The Verification Bottleneck: [1]
What AI-Generated Engineering Means for Construction

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AI-generated engineering is not only an engineering issue; it is becoming a project delivery issue. As design output accelerates, someone has to govern how that output is reviewed, accepted, contracted, and paid for, and that responsibility increasingly falls to the project manager. Procurement, risk allocation, schedule, and professional accountability all sit downstream of an assumption that design work arrives checked, and that assumption is now breaking. The story of how we got here starts more than a decade ago.

The decade that taught us the pattern

A dozen years ago while engaged in a research partnership between a major US EPCM firm and IBM's Watson team, I witnessed and helped shape one of the earliest applications of AI to project prediction.

The team treated each project like a medical patient:

- 3,000 data elements became the "symptoms"
- Project managers filtered them to 300
- Executives narrowed them to 30
- AI learned from 80 historical "patients" and tested predictions on 20 more

The first model predicted failure with 83 to 85 percent confidence. But the breakthrough came when they added unstructured data – specifically, the project manager's monthly, brief narrative.

"We reran the AI…and now the confidence level was 93 to 94 percent" (Prieto, 2026).

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The lesson was profound: what people say matters as much as what they measure. And more importantly, complex systems reveal themselves through patterns, not checklists.

Subsequently, the limitations associated with the inherent bias in the training data became evident. Oil, gas and mining projects executed with the same project execution methodology were used by design at this Proof of Concept (POC) stage. Subsequent extension of the model to other domains such as power, life sciences and infrastructure delivered erroneous or incomplete performance insights.

Importantly, we learned a lot about the condition of our data, and what data was used in managing a project and by whom. More importantly we learned what management data wasn't used despite its rigorous collection. This did not necessarily mean the data wasn't valuable, but suggested we had yet to discover its value.

AI is delivering real value, and the industry's caution is not what it seems

The gains are real and growing. Across design and construction organizations, AI is streamlining document processing, reporting, specification review, meeting and RFI summarization, clash detection, and schedule analysis, with adopting firms reporting meaningful time savings and quality improvements in documentation-heavy work. Generation is advancing too: large design firms are deploying AI tools that produce mechanical and plumbing layouts, and the stated ambitions are larger still, with Prometheus, the most heavily funded entrant, publicly targeting design cycles ten times faster (public statements, 2026). A 2026 global survey of one thousand AEC professionals found that while only about a quarter of firms use AI in operations today, nearly all of those adopters plan to expand usage this year (Bluebeam, 2026). The direction is not in question.

What deserves a closer look is the industry's measured pace, which is often misread as technophobia. Engineering and construction are trades in which hallucination is not permitted: designs carry life-safety consequences, adopted codes are legally enforceable, and licensed professionals remain professionally responsible for the work they sign and seal. A profession built on verifiable correctness adopts probabilistic tools carefully because its obligations demand it. The observed pattern follows directly: AI adoption is succeeding fastest where occasional error is tolerable, in productivity and documentation work, and moving deliberately where it is not, in certified engineering output. That is not resistance to innovation. It is professional discipline, and it points to what the industry actually needs next: not slower generation, but verification that lets confident adoption extend into the engineering core. Independent verification of generated output remains largely unaddressed.

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When an AI-generated engineering design is used in procurement, the organization that deploys and relies on the AI output typically carries the majority of the risk. In other words, the procuring organization is the primary risk holder. AI is treated as a tool, not a legal actor. The user of the AI output in a consequential process such as design, procurement, construction is the responsible party. AI vendor liability caps, if any, are low and typically exclude consequential damages.

If the AI design is used as-is in the procurement documents, the procuring organization (owner, CM) carries the risk unless the design contract includes AI-specific design indemnification for design errors & omissions, data-related issues, and IP infringement; performance warranties related to fit-for-purpose, compliance, and accuracy; and limited liability carve-outs including no cap for safety-critical failures.

For AI output that is reviewed and stamped by a licensed engineer, the engineer of record assumes professional liability, including for incorporated AI-generated outputs. Normal risks associated with spec mismatches, bid package defects, and discriminatory or non-compliant automated evaluations remain with the procuring organization.

The individual engineer's professional responsibility is distinct from the contractual and economic exposure of the organization delivering the design. In U.S. construction, that exposure is allocated differently across the three common delivery methods: design-bid-build, CM-at-risk, and design-build. AI does not remove that exposure; it introduces a new source of design risk within those existing contractual structures.

Table 1 – AI Design Risk Under Varying Contracting Structures

Delivery Method	AI-Related Risk Allocation	Similarities	Differences	Modifications for Engineers
Design-Bid-Build	Primary design risks remain with the design professional.	Engineers retain professional responsibility in all methods.	Risks remain largely on the design professional.	Engineers must now consider AI as a factor in design risk.
CM-at-Risk	Design risk is shared with the construction manager.	AI introduces new risk factors in all methods.	Construction manager also has input into the design phase.	Engineers must collaborate closely with construction managers on AI-related design elements.

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Delivery Method	AI-Related Risk Allocation	Similarities	Differences	Modifications for Engineers
Design-Build	Design and construction risks are more integrated and shared within a single entity.	All methods still require the engineer to oversee AI factors.	Design and construction team share the design risks in a unified structure.	Engineers work within an integrated team, balancing AI risks across design and construction phases.

The engineer of record becomes the convergence point

Consider where accelerated generation actually lands. On any project, design information flows toward the engineer of record from every direction: the owner's requirements and changes, the architect-engineer team's evolving design, the construction manager's constructability input, the constructor and trade contractors' shop drawings and substitutions, suppliers' component data. AI is now multiplying the volume and speed of every one of those streams, while the capacity of the professionals who must verify and take responsibility for them scales not at all. Many engineers already feel this in daily practice.

At the same time, AI is moving the boundaries between disciplines in a subtler way. When a mechanical engineer is unhappy with the power budget or footprint another discipline has imposed, it is now trivial to generate an alternative electrical or architectural concept and bring it to the table; when an architect is squeezed by mechanical space requirements, the same tools produce a counter-proposal in minutes. Each move is rational and often well intentioned, an engineer trying to relieve constraints and requirements that drive their own scope. In aggregate, the effect is a new kind of chaos: every discipline now receives design suggestions generated outside its own review chain, by non-specialists, prompted to favor the requester's needs. Subject-matter experts spend growing hours verifying advocacy dressed as design, and the verification load concentrates precisely where authority concentrates: on the licensed professionals whose stamp closes the loop. The bottleneck is not a distant forecast. It is the present tense of engineering practice, and it grows with every improvement in generation.

Enterprise and functional risk registers must be expanded and strengthened. Responsibility, Accountability, Consulted, Informed (RACI) matrices and contract structures must evolve, addressing not just new risks but also the changes in project execution methodologies that are required to minimize risk while capturing the promise of AI. The following list highlights some of these new risks.

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New AI-Related Risks

- IP infringement
- Data not fit-for-purpose (bias or inappropriate training data/training data provenance)
- Data misuse
- Model errors causing procurement, construction or operations defects
- Fitness for procurement use
- Incomplete professional review (qualified human-in-the-loop)
- Transparency, Auditability, Model version control
- Incomplete or inadequate stress testing for hallucination
- Incomplete prompt history

As AI-generated design broadens, the human capacity for review risks becoming overwhelmed. It is here where responsibility matrices must shift in meaningful ways. Human centric validation cannot scale with AI-generated volume; it must be augmented by system-centric assurance. That change cannot be accomplished by fiat. It must evolve beginning with redefining the roles, duties and capabilities required at each step in the project execution process. As today's roles evolve, new AI-specific roles will come to the forefront. System-centric assurance will reallocate responsibilities and liabilities based on process capabilities and performance, not today's professional engineering review.

This shift from human-centric to process-centric must be accompanied by new contractual clauses and mechanisms. Table 2 outlines some of the changes to be considered.

Table 2 – Contract Clauses and Mechanisms

Mechanism	Purpose / Requirement
Model performance warranties	These serve to instill process confidence and will go a long way to addressing the verification bottleneck. Specifically they must provide clear and meaningful validation metrics; error (hallucination) rates; accuracy (to ascertain fit-for-purpose)
Quality guarantees	Satisfied through deterministic verification of completeness, code compliance, and consistency
Hallucination frequency and patterns	Potential failures and errors to aid in targeted reviews
Version stability	Avoid mid-design model changes or updates

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Mechanism	Purpose / Requirement
Changed review requirements	Review everything shifts to review by exceptions. This necessitates automated triage (same AI or different AI). Risk grading in triage process (safety critical?). Mandatory human-in-the-loop review for all flagged items.
Sampling reviews	Non-safety critical elements (similar to QA)

New risks and a changed process will require new roles in the project execution chain. These new roles must feature prominently in the changed RACI matrix, and governance and contract protocols. Table 3 suggests some additional roles that should be considered.

Table 3 – New AI-Specific Roles

Role	Responsibility
AI System Owner (ASO)	Accountable for AI configuration, version control, integrity. The ASO must confirm the AI system's configuration is documented, version-controlled, and tested, and that its outputs are routed through deterministic verification. Has audit rights for model lineage and training data.
Vendor AI Assurance Officer (VAO)	Protects model lineage and provenance of the training data. Provides the reports required to address risks listed above and the clauses and mechanisms outlined in Table 2.
AI Validation Lead (AVL)	Responsible for designing, maintaining and automating the validation pipelines. They must answer the question “Does the AI system meet the real-world need it’s supposed to solve?”
Human Oversight Authority (HOA)	Reviews all exceptions. Approves AI risk tiers.

When AI-generated designs overwhelm human capacity to review them, the seal still anchors professional responsibility: the engineer remains responsible for work performed under their responsible charge, regardless of the tools used to produce it. What may expand is exposure within the project delivery chain, as contractual responsibility extends to parties that select, configure, and control the use of the AI system, without displacing the licensed engineer’s obligations for work signed and sealed. That exposure does not necessarily extend to the AI software provider,

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whose contractual terms may limit or exclude such liability. NSPE's Board of Ethical Review has already drawn this line in its first case on AI in engineering practice: AI-generated technical work requires at least the same scrutiny as work produced by humans, and a high-level review before sealing does not satisfy responsible charge (NSPE Board of Ethical Review, 2024). Licensing boards and the professional liability bar need to not just catch up with the challenges AI-generated design will represent, but help lead the systemic transformation that is required.

AI-generated design liability frameworks must ask:

- Who controls the model – they should carry model performance liability
- Who configures the model - they should carry configuration liability
- Who is responsible for unreviewed items – these represent shared liabilities
- What are the procurement-specific AI thresholds
- What are the continuous monitoring and rollback rights

The price of the bottleneck

Published estimates of construction error and rework vary materially because studies measure different phenomena with different methods. CII's early study of nine industrial projects found deviations requiring rework averaging 12.4 percent of installed project cost, with design changes, errors, and omissions accounting for 79 percent of deviation cost. Later CII benchmarking found mean field rework above 3 percent of construction-phase cost on heavy industrial projects (CII RS153-1, 2001). A questionnaire study of 139 Australian projects reported practitioners' mean estimates of direct and indirect design-error costs of 6.85 and 7.36 percent of contract value (Lopez and Love, 2012), with the authors noting that actual costs remain relatively unexplored. A federal study reported by the National Research Council found average cost growth of about 6 percent, attributed primarily to design error, 50 to 65 percent, and owner changes, 23 to 35 percent. GIRI, using a much broader definition that includes unrecorded process waste, latent defects, and indirect costs, estimates total avoidable error at 10 to 25 percent of project cost, roughly seven times annual UK construction-industry profit (GIRI, 2016). And a 2026 ASCE study based on actual contractor records reported far lower measured field rework, 0.38 percent before completion and roughly 0.76 percent including estimated post completion corrections, illustrating why these figures should not be treated as directly comparable (Love, 2026).

The common signal is not one universal percentage. Error is economically material, design-related causes are consistently among the largest drivers, and correction grows more disruptive as decisions become embedded in procurement, construction, and operation (MacLeamy, 2004). In the first author's experience leading facility engineering at a national laboratory, nearly all

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operations rework traced back to design. Verification at design time addresses design error directly and, by making requirements explicit and complete before design proceeds, part of change-driven rework as well. Independent industry work points the same direction: GIRI's 2025 review of artificial intelligence and error reduction calls for human oversight and assurance of AI outputs, including rules-based verification of designs against standards (GIRI, 2025).

Why verification is the hard half

A verification layer, unlike a generation tool, is not allowed to hallucinate. A verification layer cannot rely on the probabilistic model to verify itself. It requires independent deterministic calculations, explicit rules and standards, controlled source data, and auditable evidence outside the generative model. The industry's bottleneck is shifting from producing designs to proving them, and the two problems demand different architectures.

Two distinct problems travel under the word verification, and the distinction matters for everything that follows. The first is AI-system assurance: whether the AI system itself is appropriately governed, tested, controlled, and used within its intended bounds. This is the territory that NIST's AI Risk Management Framework and its Generative AI Profile address through testing, evaluation, verification, and validation (TEVV) (Tabassi, 2023; Autio et al., 2024), and it is the problem the governance framework in this article takes on. Assurance operates on the process and the system. Because a generative model is stochastic, a process assured under TEVV can still produce different outputs from the same inputs on different runs; assurance constrains how the system behaves, it does not certify any single result. The second is engineering-output verification: whether a specific design satisfies physics, applicable codes and standards, and the constraints of real components. That determination is deterministic, and it is independent of the model that produced the design. Engineering already institutionalizes this kind of check: high-consequence structures such as bridges require category 3 independent design checks in which a separate organization re-derives the calculations from scratch. What changes with AI is the volume of design that must pass through such a layer.

Governance can assure the AI system. It cannot substitute for independent verification of the engineering output. Both are required, and the remainder of this article treats them as separate obligations. Neither layer by itself displaces the licensed engineer's professional obligations for work performed under responsible charge. In the layered defense terms long used in safety engineering, both sit before the seal as additional slices that catch what earlier reviews miss (Reason, 2000). The verification layer can serve that role only if it is itself deterministic: reproducible, version controlled, and traceable, so the engineer who signs can rely on it. A design may be generated by any method; a verification layer that is itself probabilistic cannot anchor trust.

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Assurance can bound how an AI system is used; it does not prove that a specific engineering design is correct. For consequential engineering outputs, system controls can constrain generation, but the design still needs an independent acceptance check before release. Autonomous driving offers a useful analogy: the AI does not operate on trust alone; it operates inside a broader safety system with defined operating limits, monitoring, fallback behavior, testing, and deployment evidence. Engineering AI will need its own equivalent before generated designs can be trusted at scale. Assurance makes the system trustworthy as a process; verification makes a specific engineering output trustworthy.

NIST focuses on governing, testing, and monitoring the AI system. NSPE focuses on the engineer's obligation to scrutinize the technical work before relying on or sealing it. Those are different obligations: the first governs the system; the second requires confidence in the engineering result. At AI scale, that second obligation requires automated, reproducible engineering verification. Industry guidance is converging on the same conclusion (GIRI, 2025), and semiconductor practice, where deterministic signoff is the norm, shows the destination. Assure the system. Verify the design.

AI-system assurance is the governance mechanism that provides justified confidence in:

- **Implementation fidelity** - Confirms that configured controls, thresholds, escalation logic, and required verification pathways operate as documented.
- **Policy compliance** - Confirms the system adheres to regulatory constraints (e.g., fairness rules, safety requirements, auditability mandates) and demonstrably meets defined acceptance criteria and operates within approved constraints and risk tolerances, including under edge-case conditions.
- **Structural integrity** - Verifies the internal architecture: model structure, rule engines, decision trees, safety rails, and fallback logic and ensures deterministic components behave deterministically and stochastic components remain within approved variability envelopes.
- **Controlled, bounded behavior** - Ensures risk-tiering thresholds, exception triggers, and escalation pathways are implemented exactly as designed. Prevents unauthorized autonomy or unbounded decision-making.
- **Auditability and traceability** – This is one of several governance methods and tools. Table 4 provides a fuller range.

It ensures that the AI system’s internal logic, decision pathways, and operational constraints strictly follow approved design intent, regulatory obligations, and organizational policy.

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Table 4 – AI-System Assurance Methods

Method	Purpose
Formal Verification	Mathematical or symbolic methods to prove that a constrained, deterministic system, including its components and interactions, cannot violate defined constraints.
Rule-Based & Policy Checks	Automated scanning of decision logic against governance rules.
Simulation & Scenario Testing	Synthetic environments to verify behavior under stress, edge cases, and adversarial conditions.
Unit & Integration Testing	Granular verification of components and their interactions.
Auditability and Traceability	Governance requires that every decision be documented, explainable, and attributable to specific logic paths, with deterministic results reproducible time after time, run after run.

What verified AI-assisted delivery looks like

A working model is emerging: AI assists with generation and explanation; deterministic methods verify results against physics, applicable codes, and real component data; engineers decide with complete, reproducible, auditable evidence. Organizations that establish such verification practices may find they can adopt AI-assisted design more confidently, not less.

This division of labor reflects the limitations of both approaches rather than a preference for either. Deterministic methods are expensive to build and slow to extend: every domain requires its own validated models, normalized data, and encoded code provisions, and the knowledge engineering that produces them has been a recognized bottleneck since the expert-system era. The resulting tools are fragmented across disciplines and vendors, and they are poor instruments for open-ended exploration; they evaluate what they are given rather than proposing what might be. Generative AI inverts each of these properties. It is fast and inexpensive at producing candidate designs, it moves across domains without retooling, and it can surface concepts a constrained search would never reach. That speed is real value, and nothing in this article argues against it. The argument is narrower: the properties that make generation fast are the same properties that make it unsuitable as its own acceptance test, and the properties that make deterministic methods slow to build are the same properties that make them reliable once built.

Any AI-enabled system, workflow, or automation used by designers, fabricators, suppliers, contractors, or commissioning agents must demonstrably meet defined acceptance criteria, operate

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within approved constraints and risk tolerances, and be policy-aligned, traceable, and auditable. As such verification must become a contractual obligation, not an asserted claim.

These are two different obligations, and contracts must secure both. Assurance of the AI systems themselves follows the governance framework above. Independent verification of the engineering outputs those systems produce is a separate requirement wherever safety or code compliance is at stake.

Owners and CMs must contractually require that every AI system in the delivery chain is subject to documented, risk-appropriate testing, evaluation, verification, and validation, with independent engineering-output verification where safety or code compliance is at stake. Verification becomes:

- A condition of acceptance
- A prerequisite for payment
- A warranty obligation
- A governance safeguard

This is how Owners prevent AI from becoming an uncontrolled actor in the project ecosystem. It is how they ensure every AI-assisted decision is verified before release, compliant, and auditable.

Two structures support this verification objective. The first is a well-founded set of mandatory contract clauses. An indicative set of such clauses is set out below. The second structure is a well-defined delivery-chain enforcement structure as illustrated in Table 5.

Mandatory Contract Clauses

- Suppliers (at each level) shall submit an AI Verification Plan prior to any AI-enabled work defining verification methods, evidence, test environments, acceptance criteria and responsible parties.
- Suppliers shall verify conformance of all AI logic to owner-approved specifications, constraints and policy. No exceptions
- All verification must be evidence based and stored in a Common Data Environment (CDE). The evidence is to be comprehensive and in accordance with owner's requirements. Evidence may include, but not be limited to, test logs, model outputs, rule-evaluation logs, any exception reports, if any.
- All AI-generated output shall include a traceable decision record covering model and version, input requirements, prompt or context where appropriate, retrieved sources, deterministic rules and checks applied, exceptions raised, outputs, and approval history.

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- All AI models and associated rules and logic are to be version controlled. Governance of change will be per owner's requirements.
- Suppliers shall verify all elements of risk control including that thresholds, escalation triggers and safety features operate as designed.
- Supplier verification shall include bias testing
- Supplier shall verify applicable regulatory, ethical, and contractual fairness requirements across AI-supported decisions. Where decisions affect people, for example employment, eligibility, or procurement scoring, verification shall include applicable documented protected-class analysis and compliance reporting.
- Owner has right to appoint an independent verification and validation agent and supplier must provide unfettered access.
- Verification failure will require remediation, re-testing and owner approval to ensure defects can't propagate.
- Supplier will warranty that all elements of AI have passed certification at each milestone/major deliverable.

Table 5 – Delivery-Chain Enforcement Structure

Delivery-Chain Party	AI Assurance / Verification Requirement
Designers	Verified rule set, constraint logic, model inputs, data governance, safety limits and rules
Fabricators	Assured automated QC/inspection AI; robotic/automated fabrication logic; SPC and anomaly detection models
Suppliers	Assured AI documentation systems with deterministically verified outputs; logistical optimization AI; chain of custody automation
Contractors	Assured scheduling, sequencing, and risk-focused AI; installation support AI; site safety AI
Commissioning Agents	Assured automation of functional tests; sensor-driven diagnostics; performance prediction models

Owners and CMs have a range of enforcement mechanisms available to them and linked to both the mandatory clauses above and the enforcement structure outlined in Table 5. These mechanisms should be included in the appropriate contract clauses and include gate-based acceptance; retention; right of rejection; and LDs. Owners and CMs should ensure they have contractual audit

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and evidence-access rights sufficient to verify compliance, through APIs, logs, reports, secure audit interfaces, or equivalent mechanisms and receive digital signatures on all verification artifacts.

The engineer's role does not shrink; it moves

The professional engineer's judgment migrates from producing calculations to directing and certifying verified outcomes. As AI becomes embedded in design workflows, the professional stamp carries more weight, not less, and delivery practices will need to be structured around that accountability. NSPE's current position statement on artificial intelligence points in the same direction, calling for rigorous verification and validation, testing, and continuous monitoring of AI systems that affect public safety, under professional engineering oversight (NSPE, 2026). The distinction drawn earlier holds to the end: governance can assure the AI system, but it cannot substitute for independent verification of the engineering output. Directing that verification is where the stamp will matter most.

In the period ahead, engineering leadership will likely need to focus on additional demands due to the expanding use of AI in design. First, there will be an emphasis on ethical oversight and governance. Leaders must ensure that AI tools are used responsibly and that the verification of AI-generated outputs is rigorous and transparent.

Second, engineering leaders will need to champion a culture of interdisciplinary collaboration, bringing together expertise from AI specialists, software engineers, and traditional engineering disciplines to ensure that AI is effectively integrated into the design process.

Finally, there will be a continued push for developing standards and best practices for the verification and validation of AI-assisted designs. This will ensure that the professional engineer's seal remains a key indicator of quality and accountability in an AI-driven environment.

To achieve those objectives, engineering capabilities will need to evolve in a few key ways. One significant change will be the development of advanced systems thinking skills, especially among engineering leaders. This means that leaders will need to understand how various systems interact and how AI fits into the larger design process.

Continuous learning will also be essential, as the rapid pace of AI advancements means that engineers will have to continually update their knowledge and skills. In addition, engineers will need to develop stronger ethical oversight capabilities to ensure responsible AI use, and they'll need to collaborate more closely across disciplines to integrate AI effectively into their work.

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