

Strategic Organization and AI Adoption in Engineering Practice

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Introduction

In the inaugural issue of the *Engineering Project Organization Journal*, Chinowsky (2011) argued that research on engineering–construction enterprises as business organizations remains significantly less mature than comparable bodies of work on manufacturing and service enterprises. This extended abstract takes that observation as its point of departure and introduces an analytical framework for AI adoption to help interpret patterns of AI adoption in architecture and engineering (A/E) delivery firms, including large multidisciplinary design and program management organizations such as AECOM and Arcadis.

While discussions of AI in engineering education and practice often suggest rapid technological transformation, everyday experience inside A/E firms points to a more restrained pattern of adoption. To date, AI use has concentrated on narrow, low-friction applications such as image-based asset classification and internal policy chatbots. Although these tools improve information processing, they do not intervene directly in core delivery workflows. At the same time, even simple decision-support tasks embedded in routine workflows, such as verifying alignment between proposed project roles and resumes during proposal preparation, often remain unsupported.

This contrast raises a central question: *where, and under what organizational conditions, can AI meaningfully intervene in A/E delivery firms?*

Emerging evidence from AEC practice suggests that implementation challenges are frequently rooted in misalignment between planning and execution, particularly in how problems are framed and how solutions are operationalized (Agrawal et al., 2023). At the same time, A/E delivery firms are characterized by project-based organization, distributed authority, and professional accountability, which shape how decisions are made and enacted in practice (Chang, forthcoming). This paper interprets the observed challenges in AI implementation through the organizational structure of A/E delivery firms. To do so, it develops a framework that distinguishes between firm organization and strategy, engineering workflows, and underlying decision types, providing a way to interpret why some AI applications are readily accommodated while others encounter resistance. The framework also highlights implications of these dynamics for engineering education and professional practice.

Analytical Framework for AI Adoption

Figure 1 presents an analytical framework that links firm organization and strategy, engineering workflows, and cross-cutting decision types to interpret patterns of AI adoption in A/E delivery firms. In this framework, AI is conceptualized as a stress test of organizational alignment, in that attempts to embed AI within workflows expose gaps between how work is structured, how decisions are made, and how responsibility is assigned.

As illustrated in Figure 1, AI can be applied at multiple points within the firm, including at the level of strategic analysis and within engineering workflows, but the nature of organizational constraint changes as AI shifts from informing predictive decisions to intervening in coordination-intensive ones.

The top layer, **firm organization and strategy**, captures how A/E firms position themselves in the market and govern professional practice. Strategic choices about project selection and delivery roles, combined with ownership structure and capital exposure, shape risk tolerance and authority. Whether a firm is employee-owned, privately held, or publicly traded influences how it absorbs losses, manages long receivables, and allocates decision rights across the organization. These strategic and financial conditions establish the outer boundaries within which workflows operate and decisions are made.

The middle layer, **engineering workflows**, represents how work is actually carried out across proposals, design, and delivery. A/E workflows are project-based, multidisciplinary, and often customized to specific clients and contracts. Coordination across disciplines, interfaces with owners and regulators, and sequencing of work are central features. While some aspects of these workflows can be standardized, much of their effectiveness relies on informal communication, professional judgment, and trust rather than tightly scripted procedures.

Decision types cut across both organizational layers, distinguishing between decisions that are primarily predictive and those that are primarily coordinative. In A/E delivery firms, predictive decisions include tasks such as cost estimating, where AI can support forecasting and scenario analysis. Coordinative decisions, by contrast, include schedule management, where outcomes depend on aligning people, disciplines, and contractual responsibilities rather than on prediction alone. This distinction helps clarify why AI is more readily applied to some tasks than others, independent of technical sophistication.

The framework provides a way to understand why AI adoption in A/E firms appears to be shaped less by computational capability than by how strategy, workflows, and decision types are aligned. AI applications are more readily accommodated in contexts where decision responsibilities are clearly defined, workflows are structured, and outputs can be evaluated against established criteria. Conversely, adoption is more constrained in coordination-intensive settings where outcomes depend on professional judgment and shared accountability.

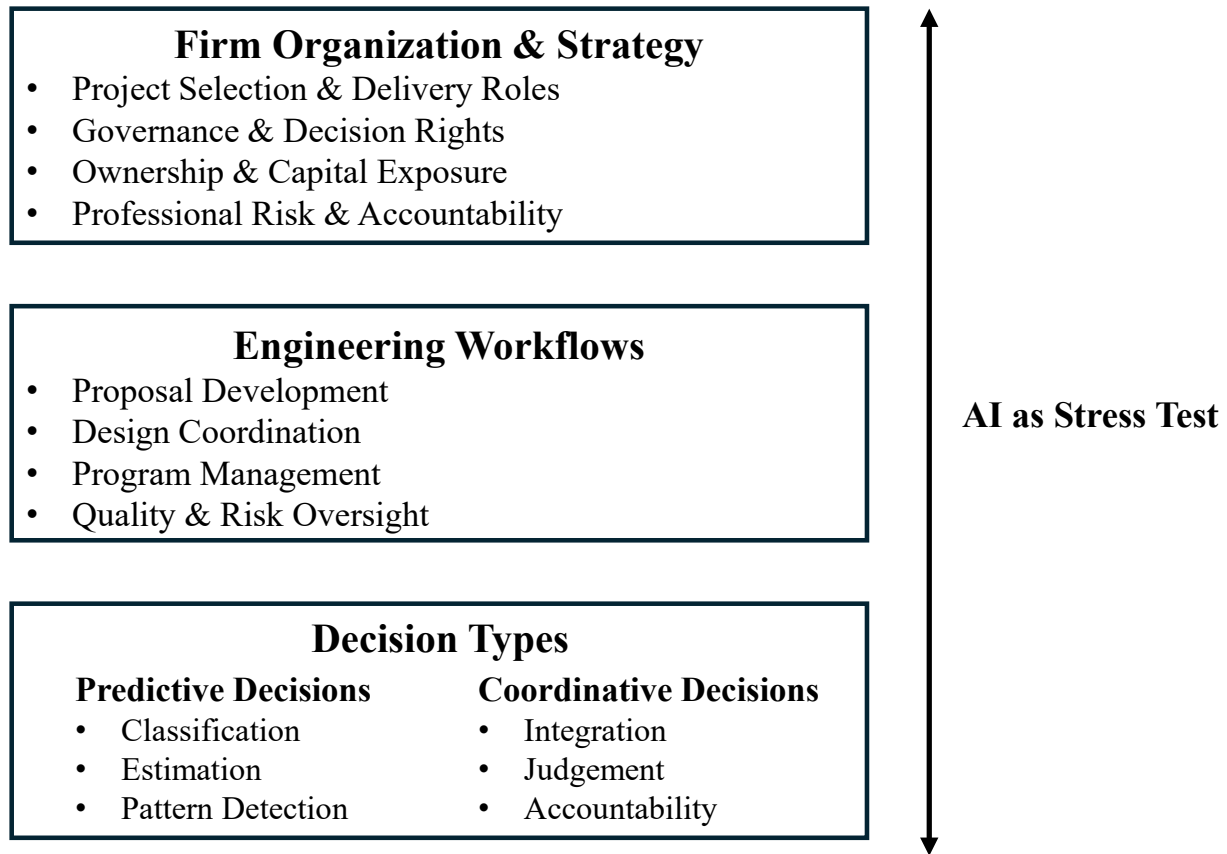


Figure 1 Analytical Framework for AI Adoption in A/E Delivery Firms.

The figure illustrates the relationship between firm organization and strategy, engineering workflows, and underlying decision types that cut across these layers. Bullet points within each box are representative examples drawn from common A/E delivery practice and are intended to be illustrative rather than exhaustive. Other organizational workflows (e.g., accounting, human resources, and legal) are not shown, as the focus here is on delivery-related workflows where AI adoption intersects most directly with professional judgment and project risk.

Methods

This paper takes an exploratory approach, drawing on practitioner-informed examples, teaching cases, and observed patterns in A/E delivery practice. These observations are used to develop and apply a framework for interpreting how AI is currently being used and where it encounters constraints. The aim is not to provide comprehensive empirical analysis, but to offer a structured way of understanding patterns in practice.

Current AI Use in A/E Practice

Interpreted through the analytical framework shown in Figure 1, current AI use in A/E delivery practice has concentrated on narrow, low-friction applications that minimize disruption to existing organizational arrangements. Common examples include image-based asset or condition classification and internal policy or procedures chatbots. These tools improve information

processing and access, but they do not intervene directly in core delivery workflows or alter how authority and responsibility are allocated. As such, they can be deployed without requiring changes to governance, escalation pathways, or professional judgment.

By contrast, even low-risk decision-support tasks embedded in routine workflows often remain unsupported. One example is the verification of alignment between proposed project roles and the resumes included in proposal submissions. Although technically straightforward and well within the capabilities of existing AI tools, such applications would require explicit intervention in established workflows. Implementing even a basic safeguard would require explicit assignment of responsibility for performing the check, clarity on who is authorized to act on discrepancies identified by the system, and agreement on how accountability is handled if errors persist. In practice, these questions intersect directly with established proposal workflows and professional responsibilities, making even technically straightforward interventions organizationally non-trivial.

The pattern suggested by these examples, and consistent with observed practice in A/E firms, is that organizations are more willing to adopt AI applications that leave existing arrangements untouched than to implement tools that would formalize checks, expose errors, or require adjustments to workflow authority and accountability. This is evident in workflows such as non-conformance reporting (NCR), where resolution depends on coordination across multiple parties and the assignment of responsibility under contractual and professional obligations. In such contexts, the challenge is not simply generating a technically plausible response, but determining who has the authority to act and how that decision is validated.

It is also important to acknowledge variation across firms. Large, publicly traded organizations with greater capital capacity may invest more visibly in AI initiatives and experimentation. However, observed differences across firms often reflect scale and resourcing rather than a departure from the organizational constraints highlighted here. Even in well-capitalized firms, AI adoption appears to cluster around predictive uses that support analysis or information retrieval rather than applications that would intervene directly in coordination-intensive workflows or reallocate professional decision rights.

Discussion and Implications

The framework reflects the idea that in A/E delivery firms, AI does not enter a neutral technical environment, but an organizational system shaped by project-based work, professional licensure, contractual risk, and long-established norms of coordination. Viewed in this light, patterns of AI adoption in these firms appear less puzzling and more closely related to organizational structure. Across A/E delivery practice, AI adoption appears to be concentrated in contexts where it supports predictive tasks, improves information access, or augments analysis without intervening in workflows or reallocating professional decision rights. This pattern reflects the distinction between predictive and coordinative decision types in the framework. Conversely, it is

reasonable to expect that even modest AI applications that would formalize checks or introduce decision-support into routine workflows would encounter resistance where they intersect with questions of authority, accountability, and professional responsibility. This suggests that AI adoption in A/E firms may be shaped less by technical feasibility than by the alignment between organizational structure, workflows, and decision types.

These observations carry several implications for how AI adoption is understood and discussed in engineering practice. First, it suggests caution in narratives that frame AI adoption primarily as a technology diffusion problem driven by tool maturity, cost, or user capability, rather than as an organizational challenge shaped by workflows, decision rights, and professional accountability. Applications that challenge these arrangements, even in small ways, require explicit decisions about who may act on AI outputs, how errors are handled, and where responsibility ultimately resides. Without addressing these questions, AI initiatives are likely to remain largely confined to low-friction applications regardless of their technical sophistication.

Second, the framework helps explain why comparisons to AI-enabled firms in other industries must be made carefully. In sectors such as e-commerce, logistics, or financial services, workflows are often more standardized, decision rights more centralized, and accountability more readily absorbed by the organization rather than individual professionals. In contrast, A/E delivery firms operate in environments where professional judgment is integral to delivery and where errors can carry significant contractual, reputational, and legal consequences. The organizational constraints identified in Figure 1 help explain why AI applications commonly used in other industries may face higher barriers in A/E contexts, even when the underlying technology is mature.

The framework also has implications for engineering education. If AI adoption in practice is conditioned by organizational structure rather than technical capability alone, then preparing engineers to engage meaningfully with AI requires more than exposure to algorithms or tools. It requires an understanding of how work is organized, how decisions are made, and how authority and responsibility are distributed within firms. From this perspective, strategic management concepts are not merely ancillary to AI education but may be foundational to its application in practice, consistent with emerging work on strategic literacy in engineering education (Chang, 2026). They provide a useful context for understanding where AI-generated prediction can be embedded productively, where it is likely to be resisted, and what organizational adjustments would be required to support more consequential forms of adoption.

Accordingly, graduate programs may consider incorporating AI explicitly into courses that address the management of infrastructure systems. Rather than presenting AI as a technical subject in its own right, a focused instructional module can use AI-generated prediction as an organizing device for examining engineering workflows, decision types, and governance arrangements. Such a module would encourage students to analyze specific tasks within delivery processes, distinguish between predictive and coordinative decisions, and consider how AI

outputs might alter escalation pathways, incentives, and professional accountability. The goal is not to train engineers as data scientists but to equip them with the organizational literacy needed to assess AI adoption as a professional and managerial challenge.

Finally, the framework suggests several directions for future research. As AI tools increasingly intersect with project delivery, questions of ownership structure, capital capacity, and risk absorption are likely to become more salient. Firms with greater financial resilience may be better positioned to experiment with AI applications that intervene more directly in workflows, while others may remain constrained to peripheral uses. Comparative studies across firms, delivery models, and institutional contexts could help refine the organizational conditions under which AI adoption moves beyond low-friction applications. More broadly, AI may provide a revealing case for advancing research on engineering enterprises as business organizations, responding directly to Chinowsky's call to deepen understanding of how these firms are structured, governed, and transformed over time.

References

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