

Trustworthy Generative Artificial Intelligence for Enterprise Applications: A Conceptual Framework for Governance, Reliability, and Human-Centered Deployment

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Abstract

The rapid diffusion of generative artificial intelligence across enterprise environments has outpaced the governance structures required to ensure that its outputs remain reliable, explainable, and aligned with organizational and societal values. This paper addresses the resulting trust deficit by asking how enterprises can operationalize trustworthy generative artificial intelligence in a manner that reconciles technical performance with ethical accountability. Adopting a qualitative, theory-building design grounded in systematic narrative synthesis, the study integrates literature from computer science, information systems, management, and technology ethics to construct an integrated conceptual framework. The review draws upon established risk taxonomies, alignment methodologies such as reinforcement learning from human feedback and retrieval-augmented generation, and regulatory instruments including the National Institute of Standards and Technology Artificial Intelligence Risk Management Framework and the European Union Artificial Intelligence Act. Findings indicate that trustworthy deployment depends on five interdependent pillars: technical reliability, transparency and explainability, governance and regulatory alignment, human-centered oversight, and organizational readiness. These pillars are represented through a lifecycle model comprising design, validation, controlled deployment, continuous monitoring, and audit, connected by a recursive feedback loop. The paper contributes to scholarship by moving beyond fragmented, single-dimension treatments of artificial intelligence trust toward an integrative, enterprise-oriented model that is empirically groundable and practically actionable. It concludes by outlining limitations associated with the conceptual method and by proposing an agenda for future empirical validation across industry sectors.

Keywords: generative artificial intelligence; enterprise governance; trustworthy AI; large language models; algorithmic accountability; human-centered design

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1. Introduction

Generative artificial intelligence has moved, within the space of a few years, from a specialized research curiosity into an operational layer embedded across procurement platforms, customer

service pipelines, software development environments, and strategic decision support systems. Enterprises now rely on large language models and adjacent generative architectures to draft contracts, summarize regulatory filings, generate design alternatives, and simulate customer interactions at a scale that would have been economically implausible only a decade ago. This diffusion has been accompanied by genuine productivity gains, yet it has also exposed a structural mismatch between the pace of technical deployment and the maturity of the governance mechanisms meant to accompany it. Executives frequently describe a paradox in which generative systems are simultaneously indispensable to competitive strategy and a source of considerable operational anxiety, because the same architectures that generate fluent, contextually persuasive text can also fabricate citations, reproduce embedded social biases, or expose proprietary information through insufficiently controlled prompts (Bommasani et al., 2021; Weidinger et al., 2021).

The problem this paper addresses is not the existence of generative artificial intelligence within the enterprise, which is now largely settled, but the absence of a coherent, integrative account of what it means for such systems to be trustworthy within organizational settings that carry legal, reputational, and fiduciary obligations. Much of the existing scholarship treats trust as a narrowly technical property, equating it with statistical accuracy or benchmark performance, while a separate stream of literature approaches trust as a matter of ethical principle detached from implementation detail (Mittelstadt, 2019). Enterprises, however, require both registers simultaneously: a system must be technically dependable and it must be governable, auditable, and comprehensible to the people whose professional judgment it is meant to augment rather than replace. The absence of a framework that bridges these registers leaves practitioners with fragmented checklists and leaves scholars without a cumulative theoretical vocabulary for comparing trust interventions across sectors.

This paper is organized around three interrelated objectives. The first is to synthesize, rather than merely catalogue, the dispersed body of scholarship on generative artificial intelligence risk, alignment, and governance, drawing connections across computer science, information systems, and organizational theory that are seldom brought into direct conversation. The second is to identify the conceptual and empirical gaps that persist once this synthesis is complete, particularly regarding the organizational conditions under which technical safeguards translate into genuine user trust. The third is to propose an integrative conceptual framework, expressed as a lifecycle model, that enterprises and researchers can use to structure both the design of generative systems and the empirical study of their adoption. The central research question guiding this inquiry is: what constitutes trustworthy generative artificial intelligence in enterprise contexts, and through which mechanisms can organizations operationalize that trust across the system lifecycle? Two subsidiary questions follow from this: first, which technical and governance mechanisms recur most consistently across the literature as determinants of trust, and second, how do these mechanisms interact with organizational and human factors that existing technical scholarship tends to treat as exogenous.

The inquiry is situated within a sociotechnical systems perspective, which holds that the reliability of any information technology cannot be assessed independently of the organizational routines, incentive structures, and human interpretive practices within which it is embedded (Shneiderman, 2020). This perspective is complemented by the organizational trust model developed by Mayer, Davis, and Schoorman (1995), which conceptualizes trust as a function of perceived ability, benevolence, and integrity, and which this paper extends analogically to the relationship between organizational users and generative artificial intelligence systems. Read together, these frameworks suggest that trust is not a fixed attribute that a model either possesses or lacks, but a relational property that emerges from the interaction between system behavior, institutional oversight, and user expectation. The remainder of the paper proceeds as follows. Section two synthesizes the relevant literature across six thematic clusters. Section three details the qualitative, conceptual research design and the procedures used to construct the synthesis. Section four presents the resulting framework and its constituent dimensions. Section five discusses the implications, limitations, and future research directions, and section six offers concluding remarks.

2. Literature Review

2.1 The Evolution of Generative Artificial Intelligence in Enterprise Contexts

The trajectory of generative artificial intelligence within enterprise settings is inseparable from the broader development of foundation models, a term coined to describe large-scale architectures trained on broad data and subsequently adapted to a wide range of downstream tasks (Bommasani et al., 2021). The demonstration by Brown et al. (2020) that a sufficiently large transformer model could perform competitively across dozens of language tasks with minimal task-specific tuning marked a turning point, because it suggested that a single pretrained artifact could substitute for the bespoke systems that enterprises had previously commissioned for individual functions such as translation, summarization, or classification. Subsequent commercial deployment accelerated this shift further, and by the mid-2020s generative systems had become embedded in functions ranging from software engineering to engineering design and manufacturing process planning. Chen et al. (2026), in framing a special issue devoted to generative artificial intelligence for design, manufacturing, and materials systems, observe that these models are increasingly expected to participate not merely in language generation but in complex engineering reasoning tasks that were previously considered resistant to automation, including generative design exploration and materials discovery. This expansion of scope is significant for the present study because it illustrates that the trust problem is no longer confined to conversational or content-generation use cases; it now extends into domains where erroneous outputs carry direct physical, financial, and safety consequences.

Enterprise adoption research situates this technical trajectory within a broader narrative of digital transformation. Davenport and Ronanki (2018) distinguish between automation-oriented and insight-oriented applications of artificial intelligence within firms, arguing that the greatest return

on investment accrues to organizations that redesign workflows around the technology rather than inserting it into unchanged processes. Brynjolfsson and McAfee (2017) extend this argument by noting that the business value of artificial intelligence is realized unevenly, concentrated among firms that possess complementary organizational capital such as data infrastructure, cross-functional coordination, and a workforce capable of interpreting probabilistic outputs critically. Taken together, this literature suggests that the enterprise adoption of generative artificial intelligence is not a purely technical event but a reorganization of decision rights, one in which questions of trust are inseparable from questions of who within the organization is authorized to accept, override, or contest a machine-generated recommendation.

2.2 Conceptualizing Trust in Artificial Intelligence Systems

Definitions of trust in the artificial intelligence literature vary considerably in their unit of analysis. Floridi and Cowls (2019) approach the question at the level of societal principle, synthesizing existing ethical codes into five overarching commitments: beneficence, non-maleficence, autonomy, justice, and explicability. Jobin, Ienca, and Vayena (2019), through a systematic mapping of more than eighty ethics guidelines issued by governments, corporations, and civil society organizations, find substantial convergence around themes of transparency, fairness, and accountability, yet they also document a persistent divergence in how these principles are to be implemented, measured, or enforced. This divergence is the basis of Mittelstadt's (2019) influential critique, which argues that high-level principles, however widely endorsed, cannot by themselves constrain organizational behavior because they lack the professional norms, licensing regimes, and enforcement infrastructures that give analogous principles force in fields such as medicine or civil engineering. Mittelstadt's argument is particularly consequential for enterprise-oriented scholarship because it implies that trust cannot be manufactured through declarative commitments alone; it must be embedded in verifiable organizational practice.

A complementary line of scholarship approaches trust through the organizational behavior literature. Mayer, Davis, and Schoorman's (1995) integrative model, although developed originally to describe interpersonal trust between employees and supervisors, has been widely adapted within information systems research to describe the relationship between users and automated systems, on the premise that people extend social heuristics to non-human agents when the agents exhibit sufficiently autonomous or communicative behavior. Applied to generative artificial intelligence, the model implies that trust judgments are shaped by perceived competence, by the perceived benevolence of the system's design intentions, and by the perceived integrity of the process through which outputs are generated and validated. This reframing is useful because it directs attention away from a purely psychometric question of whether users subjectively feel confident in a system and toward the organizational and technical antecedents that make such confidence warranted, which is the orientation adopted in the present paper.

2.3 Technical Sources of Untrustworthiness: Hallucination, Bias, and Opacity

A substantial body of technical scholarship has documented the specific failure modes that undermine confidence in generative outputs. Ji et al. (2023), in a comprehensive survey of hallucination in natural language generation, distinguish between intrinsic hallucination, in which a model contradicts its own source material, and extrinsic hallucination, in which a model introduces content that cannot be verified against any available source, and they demonstrate that both forms persist across model scales and architectures despite substantial mitigation effort. This finding is critical for enterprise contexts because it indicates that scale alone, contrary to early optimism, is not a sufficient remedy; organizations cannot assume that a more capable model is automatically a more trustworthy one for high-stakes tasks.

Bias constitutes a second, closely related failure mode. Bender, Gebru, McMillan-Major, and Shmitchell (2021), in an argument that proved foundational for subsequent risk scholarship, contend that models trained on uncensored internet-scale corpora inevitably encode the social biases, exclusions, and power asymmetries present in that data, and that the fluency of generated text can obscure rather than reveal these embedded distortions, a phenomenon they describe through the metaphor of the stochastic parrot. Weidinger et al. (2021), writing from within a major artificial intelligence laboratory, extend this analysis into a broader taxonomy of harms, distinguishing discrimination and exclusion, information hazards, misinformation harms, malicious use, human-computer interaction harms, and environmental and socioeconomic harms. Their taxonomy is valuable for enterprise governance because it demonstrates that risk cannot be reduced to a single metric; different harms require different detection instruments, different organizational owners, and different points of intervention across the system lifecycle.

Opacity, the third recurring theme, concerns the difficulty of explaining why a model produced a particular output. Doshi-Velez and Kim (2017) argue that interpretability should be treated as a rigorous scientific objective rather than an afterthought, proposing that explanations be evaluated against explicit criteria of fidelity and comprehensibility rather than assessed impressionistically. Two influential technical methods have attempted to operationalize this objective for complex models: Ribeiro, Singh, and Guestrin's (2016) locally interpretable model-agnostic explanations, which approximate a complex model's behavior in the neighborhood of a specific prediction using a simpler surrogate model, and Lundberg and Lee's (2017) Shapley additive explanations, which draw on cooperative game theory to attribute a prediction to the contribution of individual input features. Although both methods were developed primarily for classification and regression tasks, their underlying logic, namely that trust requires some form of post hoc accountability for individual outputs, has informed subsequent efforts to audit generative language systems, even though the generative setting complicates the notion of a single attributable prediction.

2.4 Alignment and Mitigation Techniques

In response to these documented failure modes, a distinct technical literature has developed around alignment, understood broadly as the set of techniques intended to make model behavior

conform more closely to human intentions and institutional norms. Ouyang et al. (2022) demonstrate that reinforcement learning from human feedback, in which human evaluators rank candidate outputs and a reward model is trained on these rankings to fine-tune the underlying language model, produces outputs that human raters judge as more helpful and less harmful than those of a substantially larger unaligned model, suggesting that alignment technique can partially substitute for raw parameter scale. Bai et al. (2022) extend this paradigm through a method they term constitutional artificial intelligence, in which a model is trained to critique and revise its own outputs according to a written set of principles, reducing reliance on large volumes of human-labeled preference data while retaining a mechanism for harm reduction. Both approaches share the premise that trustworthiness can be engineered into a model's behavior during training, though critics note that such techniques address symptomatic behavior more reliably than they address the underlying representational biases inherited from pretraining data.

A second family of mitigation techniques addresses hallucination and factual grounding directly through architectural rather than purely behavioral means. Lewis et al. (2020) introduce retrieval-augmented generation, in which a language model is coupled with a retrieval mechanism that supplies relevant documents from an external corpus at inference time, allowing the model to condition its output on verifiable source material rather than relying solely on parameters learned during training. Gao et al. (2023), surveying the subsequent proliferation of retrieval-augmented approaches, distinguish naive, advanced, and modular retrieval architectures, and they observe that retrieval augmentation has become a default enterprise strategy precisely because it allows organizations to constrain a general-purpose model to a bounded, auditable knowledge base, such as internal policy documents or regulatory filings, thereby converting an otherwise open-ended generative task into a more verifiable retrieval and synthesis task. This architectural strategy is significant for the present framework because it illustrates that trust can be engineered not only through model training but through the surrounding information architecture within which a model operates.

2.5 Regulatory and Governance Instruments

Parallel to this technical literature, a governance and policy literature has sought to translate ethical principle into enforceable or quasi-enforceable structure. The National Institute of Standards and Technology's Artificial Intelligence Risk Management Framework (2023) organizes organizational practice around four functions, namely governing, mapping, measuring, and managing risk, and it explicitly positions trustworthiness as a multidimensional property encompassing validity, reliability, safety, security, accountability, transparency, explainability, privacy, and fairness. Its significance for enterprise practice lies less in any single prescription than in its insistence that risk management be treated as a continuous organizational function rather than a discrete certification event, a position that resonates with the lifecycle orientation adopted in this paper. The European Union's Artificial Intelligence Act (European Commission, 2024) advances a more prescriptive, risk-tiered regulatory model, imposing graduated obligations according to whether a system is classified as posing unacceptable, high, limited, or

minimal risk, with high-risk systems subject to conformity assessment, technical documentation, and human oversight requirements before market placement. The Act's extraterritorial reach means that multinational enterprises operating outside the European Union are nonetheless compelled to consider its provisions when designing generative systems intended for global deployment, a dynamic that has accelerated the convergence of governance practice across jurisdictions.

Complementing these instruments, a growing body of scholarship addresses the operational mechanics of algorithmic auditing. Raji et al. (2020) propose an end-to-end internal auditing framework that spans the full development lifecycle, from scoping and design through testing and post-deployment monitoring, arguing that auditing must be embedded within existing engineering workflows rather than appended as an external compliance exercise if it is to be effective. Mökander, Schuett, Kirk, and Floridi (2023), writing specifically about large language models, propose a three-layered auditing approach comprising governance audits of the organization's internal decision structures, model audits of the system's capabilities and limitations, and application audits of specific deployed use cases, on the grounds that no single audit level can capture risks that emerge from the interaction between organizational context and technical artifact. This layered logic informs the present paper's contention that trust mechanisms operating exclusively at the model level are insufficient without corresponding organizational and application-level controls.

2.6 Enterprise Adoption, Organizational Readiness, and Human-Centered Design

A further stream of literature examines the organizational conditions that mediate whether technical and governance safeguards actually translate into trust among the employees who interact with generative systems daily. Shneiderman (2020) argues for a human-centered artificial intelligence paradigm in which reliability, safety, and trustworthiness are pursued jointly through a combination of software engineering practices, internal auditing, and external regulation, and he emphasizes that meaningful human control, rather than full automation, should remain the design objective for consequential decisions. This position is consistent with the broader finding across the adoption literature that employees are more willing to rely on generative outputs when they retain clear authority to override or contest them, and when organizational incentive structures do not penalize the act of questioning a system's recommendation. Zhang et al. (2023), reporting aggregate industry and investment trends in the Stanford Institute for Human-Centered Artificial Intelligence's annual index, document a widening gap between the pace of capability improvement and the pace of responsible artificial intelligence investment across firms, suggesting that organizational readiness, measured in terms of governance staffing, internal audit capacity, and employee training, lags behind technical deployment even among firms that publicly commit to responsible artificial intelligence principles.

2.7 Synthesis and Identified Gaps

Read collectively, this literature reveals a field that has matured rapidly along several parallel but loosely connected tracks. Technical scholars have made considerable progress in characterizing specific failure modes and in developing mitigation techniques such as reinforcement learning from human feedback and retrieval augmentation. Governance scholars and regulators have translated ethical principle into structured frameworks and, increasingly, into binding legal obligation. Organizational scholars have documented the human and institutional conditions under which technology adoption succeeds or falters. What remains comparatively underdeveloped, however, is an integrative account that treats these tracks as interdependent rather than sequential, one that specifies how a technical mitigation such as retrieval augmentation interacts with an organizational condition such as employee override authority, or how a regulatory obligation such as conformity assessment is operationalized through an internal audit structure. This paper responds to that gap by synthesizing the reviewed literature into a lifecycle framework that makes these interdependencies explicit, thereby offering both a theoretical contribution to the trust literature and a practical reference structure for enterprise governance.

3. Methodology

3.1 Research Design

This study adopts a qualitative, theory-building research design conducted through an integrative and systematic narrative synthesis of existing scholarship, rather than through primary empirical data collection. This design was selected because the research question concerns the conceptual integration of dispersed literatures, spanning computer science, information systems, organizational behavior, and technology policy, a task for which synthesis methods are particularly well suited. Integrative reviews, unlike purely descriptive summaries, are directed toward the generation of new conceptual frameworks by identifying patterns, tensions, and complementarities across bodies of work that are not typically read in conjunction with one another (Torraco, 2005, as adapted within information systems synthesis practice). The design is theoretical rather than empirical in the strict sense, yet it follows a disciplined and auditable procedure intended to approximate the rigor associated with systematic review methods while retaining the interpretive latitude necessary for conceptual framework development.

3.2 Source Identification and Selection Criteria

Sources were identified through a structured search of established academic databases and repositories, including those indexing peer-reviewed journal articles, major conference proceedings in artificial intelligence and human-computer interaction, and authoritative policy documents issued by recognized standards bodies and regulatory authorities. Search terms combined constructs relating to generative artificial intelligence and large language models with constructs relating to trust, governance, risk, alignment, explainability, and enterprise adoption.

Inclusion was restricted to sources that met three criteria: first, publication in a peer-reviewed venue, a recognized standards body, or an official regulatory instrument; second, direct relevance to at least one of the six thematic clusters identified during initial scoping, namely technical evolution, conceptualizations of trust, technical failure modes, alignment techniques, governance instruments, and organizational adoption; and third, sufficient methodological or conceptual transparency to allow the claims made within the source to be evaluated against the original argument rather than accepted on the basis of citation count alone. Sources published prior to the emergence of the transformer architecture were excluded unless they contributed foundational organizational theory, such as the trust model of Mayer, Davis, and Schoorman, that remains directly applicable to contemporary technical contexts.

3.3 Analytical Procedure

The analytical procedure followed three iterative stages. In the first stage, each selected source was read in full and coded according to the trust dimension or dimensions it primarily addressed, using an open coding approach in which dimensions were allowed to emerge from the material rather than being imposed in advance. In the second stage, these codes were consolidated through constant comparison, a technique adapted from grounded theory in which newly coded material is continually checked against previously coded material to identify convergence, divergence, and conceptual redundancy; this process yielded the five overarching dimensions presented in the findings section. In the third stage, the relationships among these dimensions were mapped temporally, in accordance with the developmental lifecycle of an enterprise generative artificial intelligence system, from initial design scoping through deployment, monitoring, and audit, producing the lifecycle model that constitutes the paper's principal conceptual contribution. Throughout this process, memoing was used to document analytical decisions and to preserve a transparent audit trail linking each element of the final framework back to specific sources in the reviewed literature.

3.4 Validity, Reliability, and Reflexivity

Because this study does not involve primary data collection from human participants, conventional statistical measures of reliability are not applicable; instead, rigor was pursued through procedural transparency, source triangulation, and reflexive attention to the limits of a literature-based method. Triangulation was achieved by ensuring that each dimension in the resulting framework was supported by convergent evidence from at least two independent literatures, for example combining a technical account of retrieval-augmented generation with an organizational account of information governance, so that no single dimension rests upon an isolated or idiosyncratic source. Reflexivity required acknowledging that the selection and interpretation of sources inevitably reflects the analytical priorities of the researcher, and that an alternative synthesis emphasizing, for instance, labor economics or environmental sustainability rather than governance and reliability might have produced a differently weighted framework.

This limitation is addressed openly in the discussion section rather than concealed, consistent with standard practice in qualitative and conceptual research reporting.

3.5 Ethical Considerations

As the study relies exclusively on publicly available, previously published material rather than on human subjects, institutional review board approval was not required under prevailing research ethics conventions. Nonetheless, ethical care was exercised in the representation of cited work, with particular attention to accurate paraphrase, avoidance of selective quotation that might distort an original argument, and transparent acknowledgment of contested or unsettled claims, particularly regarding the comparative effectiveness of specific alignment techniques, where the literature does not yet offer definitive consensus. The paper further adopts a stance of regulatory neutrality when discussing instruments such as the European Union Artificial Intelligence Act, describing their provisions and rationale without advocating for or against their broader political merit, consistent with scholarly convention in policy-adjacent research.

4. Results and Findings

The synthesis yields an integrative framework organized around five interdependent pillars of trustworthy generative artificial intelligence in enterprise contexts, summarized in Table 1. The first pillar, technical reliability, encompasses the model-level properties most directly addressed by the hallucination and bias literature, including factual grounding, robustness to adversarial or ambiguous prompts, and consistency of output across repeated queries. The second pillar, transparency and explainability, extends beyond model interpretability techniques such as locally interpretable model-agnostic explanations and Shapley additive explanations to encompass documentation practices that allow non-technical stakeholders to understand a system's intended scope and known limitations. The third pillar, governance and regulatory alignment, captures the structural mechanisms, ranging from internal risk management functions modeled on the National Institute of Standards and Technology framework to external conformity obligations under instruments such as the European Union Artificial Intelligence Act, through which organizations formalize accountability. The fourth pillar, human-centered oversight, reflects the recurring finding across the adoption literature that meaningful override authority and appropriately calibrated user trust are necessary complements to any purely technical safeguard. The fifth pillar, organizational readiness, denotes the staffing, training, and incentive conditions that determine whether the preceding four pillars are implemented in practice rather than merely codified in policy documents that remain disconnected from daily operations.

These five pillars do not operate as an unordered checklist but as elements of a recursive lifecycle, illustrated in Figure 1. The lifecycle begins with design and requirement scoping, during which organizations articulate the risk appetite and stakeholder requirements appropriate to a given application, drawing on the risk-tiering logic embedded in contemporary regulatory instruments. It proceeds to data and model validation, in which technical reliability is empirically

tested through bias auditing and benchmarking prior to deployment. The third stage, controlled deployment, introduces human oversight mechanisms and operational guardrails, often through staged rollouts or sandboxed environments that limit the consequences of undetected failure. The fourth stage, continuous monitoring, addresses the well-documented tendency of model behavior to drift as usage patterns, underlying data distributions, or adjacent system components evolve after initial deployment. The fifth stage, audit and accountability review, closes the lifecycle through independent evaluation, whether conducted internally or by external assessors, and its findings are then fed back into the design stage through the recursive loop depicted in the figure, ensuring that governance evolves in response to observed rather than merely anticipated risk.

Figure 2 depicts these five pillars as interdependent supports for a single overarching outcome, namely enterprise trust in generative artificial intelligence outcomes, emphasizing that the absence or weakness of any single pillar constrains the trustworthiness of the system as a whole regardless of strength in the remaining pillars. This interdependence helps to explain a pattern noted repeatedly across the reviewed literature, wherein organizations that invest heavily in technical alignment techniques nonetheless report persistent user skepticism when governance documentation is opaque or when employees lack clear authority to contest system outputs, and conversely, organizations with robust governance charters but limited technical validation continue to experience reliability failures that governance structure alone cannot remedy.

Table 1. Dimensions of the Trustworthy Generative Artificial Intelligence Framework

Pillar	Core Mechanisms	Representative Literature
Technical reliability	Factual grounding, robustness testing, hallucination mitigation, retrieval augmentation	Ji et al. (2023); Lewis et al. (2020); Gao et al. (2023)
Transparency and explainability	Post hoc interpretability methods, model documentation, disclosure of known limitations	Ribeiro et al. (2016); Lundberg & Lee (2017); Doshi-Velez & Kim (2017)
Governance and regulatory alignment	Risk management functions, conformity assessment, layered internal and external auditing	NIST (2023); European Commission (2024); Raji et al. (2020); Mökander et al. (2023)
Human-centered oversight	Override authority, calibrated reliance, meaningful human control in consequential decisions	Shneiderman (2020); Mayer et al. (1995)
Organizational readiness	Governance staffing, employee training, incentive structures supporting responsible use	Brynjolfsson & McAfee (2017); Davenport & Ronanki (2018); Zhang et al. (2023)

Figure 1. Lifecycle Framework for Trustworthy Generative AI Governance in Enterprise Settings

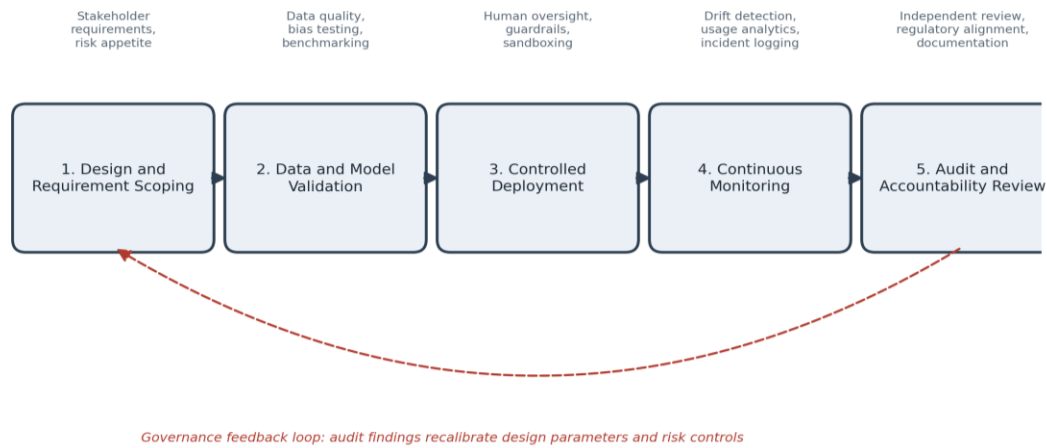
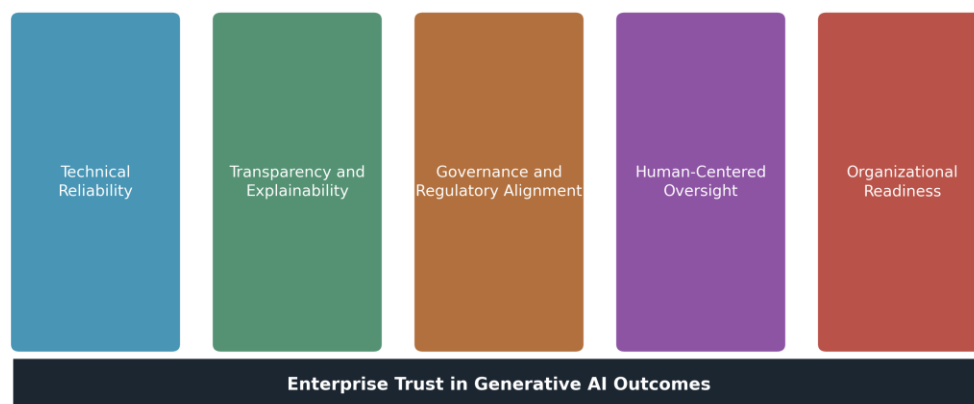


Figure 2. Five Interdependent Pillars Supporting Trustworthy Generative AI Adoption



5. Discussion

The findings speak directly to the research questions posed at the outset. Trustworthy generative artificial intelligence in enterprise contexts is best understood not as a property inherent to a model but as an emergent outcome of interaction among technical, governance, and human factors distributed across a system's operational lifecycle. This reframing extends the organizational trust model of Mayer, Davis, and Schoorman (1995) into the sociotechnical domain by demonstrating that perceived ability corresponds most closely to technical reliability, perceived integrity corresponds to governance and regulatory alignment, and perceived benevolence corresponds to human-centered oversight, with organizational readiness functioning as the enabling condition that determines whether these correspondences are realized in practice. The framework also clarifies why single-dimension interventions, such as adopting retrieval-

augmented generation without corresponding governance investment, tend to produce partial rather than durable improvements in user trust, since the interdependence among pillars means that weakness in one dimension constrains the returns available from strength in another.

These findings carry practical implications for enterprise leaders, suggesting that governance investment should be sequenced according to the lifecycle model rather than concentrated disproportionately at the deployment stage, where much current practice remains focused. They also carry implications for regulators and standards bodies, indicating that compliance regimes are more likely to succeed when they are structured around continuous lifecycle obligations, in the manner of the National Institute of Standards and Technology framework, rather than around a single point-in-time certification, in the manner more characteristic of traditional product safety regulation. Several limitations nonetheless qualify these conclusions. The synthesis is conceptual rather than empirical, and the framework's dimensions, while grounded in convergent literature, have not yet been tested against quantitative measures of organizational trust or adoption outcomes. The literature itself is also unevenly distributed across sectors, with considerably more published evidence available from technology and financial services firms than from manufacturing, healthcare, or public sector contexts, which may limit the generalizability of the organizational readiness pillar in particular. Future research should pursue empirical validation of the framework through comparative case studies or survey instruments capable of measuring each pillar independently, and should examine whether the relative weighting of the five pillars varies systematically by industry, regulatory environment, or national context, particularly as jurisdictions beyond the European Union develop their own binding artificial intelligence governance instruments.

6. Conclusion

This paper has argued that trustworthy generative artificial intelligence in enterprise settings cannot be reduced to a single technical or ethical property but must instead be understood as the joint product of technical reliability, transparency, governance alignment, human oversight, and organizational readiness, operating across a recursive lifecycle rather than at a single point of deployment. By synthesizing scholarship that has largely developed along separate technical, regulatory, and organizational tracks, the paper offers an integrative conceptual framework that clarifies how these tracks interact and where their interdependencies are most consequential for practice. The framework's principal scholarly contribution lies in demonstrating that fragmented, single-dimension treatments of artificial intelligence trust obscure the compounding effects that occur when technical and organizational safeguards are misaligned. For practitioners, the framework offers a structured reference point for sequencing governance investment across the system lifecycle rather than concentrating it narrowly at deployment. Future scholarship should prioritize empirical validation of the proposed pillars across diverse industry and regulatory settings, thereby transforming the conceptual architecture advanced here into a measurable and comparative instrument for enterprise governance research.

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