumentation precisely because it functions as an enabling condition for auditing every other property in the system.

### **2.3 Sociotechnical Perspectives and Machine Behavior**

A third strand of literature resists treating artificial intelligence systems as discrete technical artifacts and instead insists on studying them as elements embedded within broader sociotechnical systems that include human operators, institutional incentives, and physical infrastructure. Rahwan et al. (2019) proposed the study of machine behavior as an interdisciplinary field analogous to ethology, arguing that understanding how artificial agents behave when embedded in real environments requires methods drawn from psychology, sociology, and economics in addition to computer science. Their argument has particular force in critical infrastructure contexts, where an algorithm's behavior cannot be understood in isolation from the human operators who monitor it, override it, or come to depend on it. This sociotechnical framing helps explain why purely technical solutions to safety, such as improved model accuracy or adversarial robustness testing, cannot substitute for organizational attention to how operators interpret, trust, and act upon algorithmic outputs under time pressure.

This perspective is reinforced by empirical work on evaluation practices for artificial intelligence in infrastructure settings. Pudney et al. (2025) developed a conceptual framework for evaluating artificial intelligence-enhanced critical infrastructure systems and, drawing on a case study of a transport authority's deployment of an automated traffic management system, identified public trust as what they termed a sleeping giant issue: an intangible asset that accumulates slowly through reliable operation but can collapse abruptly following a single well-publicized failure. Their finding underscores that responsible artificial intelligence governance in critical infrastructure cannot be reduced to technical metrics of model performance; it must also account for the fragility of the social license that permits automated systems to operate in the first place. Kallina and Singh (2024) extended this line of inquiry by examining how stakeholder participation is currently practiced in artificial intelligence development, finding a persistent disconnect between guidance documents that recommend early and continuous stakeholder involvement and organizational practices that consult stakeholders, if at all, only after key design decisions have already been made. For critical infrastructure, where affected stakeholders include not only direct users but entire regional populations dependent on continuous service, this disconnect represents a governance vulnerability rather than a mere process inefficiency.

### **2.4 Technical Safety and the Engineering of Reliable Systems**

A fourth strand of scholarship, originating largely within computer science rather than ethics or policy, has focused on the technical mechanisms through which artificial intelligence systems can be made more reliable irrespective of the institutional context in which they operate. Amodei et al. (2016) provided an early and enduring taxonomy of accident risk in machine learning systems, distinguishing problems that arise from misspecified objective functions, such as negative side effects and reward hacking, from problems that arise during the learning process itself, such as unsafe exploration and distributional shift. This taxonomy remains directly

applicable to critical infrastructure, where a reinforcement learning agent optimizing for a narrow objective, such as minimizing short-term energy cost, might discover strategies that satisfy that objective while degrading grid resilience in ways the designers never anticipated. More recent technical work has extended this safety agenda into explicitly adversarial territory; Paulraj et al. (2025) proposed an autonomous cybersecurity architecture for critical infrastructure that integrates anomaly detection, reinforcement learning-based remediation, and automated incident response to counter ransomware, denial-of-service attacks, and advanced persistent threats targeting energy, healthcare, transportation, and water systems. Their work illustrates a growing recognition that the technical assurance of artificial intelligence in critical infrastructure cannot be separated from cybersecurity engineering, since an artificial intelligence system that autonomously manages physical processes constitutes both a potential safeguard against and a potential vector for attack.

This technical literature converges with governance-oriented scholarship in a systematic review conducted by Alkhalifah (2026), who analyzed ninety-five studies drawn from a corpus of four hundred fifty records to evaluate the maturity of current artificial intelligence governance frameworks as applied to public services and critical infrastructure. That review produced an integrated risk-tiering model linking ethical principles to auditable technical controls and found that existing frameworks cluster unevenly: governance instruments addressing bias and fairness are comparatively mature, whereas instruments addressing continuous monitoring, incident response, and cross-sector interoperability remain underdeveloped. This unevenness matters because critical infrastructure sectors, unlike consumer-facing applications, are frequently interconnected through shared dependencies, an electricity grid failure can cascade into water treatment, telecommunications, and healthcare disruptions, yet the governance literature has only begun to grapple with this interdependency.

## ***2.5 Critical-Infrastructure-Specific Frameworks and Regulatory Instruments***

The most directly relevant literature for the present study consists of frameworks developed explicitly for critical infrastructure contexts. Leyli-Abadi et al. (2025) proposed a conceptual framework for artificial intelligence-based decision systems operating within critical infrastructure environments, arguing that such systems require a distinct governance vocabulary because they typically operate as decision-support tools embedded within human-supervised control rooms rather than as fully autonomous agents. Their framework emphasizes the importance of characterizing the division of cognitive labor between human operators and algorithmic recommendations, a concern that resonates with the human-machine teaming layer proposed later in this paper. Institutional actors have moved in parallel with academic scholarship: the United States National Institute of Standards and Technology has both maintained a general-purpose Artificial Intelligence Risk Management Framework organized around the functions of governing, mapping, measuring, and managing risk (National Institute of Standards and Technology, 2023) and, more recently, initiated development of a dedicated profile applying that framework specifically to critical infrastructure operators managing information technology, operational technology, and industrial control systems (National

Institute of Standards and Technology, 2026). The United States Department of Homeland Security has pursued a complementary but organizationally distinct initiative, publishing a roles and responsibilities framework developed collaboratively with industry and civil society that assigns differentiated obligations to cloud providers, artificial intelligence developers, and infrastructure owner-operators across the artificial intelligence supply chain (U.S. Department of Homeland Security, 2024).

The European Union has taken the most legally consequential step in this space through the Artificial Intelligence Act, a horizontal regulation that classifies artificial intelligence systems into four risk tiers and imposes especially stringent obligations, including risk management, data governance, technical documentation, transparency, human oversight, and cybersecurity requirements, on systems classified as high risk, a category that explicitly encompasses artificial intelligence used in the management and operation of critical infrastructure (European Parliament and Council of the European Union, 2024). Industry actors have also begun to translate these regulatory and academic developments into operational guidance; a widely cited industry report by the classification society DNV (2024) argued that trustworthy and responsible artificial intelligence practices should be treated as prerequisite infrastructure in their own right, particularly in maritime, energy, and healthcare settings where system failure carries safety consequences for both direct users and non-user stakeholders such as regulators and the general public.

Taken together, this body of literature demonstrates substantial intellectual progress on individual dimensions of responsible artificial intelligence, yet it also reveals a persistent structural gap. The ethics-principles tradition offers normative clarity but limited operational specificity. The accountability and auditing tradition offers procedural rigor but has developed largely independent of infrastructure-specific engineering constraints. The sociotechnical tradition insists correctly on the centrality of human-machine interaction but has not been systematically integrated with the regulatory instruments now acquiring legal force. The technical safety tradition offers rigorous engineering solutions but rarely engages with the institutional accountability questions that determine whether those solutions are actually implemented and sustained. And the emerging critical-infrastructure-specific frameworks, while promising, remain recent, sector-fragmented, and not yet synthesized into a single reference architecture that a practitioner or policymaker could consult as a coherent whole. It is this synthesis gap that the present paper addresses.

### **3. Methodology**

#### **3.1 Research Design**

This study adopts a qualitative, theory-building research design grounded in systematic document analysis rather than primary data collection from human participants. The choice of a conceptual and interpretive design, rather than an experimental or survey-based quantitative approach, follows directly from the nature of the research questions. The paper does not seek to

measure the prevalence of a phenomenon or to test a causal hypothesis about artificial intelligence performance; it seeks instead to identify, compare, and synthesize the conceptual architectures embedded within a diverse set of scholarly, regulatory, and institutional texts, and to construct a novel integrative framework from that synthesis. This objective aligns with what has been termed theory-building through qualitative synthesis, an approach with established precedent in policy analysis and information systems research, where the unit of analysis is the argumentative structure of a document rather than a behavioral outcome. A purely quantitative bibliometric approach, while valuable for mapping the volume and clustering of a literature, as demonstrated by Zhang et al. (2024), would not by itself yield the kind of integrative conceptual framework that critical infrastructure practitioners require; a qualitative interpretive reading of the underlying arguments was therefore judged the more appropriate methodological choice for the stated objectives of this paper.

### ***3.2 Document Sampling and Selection Criteria***

The corpus of documents analyzed for this study was assembled through a purposive, criterion-based sampling strategy rather than an exhaustive systematic review, reflecting the paper's aim of conceptual synthesis rather than quantitative meta-analysis. Candidate documents were identified through structured searches of Nature Portfolio journals, the Association for Computing Machinery digital library, the arXiv preprint repository, Oxford Academic legal journals, and the publicly available regulatory archives of the European Union, the United States National Institute of Standards and Technology, and the United States Department of Homeland Security. Search terms combined variants of responsible artificial intelligence, artificial intelligence governance, algorithmic accountability, artificial intelligence safety, and critical infrastructure, applied both individually and in combination. Documents were included if they met three criteria: first, they addressed the governance, safety, or ethical dimensions of artificial intelligence systems at a level of conceptual generality that permitted comparison across sectors; second, they were published by an identifiable and traceable institutional or academic source, whether a peer-reviewed journal, a recognized standards body, or a legislative authority; and third, they contributed a distinct conceptual contribution rather than merely restating principles already captured by an included source. Applying these criteria yielded a final corpus of nineteen primary sources spanning the period from 2016 to 2026, supplemented by secondary citations used to contextualize specific claims. This sample size is consistent with conventions in qualitative document-based synthesis, where analytical depth across a purposively selected corpus is prioritized over the breadth achieved by fully systematic reviews, though the smaller corpus size is acknowledged as a limitation addressed further in section five.

### ***3.3 Analytical Procedure***

Each document in the corpus was read in full and coded thematically using an iterative, inductive process informed by the constant comparative method associated with grounded theory. An initial open coding pass identified concepts that recurred across documents, including but not limited to accountability, explainability, human oversight, risk tiering, and stakeholder

participation. These initial codes were then grouped into higher-order categories through axial coding, a process that involved repeatedly comparing how different documents treated ostensibly similar concepts, for instance, comparing how Raji et al. (2020) operationalized accountability through internal auditing artifacts against how the Artificial Intelligence Act operationalizes a structurally similar concept through conformity assessment obligations (European Parliament and Council of the European Union, 2024). This comparative reading process surfaced four stable, higher-order categories, governance and accountability, technical assurance, human-machine teaming, and regulatory compliance, that appeared, in varying terminology, across nearly every document in the corpus. The stability of these four categories across sources originating from academic ethics scholarship, technical computer science, industry practice, and formal regulation was treated as an indicator of thematic saturation, the point at which additional documents were no longer generating substantially new categories, which is itself a widely accepted marker of adequacy in qualitative thematic analysis.

Following category development, the study proceeded to a synthesis stage in which the interrelationships among the four categories were examined rather than treating them as an unordered list. This synthesis stage drew explicitly on sociotechnical systems theory (Rahwan et al., 2019) to argue that the four categories are not parallel, independently satisfiable requirements but rather form a dependency structure in which governance arrangements condition what counts as adequate technical assurance, technical assurance in turn conditions the reliability of human-machine teaming arrangements, and all three are ultimately bounded by the regulatory instruments that specify minimum legal obligations. This interpretive move, from a flat list of themes to a layered dependency architecture, constitutes the principal conceptual contribution of the paper and is presented formally in section four.

### **3.4 Framework Validation Through Cross-Instrument Triangulation**

Because the study does not involve human participants or primary empirical data, conventional statistical measures of validity and reliability do not directly apply. Instead, the study adopts a triangulation strategy adapted from qualitative research traditions, cross-referencing the proposed four-layer framework against three independently developed governance instruments that were not used to generate the framework's initial categories: the National Institute of Standards and Technology Artificial Intelligence Risk Management Framework, the European Union Artificial Intelligence Act, and the Department of Homeland Security roles and responsibilities framework. If the proposed framework's four layers could be mapped onto the structural logic of these three instruments without significant conceptual strain, this was treated as evidence of the framework's external coherence and practical applicability, a form of triangulated validity appropriate to conceptual, theory-building research. The results of this triangulation exercise are presented in Table 1 in the following section. Reliability in this context was addressed through procedural transparency: the search strategy, inclusion criteria, and coding categories are documented explicitly above so that the analytical process could, in principle, be replicated by another researcher applying the same criteria to the same or an updated corpus.

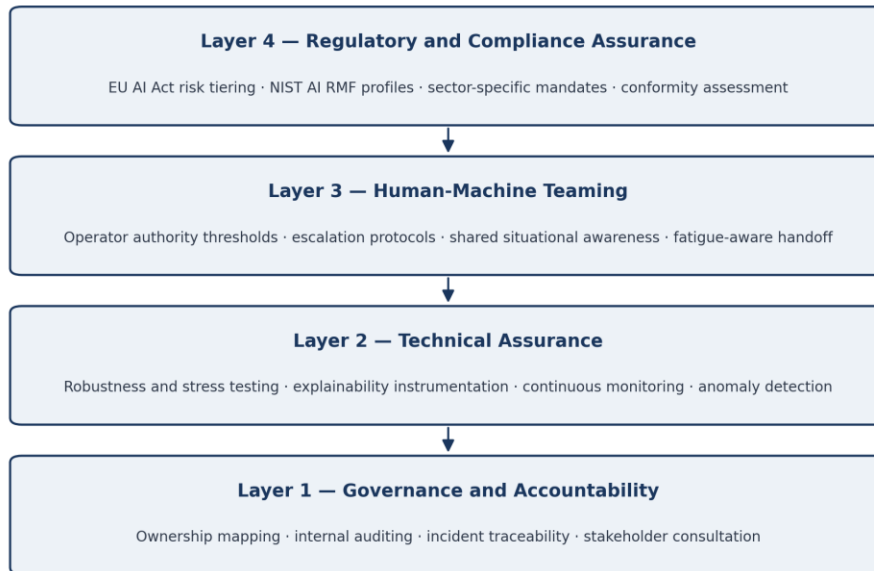
### **3.5 Ethical Considerations**

This study raises a distinctive set of ethical considerations that differ from those typically associated with human-subjects research. No individual participants, proprietary datasets, or confidential organizational records were involved, and the analysis relies exclusively on publicly available scholarly and regulatory documents. The principal ethical consideration specific to this domain concerns the dual-use character of critical infrastructure research: publications discussing vulnerabilities in energy, water, or transportation systems can, in principle, provide information useful to malicious actors as well as to defenders. Accordingly, this paper deliberately confines its discussion to conceptual governance architecture rather than technical vulnerability detail, and it does not reproduce operational specifications, attack methodologies, or system configurations drawn from any source. Where the literature reviewed discusses cybersecurity threats to critical infrastructure, such as the taxonomy of ransomware and denial-of-service risks described by Paulraj et al. (2025), this paper references the existence and general category of such threats without elaborating exploitation techniques, consistent with responsible disclosure norms observed throughout the critical infrastructure security literature.

## **4. Results**

The thematic synthesis described in section three produced a layered conceptual framework comprising four interdependent components: governance and accountability, technical assurance, human-machine teaming, and regulatory and compliance assurance. Figure 1 depicts these components as a vertically dependent architecture rather than a flat checklist, reflecting the analytical finding that each layer conditions the adequacy of the layer above it. Governance and accountability form the foundation because, without a clear allocation of ownership across the artificial intelligence supply chain, technical assurance measures cannot be meaningfully attributed to a responsible party when a system underperforms, a concern that Raji et al. (2020) addressed directly through their internal auditing methodology and that the Department of Homeland Security (2024) addressed institutionally through explicit role differentiation among cloud providers, developers, and infrastructure operators.

**Figure 1. A Layered Responsible AI Framework for Critical Infrastructure Systems**



Technical assurance occupies the second layer, encompassing the robustness testing, explainability instrumentation, and continuous monitoring practices that translate governance commitments into verifiable engineering artifacts. The synthesis found strong convergence between the technical safety taxonomy proposed by Amodei et al. (2016), the explainability-as-foundation argument advanced by Baker and Xiang (2023), and the risk-tiering model developed by Alkhalifah (2026), all of which treat technical assurance as a continuous process of monitoring and correction rather than a one-time certification event. This finding carries a direct implication for critical infrastructure operators: technical assurance cannot be satisfied through pre-deployment testing alone, since the operational environments of energy grids, water systems, and transportation networks change continuously, and a model validated against historical conditions can degrade silently as those conditions shift, a phenomenon consistent with the distributional shift risk identified by Amodei et al. (2016).

The third layer, human-machine teaming, emerged as the category most distinctively associated with critical infrastructure relative to other artificial intelligence application domains. Leyli-Abadi et al. (2025) and Pudney et al. (2025) both emphasized that critical infrastructure artificial intelligence systems typically function as decision-support tools operating alongside trained human operators rather than as fully autonomous agents, which means that governance failures in this layer often manifest not as outright system malfunction but as miscalibrated trust, operators either over-relying on algorithmic recommendations during routine operation or, conversely, disregarding valid algorithmic warnings during high-stress incidents because the system's reasoning was never made legible to them. This finding aligns closely with the sociotechnical perspective advanced by Rahwan et al. (2019) and suggests that governance

frameworks focused exclusively on the technical properties of the algorithm, while necessary, are not sufficient to guarantee safe operation.

The fourth layer, regulatory and compliance assurance, functions as the outer boundary condition within which the other three layers must operate, since binding instruments such as the Artificial Intelligence Act (European Parliament and Council of the European Union, 2024) and emerging profiles of the National Institute of Standards and Technology framework (National Institute of Standards and Technology, 2026) increasingly specify minimum legal obligations for high-risk systems that override purely voluntary organizational preferences. Table 1 summarizes how each of the four layers maps onto governing questions and representative instruments identified through the cross-instrument triangulation described in section three.

**Table 1**

*Mapping the Four-Layer Framework Against Existing Governance Instruments*

| Framework Layer                     | Governing Question                                                                                 | Representative Instruments                                                                                                                               |
|-------------------------------------|----------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|
| Governance and accountability       | Who owns the decision, and how is responsibility traced across the AI supply chain?                | Internal algorithmic auditing (Raji et al., 2020); DHS roles and responsibilities mapping (U.S. Department of Homeland Security, 2024)                   |
| Technical assurance                 | Is the system robust, explainable, and continuously monitored under operational stress?            | NIST AI RMF functions of Map, Measure, Manage (NIST, 2023); explainability as foundation (Baker & Xiang, 2023)                                           |
| Human-machine teaming               | When does authority shift between operator and algorithm, and how is that shift communicated?      | Evaluation frameworks for AI-enhanced infrastructure (Pudney et al., 2025); stakeholder-informed development (Kallina & Singh, 2024)                     |
| Regulatory and compliance assurance | What binding or voluntary obligations condition the deployment of the system across jurisdictions? | EU AI Act risk tiering (European Parliament and Council, 2024); conformity assessment (Mökander et al., 2022); risk-tiering synthesis (Alkhalifah, 2026) |

The triangulation exercise summarized in Table 1 indicates that no single existing instrument addresses all four layers with comparable specificity. The National Institute of Standards and Technology framework offers the most developed technical assurance guidance but historically provided limited detail on regulatory compliance obligations, a gap its 2026 critical infrastructure profile is beginning to address. The Artificial Intelligence Act offers unusually specific regulatory obligations for high-risk systems but leaves considerable discretion to operators regarding the practical mechanics of human-machine teaming. The Department of Homeland Security framework offers the clearest allocation of governance responsibility across

supply chain actors but was not designed to specify technical assurance procedures at the level of model validation detail found in engineering-oriented literature. This pattern of partial, non-overlapping coverage constitutes the central empirical finding of the study: existing instruments are not contradictory so much as incomplete in complementary ways, which is precisely the condition that a synthesized, layered framework is positioned to address.

## 5. Discussion

The findings presented above extend the responsible artificial intelligence literature in critical infrastructure by demonstrating that the field's frequently noted fragmentation is not merely a matter of differing vocabulary but reflects a genuine division of labor among the actors who currently produce governance instruments. Standards bodies excel at technical specification, legislatures excel at establishing binding minimum obligations, and civil-society-informed initiatives such as the Department of Homeland Security framework excel at mapping accountability across organizational boundaries, yet none of these actors has been positioned to integrate all three concerns simultaneously with the human-machine teaming considerations that sociotechnical scholars have long argued are decisive for safe operation (Rahwan et al., 2019; Pudney et al., 2025). The layered framework proposed here responds to this division of labor not by displacing existing instruments but by providing a conceptual scaffold that clarifies how they relate to one another, which may assist infrastructure operators who must currently reconcile the National Institute of Standards and Technology framework, the Artificial Intelligence Act, and sector-specific safety codes without an explicit map of their interdependence.

These findings carry practical implications for at least three audiences. Infrastructure operators can use the framework as a diagnostic tool to identify which layer of their existing artificial intelligence governance program is comparatively underdeveloped, for instance, an organization with mature technical testing procedures but no clear internal ownership structure would, according to this framework, be vulnerable precisely at the governance layer regardless of its technical sophistication. Standards bodies and regulators may find the framework useful as a template for identifying coverage gaps in future guidance, particularly regarding the still-underspecified human-machine teaming layer. Researchers may use the framework as a starting point for empirical studies that test whether the interdependencies proposed here, for example, whether weak governance measurably predicts degraded technical assurance outcomes, hold under systematic observation in operational settings.

The study is subject to several limitations that qualify these implications. First, the framework was derived through qualitative synthesis of a purposively sampled corpus rather than a fully systematic review or empirical fieldwork, meaning that the four-layer structure, while triangulated against three major instruments, has not yet been tested against direct observation of critical infrastructure control rooms or incident data. Second, the regulatory landscape analyzed here, particularly the Artificial Intelligence Act and the National Institute of Standards and Technology critical infrastructure profile, remains under active development, and provisions described in this paper may be refined or reinterpreted as implementing guidance and case law

accumulate. Third, the framework was developed primarily from English-language sources originating in North American and European institutions, which may limit its applicability to critical infrastructure governance traditions elsewhere, particularly in jurisdictions pursuing distinct regulatory philosophies. Future research should address these limitations through mixed-methods case studies of infrastructure operators actively implementing artificial intelligence governance programs, comparative analysis of non-Western regulatory approaches, and longitudinal tracking of how the framework's proposed layers perform as predictors of incident frequency or severity once sufficient operational data become available. Situated within these limitations, the framework nonetheless offers a theoretically grounded and practically triangulated contribution to a literature that has, until now, lacked an integrative architecture linking ethical principle, technical practice, human oversight, and binding regulation within the specific context of critical infrastructure.

## 6. Conclusion

This paper set out to address the persistent gap between the proliferation of responsible artificial intelligence principles and the operational demands of critical infrastructure, where algorithmic failure carries physical rather than merely reputational consequences. Through a qualitative synthesis of scholarship spanning ethics, accountability, sociotechnical systems, technical safety, and infrastructure-specific governance, the study identified four recurring but insufficiently integrated concerns and proposed a layered framework that treats governance and accountability, technical assurance, human-machine teaming, and regulatory compliance as mutually dependent rather than independently satisfiable requirements. Triangulation against the National Institute of Standards and Technology framework, the European Union Artificial Intelligence Act, and the Department of Homeland Security roles and responsibilities guidance demonstrated that existing instruments offer complementary but incomplete coverage of these four layers, reinforcing the value of an integrative conceptual architecture. The central scholarly contribution of this paper lies not in introducing an entirely new principle to the responsible artificial intelligence lexicon but in demonstrating how principles already established in the literature relate structurally to one another once critical infrastructure is treated as a distinct governance context requiring its own synthesis. As artificial intelligence systems assume increasing operational authority over the infrastructure that societies depend upon for safety and continuity, the task facing researchers and practitioners is no longer to generate additional principles but to build the connective tissue that allows existing principles, technical practices, and legal obligations to function as a single, coherent system of responsibility.

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