AI Across the Industrial Project Value Chain: From Tools to Decision Assurance [1]

A cross-domain review of recent professional and academic literature from 2023 to mid-2026

By Konstantin Lagutin

Abstract

This review maps professional and academic literature published from 1 January 2023 through mid-July 2026 on the applicability of artificial intelligence (AI) across the industrial project value chain – from front-end planning and design through construction, commissioning, operational readiness, and production. It draws on a curated, deduplicated corpus of 118 publications covering project management (PM), design and engineering (D&E), industrial construction, and mining. The selected platforms connect directly or indirectly to capital-intensive industrial projects and reflect the author's professional experience and specialization. The evidence base is predominantly practice-led: 83 publications are practical or applied and 35 are theoretical or academic, a ratio of roughly 7:3.

- PM writing concentrates on adoption, governance, decision support, project controls, and PMO transformation.
- D&E, despite its high value potential, remains the smallest stream, with early work on AI-BIM interaction, generative structural design, design-to-cost, and asset-life decisions.
- Construction emphasizes schedule risk, field evidence, safety, coordination, and automation.
- Mining remains the most research-intensive sectoral stream, addressing planning under geological uncertainty, geotechnical design, predictive maintenance, safety, and production optimization.

The review shows that substantive industrial applications were already emerging in 2023 and that governance, risk, assurance, and ethics have become the largest cross-domain topic. The literature is moving from day-to-day productivity tools toward governed decision infrastructure. Viewed along the industrial project value chain, AI creates its strongest value when earlier, better-evidenced intervention can prevent design, cost, schedule, safety, or production losses before commitments become difficult to reverse.

[1] How to cite this paper: Lagutin, K. (2026). AI Across the Industrial Project Value Chain: From Tools to Decision Assurance; *PM World Journal*, Vol. XV, Issue IX, September.

For sponsors, project managers, PMOs, project controls teams, and technical leaders, the findings provide a practical framework for selecting high-value use cases by project phase, defining governance requirements, assigning accountability, and measuring whether AI improves decisions across the industrial project value chain.

Keywords: *artificial intelligence; industrial projects; project management; design and engineering; construction; mining; CAPEX; project controls; anticipatory assurance*

1. Introduction

AI has entered industrial project delivery through many routes, from generative assistants and forecasting tools to design optimization, computer vision, autonomous equipment, and mine-planning models. The label therefore covers applications with very different consequences. A chatbot that drafts a status report and an optimization engine that changes a major development sequence should not face the same value test or control regime.

This review is both a look back and a point-in-time map. It traces **where AI can add value along the industrial project value chain**, which uses deserve priority, and how those priorities differ across PM, D&E, construction, and mining. Its guiding idea is that AI applicability and assurance intensity should be assessed against the sequence of consequential decisions from front-end definition and design through construction, commissioning, operational readiness, and production, rather than folded into one generic category of "AI in project management." Capital-intensive projects combine staged commitments, long lead times, technical interdependence, multiple delivery organizations, and decisions that are costly to reverse. Protecting value therefore depends on governed data, clear processes and decision rights, and human accountability, so that reliable evidence reaches the right decision-maker while there is still time to act.

2. Review Method and Corpus

The review uses a literature-review workbook covering the common period from 1 January 2023 through mid-July 2026. It combines Project Management Journal (PMJ) and PM World Journal (PMWJ) materials with AACE International transactions and conference sessions, Independent Project Analysis materials, Construction Executive, Engineering & Mining Journal, and selected academic, technical, and industry publications. These platforms connect, in different ways, to **capital-intensive industrial projects across planning, design, construction, commissioning, and operational readiness**. The selection also reflects the author's experience delivering complex mining and metals projects.

Titles were normalized and deduplicated, producing 118 unique publications. Each item was classified by primary domain, evidence orientation, and one of seven common topics. Theoretical or academic publications include peer-reviewed research, reviews, experiments, computational studies, and research preprints. Practical or applied publications include professional papers, industry features, conference transactions, case studies, guidance, and practitioner commentary. A source qualified only if it described a concrete AI or automated-decision mechanism – such as machine learning, optimization, computer vision, prediction, or an agentic workflow – linked to cost, schedule, design value, governance, safety, or field performance.

The corpus is a targeted professional scan, not a bibliometric census. Publication counts indicate attention and the character of available evidence, not proven economic impact. Cross-listed records are counted once under a primary-domain rule, and the selected platforms do not represent every engineering, construction, or mining journal. The review's value lies in structured comparison and interpretation rather than exhaustive coverage.

PMI's June 2026 publication, The Standard for Artificial Intelligence in Portfolio, Program, and Project Management, is not counted among the 118 publications. The corpus maps theoretical and practical discourse, whereas the Standard is a consensus-based normative publication issued by a standard-setting institution. It serves here as an external benchmark for the recommendations in Sections 8 and 9, not as an item in the publication counts. This distinction allows the article to complement PMI's technology-agnostic principles and performance domains with a sector-specific map of AI applicability along the industrial project value chain (Project Management Institute [PMI], 2026).

Mining was selected as a demanding contrast to PM, D&E, and construction. Mine projects combine capital-intensive delivery with geological uncertainty, long-lived asset economics, remote and safety-critical operations, and a direct transition from project completion to production. For it, prediction, optimization, and sequential decision-making are central rather than peripheral. Mining therefore tests whether project-governance lessons still hold where AI also shapes operating value.

The review confirms a persistent gap in the D&E literature. Only six publications, or 5.1% of the corpus, were classified primarily as D&E, although they cover AI-BIM interaction, generative structural design, and BIM-supported cost assessment. None of the 2026 year-to-date publications falls primarily in this domain. Some of the shortage reflects classification: engineering applications often appear under AEC [2], construction, manufacturing, asset management, project controls, or mining. Yet a substantive gap remains in work connecting AI-enabled design with value engineering, CAPEX decisions, design maturity, and industrial-project governance.

[2] AEC stands for architecture, engineering, and construction.

Table 1. Profile of the 118-publication corpus by primary domain and evidence orientation. Source: author's analysis of the literature-review workbook.

Primary domain	Theoretical	Practical	Total (corpus share)	Interpretation
Project management	17	58	75 (63.6%)	This practice-led stream focuses on adoption, PMO governance, project controls, decision support, and digital transformation.
Design and engineering	2	4	6 (5.1%)	This small mixed stream covers AI-BIM interaction, generative design, design-to-cost, engineering context, and asset-life decisions.
Industrial construction	5	16	21 (17.8%)	This strongly practical stream focuses on schedule risk, field evidence, safety, BIM-enabled coordination, and automation.
Mining	11	5	16 (13.6%)	This research-led stream addresses uncertainty, mine planning, geotechnical design, automation, equipment performance, and safety.
Total	**35 (29.7%)**	**83 (70.3%)**	**118 (100%)**	**The corpus is predominantly practice-led, although the balance differs substantially by domain.**

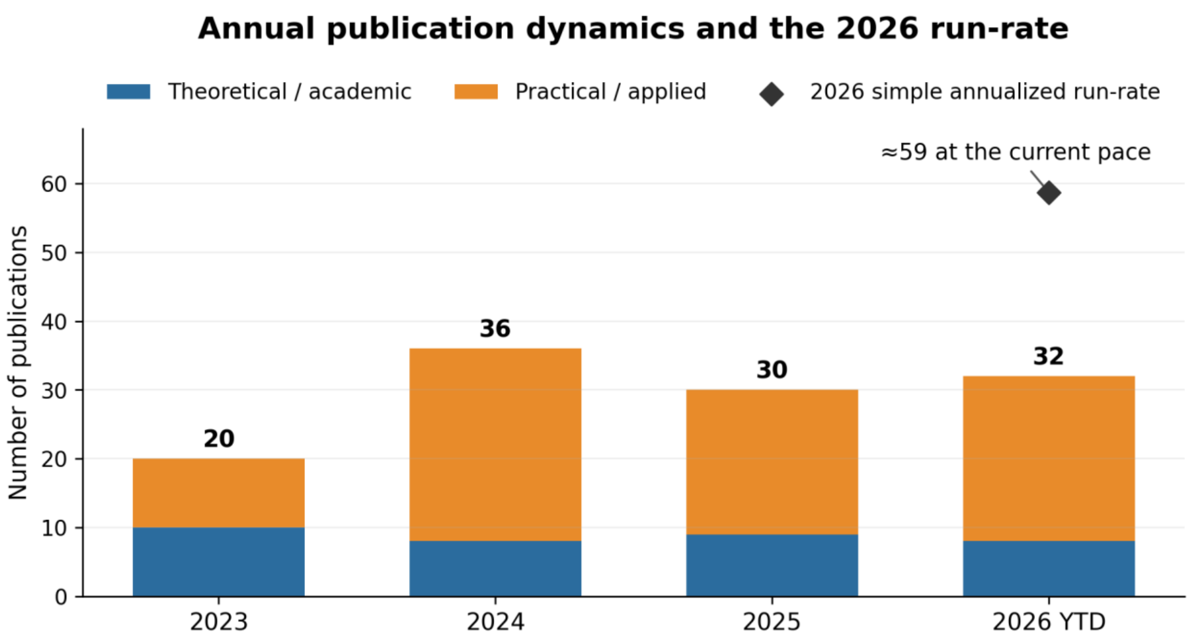

Figure 1. Annual publication pattern in the curated corpus*. The 2026 bar contains 32 publications through mid-July; the diamond shows a simple annualized run rate of about 59, not a forecast. **Source: author's analysis.*

3. Industrial Project Management: From Assistance to Assurance

Project management is the largest domain, with 75 publications: 17 theoretical and 58 practical. In 2023, professional work already addressed AI and machine learning in portfolio controls, large-project schedule-risk forecasting, top-down estimating, BIM-supported cost assessment, and forensic analysis (Ahmad Baharom & Abd Rahman, 2023; Hovhannisyan et al., 2023). Generative assistants were part of the conversation, but they were not the whole story.

AI nevertheless remains a minority theme in the wider PM literature. In PMJ, the monitored share of AI and digital-transformation content was approximately 8.9% in 2023, 3.6% in 2024, 8.3% in 2025, and 22.2% through mid-2026. In the much larger PMWJ, the estimated shares were approximately 0.2%, 3.8%, 1.7%, and 2.9%, respectively. These estimates are not a bibliometric census, but the contrast is informative. Research attention has accelerated sharply, while practitioner publishing remains broader and more selective. AI is becoming an established research and governance concern, yet it still occupies a relatively small share of the practitioner conversation.

Five general-purpose uses stand out in project controls – AI can:

1) Retrieve and summarize information from scope documents, correspondence, meeting records, risk registers, and lessons learned.
2) Detect anomalies across cost, schedule, procurement, engineering, and change data.
3) Support estimating, forecasting, and scenario comparison.
4) Improve access to controlled knowledge through specialist retrieval systems.
5) It can also automate repetitive communication and control routines through agentic workflows (Weaver, 2025; Phillips & Amratia, 2026; Pirozzi, 2026).

The literature increasingly draws a line between automation and governance. Simard and Aubry (2025) show that PMO participation in digital transformation is an organizational journey marked by expanding boundaries and tensions, not simply a software rollout. Kögel et al. (2026) compare AI and top-management decision-making and emphasize steering logic. Meltser (2026) argues for balancing AI analysis with context, ethics, and accountability. The key question is no longer whether AI can produce a report, but whether the organization can validate, question, and act on the output before the decision window closes.

This distinction can be expressed through **control latency and information asymmetry**. Control latency is the time between the emergence of a project-relevant condition and the arrival of validated, decision-ready evidence at the right governance level. Information asymmetry is the gap between what delivery teams know and what sponsors can independently verify. An AI-enabled PMO closes these gaps only when it uses governed data, preserves traceability, and has enough assurance independence to question optimistic reporting. Otherwise, AI may produce only a faster, more polished retrospective narrative (Bakhshi et al., 2025; Braun et al., 2025).

The practical literature also speaks more plainly about failure modes: hallucinations, data bias, cybersecurity, privacy, hidden assumptions, and the accountability gap (Patel & Kumbharathi, 2026; Construction Executive, 2026). Across sources, **the emerging model is bounded and human-in-the-loop (HITL)**. AI may detect, compare, retrieve, forecast, and generate options or questions, while accountable people interpret exceptions, authorize action, and remain responsible for the consequences.

4. Design and Engineering: Expanding the Option Space

D&E remains the smallest primary-domain category, with six publications: two theoretical and four practical. Yet its 2023 work already reached beyond simple automation. Jang and Lee (2023) linked a large language model (LLM) with BIM to support interactive design, while He, Wang, and Zhang (2023) developed a generative structural-design pipeline incorporating physical conditions and design criteria. Kusumadjaja (2023) connected BIM, automation, and machine learning with future cost assessment of energy-conservation measures.

Later work carries these ideas into industrial cost and asset decisions. Leitão, Holanda, and da Silva (2024) apply machine learning to industrial-goods cost estimating, supporting faster benchmarking and design-to-cost comparisons for machinery and equipment. Schwartz et al. (2024) combine IoT sensing with AI prognostics to support asset longevity, with implications for material selection, redundancy, maintainability, spares, commissioning strategy, and life-cycle cost. Broader AEC reviews map Generative AI across design, planning, procurement, inspection, and maintenance (Taiwo et al., 2024; Malla et al., 2025).

For value engineering, AI's most promising role is not to replace the multidisciplinary workshop, but **to widen and structure the option space.** Models can retrieve precedents, identify requirements, compare equipment and material alternatives, generate candidate configurations, estimate cost and carbon effects, and test uncertain assumptions. These capabilities can enrich both creative and evaluation work and reduce low-value iteration when approved requirements, model maturity, cost data, and lessons learned are connected through a governed digital project environment.

The risk is that option generation can outrun design maturity. Generative systems may produce plausible configurations without understanding operability, constructability, licensing, maintainability, safety, or interface constraints. Better prompts and richer context improve performance, but they do not create technical accountability. D&E leaders should therefore begin with bounded tasks and explicit acceptance criteria, such as approved-source retrieval, requirements traceability, equipment-cost benchmarking, anomaly detection, and controlled option generation. High-consequence calculations, design releases, and safety-critical decisions still require competent engineering review and traceable verification.

D&E underrepresentation is partly a classification issue and partly a real evidence gap. Engineering work is spread across adjacent domains, while unfortunately **a dedicated industrial D&E stream remains small and discontinuous**. The imbalance matters because early design choices shape much of eventual CAPEX, constructability, start-up risk, and operating performance. The literature is richer in AI-enabled reporting and field applications than in governed **AI for value creation through design – precisely where many irreversible commitments take shape**.

5. Industrial Construction: The Fastest Practical Experimentation

Construction contains 21 publications: 16 practical and five theoretical. The evidence spans deep neural network analysis of real-time location data and 3D point clouds, machine-learning forecasts of schedule risk on megaprojects, predictive jobsite safety analytics, and AI-enhanced BIM for conflict detection (Bardareh & Moselhi, 2023; Hovhannisyan et al., 2023; Kanner, 2023; Gallagher, 2023).

Construction is also the fastest-growing practical domain in the corpus. Nine records appeared by mid-July 2026, more than double the four recorded for all of 2025. This is not proof of widespread adoption, but it shows the conversation moving quickly from general interest toward specific applications in schedule quality, predictive oversight, connected evidence, autonomous equipment, and controlled AI agents.

Planning and scheduling are especially prominent. Schneider and Barbosa (2025) discuss AI in construction planning and scheduling; Cardoso et al. (2025) generate and iterate schedules from scope documents; Jackson (2026) reports an AI-agent review of schedule quality that matched many expert findings while reducing review time; and related AACE work uses machine learning to measure schedule robustness and predict residual delay impacts (Lozada et al., 2024). These applications matter because weak logic, missing constraints, unrealistic productivity, and disconnected engineering or procurement milestones can create false confidence in completion forecasts.

Field evidence forms the second major cluster. Computer vision can turn photographs and video into progress, productivity, quality, and safety signals. Predictive systems can combine field, cost, schedule, and weather data, while autonomous and AI-assisted equipment can reduce hazardous exposure and improve utilization (Lozada, 2025; Schwartz et al., 2026; Scarpati, 2026). The goal is not another dashboard. It is earlier reconciliation of field conditions with the schedule, cost system, change record, and contractual evidence.

Construction also brings governance hazards into sharp view. Different contractors may control the data, capture it inconsistently, or use it in claims. Models trained on one project type or geography may not transfer. Automated progress measurements may be contested when assumptions are opaque, and generative agents may retrieve the wrong drawing revision or summarize an unapproved instruction. The literature's response is increasingly specific: use task-bounded agents, connect authoritative data, establish central guardrails, retain human review, and define accountability and independent review (Giffin, 2026; Construction Executive, 2026).

6. Mining Projects: Optimization Under Uncertainty

Mining contains 16 publications: 11 theoretical and five practical. It reverses the corpus-wide pattern, with theoretical work representing 68.8% of the mining stream. A 2023 surface-mining survey shows that the sector's AI discussion already covered mine development, haulage, processing, rail, and mine-to-port interfaces before the later surge in generative AI (Leung, Hill, & Melkumyan, 2023).

Mine planning and design are at the center of the mining discussion because geological information is incomplete and decisions unfold over long horizons. Blom, Pearce, and Côté (2024) use large-neighborhood search for long-term mine planning. Khalifi et al. (2026) frame adaptive planning under geological uncertainty as a partially observable Markov decision process that updates decisions as information arrives[3]. Zvarivadza et al. (2025) apply advanced machine learning to pillar-stress prediction and design optimization in hard-rock platinum mining. These applications directly influence ore recovery, NPV, geotechnical risk, sequence, and capital deployment.

Mining also shows how AI links project delivery to operational readiness and asset performance. TinyML-enabled predictive maintenance uses compact machine-learning models on low-power edge devices to monitor equipment, detect anomalies, and identify early signs of failure near the data source. Collision-avoidance and operator-alertness systems, continuous dust monitoring, and intelligent processing operations affect commissioning, reliability, ramp-up, throughput, and safety (de la Fuente et al., 2024; Fiscor, 2024; Codoceo-Contreras et al., 2024). Early project decisions can therefore shape operating value long after construction ends.

Cost and governance applications are emerging more slowly. Costmine (2026) presents machine-learning benchmarking for mining CAPEX and OPEX, while Lagutin (2026) reframes the mining-and-metals PMO as an AI-augmented investment-protection system. The logic is especially relevant during studies and at stage gates, where technical, financial, operational, regulatory, and stakeholder readiness must be judged together before capital exposure increases.

The mining literature also keeps system consequences in view. Surveys and reviews identify data infrastructure, cost, skills, governance, workforce change, and community impact as material barriers (Kouhi et al., 2025; Codoceo-Contreras et al., 2024).

[3] Large-neighborhood search and partially observable Markov decision processes are advanced optimization and decision-making methods used in AI and machine-learning systems. The former searches for improved plans; the latter models sequential decisions under uncertainty and incomplete information.

Geological models can create false precision, sensors can fail, and automated equipment changes emergency procedures and human roles. **The most useful mining systems are (must be) therefore adaptive, auditable, and designed for uncertainty, connectivity failures, and safety-critical intervention.**

7. Cross-Domain and Value-Chain Synthesis: What the Concurrent Evidence Shows

Across the 118-publication corpus, 83 practical publications outnumber 35 theoretical works by 2.4 to 1. The practical share is 70.3%. The 20 records from 2023 divide evenly between theory and practice, but from 2024 onward practical work accounts for 70% to 78% of annual output. **The move toward application is therefore clear, even though the field began from a more balanced base.**

The annual pattern no longer fits a simple surge-and-plateau story. Publications rose from 20 in 2023 to 36 in 2024, an 80% increase, then eased to 30 in 2025. By mid-July 2026, the corpus already contained 32 publications, 6.7% more than the full-year 2025 count. A simple annualized run rate gives ~60 publications, double the 2025 total. This is not a forecast because publication schedules and search coverage are uneven. Applying an illustrative margin of plus or minus 15% produces a range of about 50 to 68 publications, still 67% to 125% above 2025. Even the lower end suggests a second expansion phase rather than a stable plateau.

The domain mix explains part of this momentum. PM dominates with 75 publications, or 63.6% of the corpus. Construction contributes 21, or 17.8%, accelerating most visibly in 2026. Mining contributes 16, or 13.6%, with a research-led profile. D&E contributes only six, or 5.1%, and remains the clearest evidence gap. **The field is broadening operationally, but not evenly across the industrial project value chain.**

The thematic ranking tells the same story (see Fig.2 below). **The governance, risk, assurance, and ethics theme now leads** with 30 publications, or 25.4%, ahead of AI adoption, tools, and human-AI collaboration with 27, or 22.9%. Together they account for 48.3% of the corpus. The field automation, safety, quality, and asset performance theme follows with 15 publications. Digital transformation and Industry 5.0 account for 13, as do design, value engineering, and mine planning. Cost and CAPEX account for 11, while schedule and time account for nine.

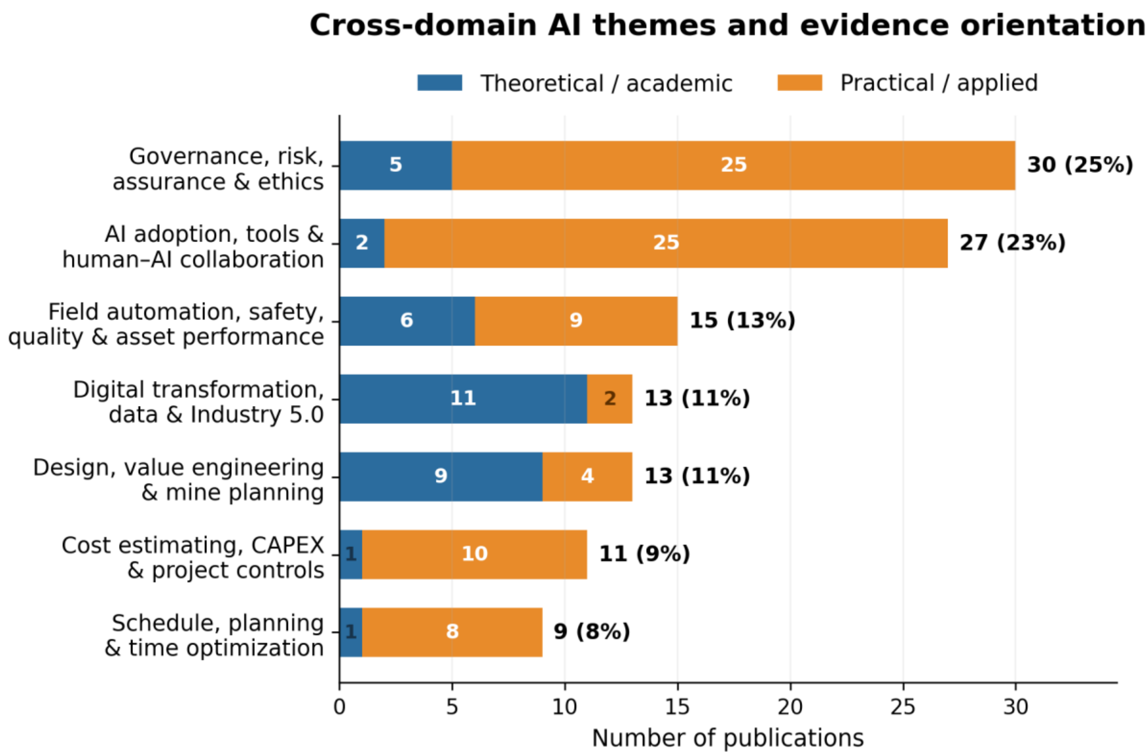

Figure 2. Distribution of the 118-publication corpus across seven cross-domain AI themes*. Segment labels show publication counts; labels at right show totals and shares of the corpus. *Source: author's analysis.

This move from adoption to governance marks a maturing field. The literature now asks not only what AI can do, but who controls the data, validates the output, makes the decision, and remains accountable.

Theory and practice, however, are concentrating in different areas. Digital transformation is 85% theoretical, while design, value engineering, and mine planning are 69% theoretical. By contrast, publications on cost and CAPEX are 91% practical; schedule and time, 89%; and AI adoption, 93%. **The problem is therefore not too little theory or too little practice, but a limited connection between system-level concepts and evidence of how they work in operational settings**.

Three conclusions follow:

- First, **the unit of value is the decision**, not the algorithm. AI creates material value when it changes/improves an estimate, design choice, sequence, readiness judgment, intervention, or capital commitment in time to matter.
- Second, **governed data and assurance independence are value-enabling infrastructure**, not administrative support.
- Third, **human-in-the-loop (HITL) oversight is a must**, not a temporary limitation that better models will remove. In capital-intensive and safety-critical settings,

accountable judgment, independent review, and escalation remain part of the control system.

These conclusions align with PMI's principles of strategic value, risk, governance and compliance, data quality, and human-in-the-loop oversight. The article extends them by showing that assurance intensity should vary with project phase, decision consequence, and reversibility along the industrial project value chain (PMI, 2026).

The evidence also suggests **a five-level maturity path**:

- At Level 1, organizations use AI for personal productivity, such as drafting, summarization, and search.
- At Level 2, they use AI for functional analytics, such as estimating, forecasting, schedule diagnostics, design comparison, computer vision, and predictive maintenance.
- At Level 3, they integrate AI-supported evidence and decisions across functions.
- At Level 4, governed data and bounded analytics support anticipatory assurance through independent validation and sponsor-level decision rights.
- At Level 5, AI becomes an enterprise-wide, cross-functional capability that learns across projects, improves decision and assurance processes, and adapts governance to changing conditions while retaining human accountability.

Many organizations still operate at Levels 1 and 2. The largest investment-protection, greater value opportunity lies at Levels 3 and 4, where organizational redesign is also greatest. Moving there requires a named integrator. That is why this article proposes the PMO's **Digital Transformation Manager (PDTM)** to coordinate AI governance and integration while leaving decisions with accountable managers, sponsors, and technical authorities.

A useful synthesis is therefore a **two-life-cycle view**. PMI's Standard addresses the AI system life cycle – how an AI system is scoped, designed, validated, deployed, monitored, modified, and decommissioned. This article adds **a second dimension: the industrial project value chain**, where capital is progressively committed from front-end definition through design, construction, commissioning, and production. Assurance arises where the two intersect: its intensity depends not only on the selected AI system, but also on project phase, decision consequence, reversibility, and the authority required to act with confidence (PMI, 2026).

8. Practical Recommendations and Role-Based Red Lines

The review points to **a role-based implementation agenda**. These recommendations complement rather than restate PMI's Standard: PMI provides technology-agnostic principles and performance domains across PPPM[4], while Table 2 turns them into value-chain actions and red lines for complex, capital-intensive industrial projects. Each group

[4] PPPM stands for portfolio, program, and project management.

should use bounded AI applications that improve a defined decision while preserving traceability, independent review, and human accountability.

Table 2. Role-based actions and red lines for responsible AI adoption in industrial projects. Source: synthesis of the reviewed literature.

Role or stakeholder group	What the group should do	What the group should not do
Investors and sponsors	They should fund decision-focused use cases, require assurance at stage gates, and measure decision time, avoided loss, and value protected.	They should not fund generic AI programs without a decision owner, evidence standards, monitoring, and contingencies for AI failure.
Project managers	Should shorten the path from signal to action, set exception thresholds, link outputs to evidence, and retain accountability.	Should not place unverified AI narratives in sponsor packs or let opaque outputs drive irreversible commitments.
PDTM[5] and Project Controls team	Should coordinate use cases and tool selection, maintain the AI register, confirm data readiness, arrange independent assurance, test outputs, and share lessons.	Should not become sole decision-makers, validate their own high-consequence outputs, or treat a successful pilot as sufficient assurance.
D&E executives and technical authorities	Should use AI for controlled retrieval, traceability, design-to-cost analysis, option generation, constructability checks, and maturity assessment while retaining technical approval.	Should not release safety-critical designs or work packages because an AI explanation appears complete or confident.
Construction managers	Should connect schedule, cost, change, field, quality, and safety evidence and use bounded tools for diagnostics, progress verification, and safer planning.	Should not automate payment, entitlement, quality acceptance, or safety decisions without transparent rules, evidence, and formal review.
Operations and asset-readiness leaders	Should connect commissioning, reliability, ramp-up, and production assumptions with project decisions and validate AI under uncertain conditions.	Should not accept false precision from incomplete data or deploy automation without updated operating and emergency procedures.
Data, IT, CS, commercial, safety, and assurance functions	Should define authoritative sources, access rights, security controls, legal constraints, validation methods, and escalation routes.	Should not treat governance as a one-time approval or allow uncontrolled tools, outdated data, hidden assumptions, or unresolved privacy, contractual, and safety risks.

Across these roles, **the test is whether AI improves a consequential decision** without weakening evidence quality, accountability, or independent review. Productivity gains matter, but they should serve capital protection, reduced delay and rework, safer delivery, and reliable production.

[5] PDTM stands for PMO Digital Transformation Manager, a dedicated role that can support several projects.

Besides, **the assurance rule is universal for every role: verify the AI engine before relying on it for a high-consequence decision.** In project-assurance terms, the engine must be fit for purpose. Its data must be governed, its model and version known, its performance tested, and its outputs traceable, with human review, contingencies for AI failure, and monitoring in place. This turns PMI's quality, validation, life-cycle, and HITL principles into one stage-gate question: Is the engine dependable enough for this decision and value at risk? (PMI, 2026).

Metrics should therefore go beyond hours saved. Depending on the phase and application, KPIs may include median signal-to-action time, forecast error, the percentage of outputs tied to authoritative evidence, exception-closure time, false-positive and missed-signal rates, validation hours, AI model drift, design maturity at release, days saved, and cost avoided. Pilots need baselines, and results should be compared with the prior process rather than vendor claims.

9. A PMO Operating Model for Responsible Scale

The maturity path in Section 7 and the role-based red lines in Section 8 imply an operating model, not merely a collection of AI tools. **At Levels 3 and 4, the PMO becomes the integration point** between project decisions, governed data, specialist assurance, and sponsor oversight. For that reason, this article proposes the **PMO Digital Transformation Manager (PDTM) as the named AI-integrator across projects**. Reporting to the project or portfolio sponsor, the PDTM coordinates AI governance and integration, maintains the AI register, requires proportionate controls, pauses unsafe pilots, and escalates unresolved risks.

Working with the roles in Table 2, the **PDTM** translates the two-life-cycle view into operating controls. Each use case should define the project phase and decision, value at risk, concrete boundaries, supporting evidence, model version, validation and ownership, as well as arrangements for monitoring, AI failure contingencies, and periodic revalidation of the AI system. **Project Controls** should test schedule, cost, progress, and forecast outputs against approved baselines and control logic. **Technical authorities and independent specialists** should challenge high-consequence conclusions, while managers and sponsors retain formal decision rights.

Portfolio reviews should then prioritize use cases by decision window, consequence, reversibility, data readiness, and assurance burden. Repeatable capabilities should be scaled, weak or unused tools retired, and lessons transferred across projects. This prevents organizations from multiplying low-value assistants while neglecting design-maturity, readiness, forecast, or production decisions where earlier intervention can protect more value.

The objective is not autonomous project management. It is **institutionalized anticipatory assurance**: bounded, traceable, and assured **AI that reduces control latency and information asymmetry** while strengthening human governance. Over time, this operating model provides the organizational foundation for Level 5 learning across projects without weakening accountability, independent challenge, or sponsor confidence.

10. Conclusion

The 118-publication corpus shows a field leaving the experimental workshop and entering the control room. By mid-July 2026, publication volume had already passed the full-year 2025 total, while governance, risk, assurance, and ethics had become the largest theme. The question is no longer simply what AI can do, but whether its outputs can support timely, accountable, and defensible project decisions.

Progress is uneven across the industrial project value chain. PM literature proper is practice-led and increasingly focused on governance. D&E remains underrepresented, even though early design decisions shape much of the project's eventual value. Construction has become the fastest practical testing ground for schedule, field evidence, safety, and AI agents. Mining provides the strongest research base for optimization under uncertainty and shows why project delivery cannot be separated from operating performance. The lesson is clear: AI should be assessed by project phase and decision purpose, not by tool category alone.

The article therefore proposes a decision- and assurance-based view of AI across industrial project delivery. The unit of value is a consequential decision made just in time, while assurance should rise with the project phase, value at risk, irreversibility, and authority required to act. This extends PMI's AI life-cycle governance into the industrial value chain, where capital is committed and consequences become real. With governed data, bounded use, human review, traceability, independent challenge, and a fit-for-purpose AI engine, organizations can turn weak signals into earlier action. Without these safeguards, AI may simply make fragmentation faster and false confidence more convincing.

AI Use Disclosure

AI-assisted tools supported the literature search, database organization, statistical analysis, comparison of draft versions, chart preparation, and cross-checking against PMI's 2026 AI Standard. The author selected and verified the sources and takes full responsibility for the accuracy and integrity of the article.

References

1) Ahmad Baharom, M. A., & Abd Rahman, M. S. (2023). Artificial intelligence & machine learning impact on robust project control improvement in portfolio management, AACE International Transactions 2023, DSAA-4064. https://web.aacei.org/docs/default-source/toc/toc_2023Trans.pdf
2) Bakhshi, J., Matous, P., & Crawford, L. (2025). Mapping theoretical developments of project governance: A systematic literature review and future research agenda, Project Management Journal. https://doi.org/10.1177/87569728251383503
3) Bardareh, H., & Moselhi, O. E. S. (2023). Integrated real-time location system information and 3D point clouds for object localization onsite using deep neural networks, AACE International Transactions 2023, DSAA-4094. https://web.aacei.org/docs/default-source/toc/toc_2023Trans.pdf
4) Blom, M., Pearce, A. R., & Côté, P. (2024). Long-Term Mine Planning with Large Neighbourhood Search, arXiv. https://arxiv.org/abs/2403.18213
5) Braun, T., Ekstedt, E., Lundin, R. A., & Sydow, J. (2025). Managing stability and change in interorganizational projects: The ambiguous role of digital tools for relational dynamics, Project Management Journal, 56(4). https://doi.org/10.1177/87569728241294204
6) Cardoso, G., Borowiec, D., Phillips, R., Mueck, L. A., & Amratia, D. (2025). Using AI to generate and iterate schedules based on scope documents, AACE International Transactions 2025, DSAA-4693. https://web.aacei.org/docs/default-source/toc/toc_2025Trans.pdf
7) Codoceo-Contreras, L., Rybak, N., & Hassall, M. (2024). Exploring the impacts of automation in the mining industry: A systematic review using natural language processing, Mining Technology, 133(3). https://doi.org/10.1177/25726668241270486
8) Construction Executive. (2026). The AI accountability gap, Construction Executive, June. https://constructionexec.com/article/the-ai-accountability-gap/
9) Costmine Team. (2026). Enhancing cost estimation and analysis with machine learning, Costmine, 26 March. https://www.costmin e.com/2026/03/26/enhancing-cost-estimation-and-analysis-with-machine-learning/
10) de la Fuente, R., Radrigan, L., & Morales, A. S. (2024). Enhancing predictive maintenance in mining mobile machinery through a TinyML-enabled hierarchical inference network, arXiv. https://arxiv.org/abs/2411.07168
11) Fiscor, S. (2024). Advancements in collision avoidance systems, Engineering & Mining Journal, October. https://www.e-mj.com/features/48307/
12) Gallagher, J. (2023). BIM and AI technology could help reduce construction disputes, Construction Executive, 27 July. https://constructionexec.com/article/bim-and-ai-technology-can-help-reduce-construction-disputes/
13) Giffin, S. (2026). Thinking of AI agents as members of a construction crew, Construction Executive, 30 June. https://constructionexec.com/article/thinking-of-ai-agents-as-members-of-a-construction-crew/
14) He, Z., Wang, Y.-H., & Zhang, J. (2023). Generative AIBIM: An automatic and intelligent structural design pipeline integrating BIM and generative AI, arXiv. https://arxiv.org/abs/2311.04052
15) Hovhannisyan, V., Zachares, P., Mosca, A., Grushka-Cockayne, Y., & Ledezma, C. (2023). Data-driven schedule risk forecasting for construction mega-projects, AACE International Transactions 2023, DSAA-4101. https://web.aacei.org/docs/default-source/annual-conference/2023-aace-conex---presentations.pdf?sfvrsn=d66babb5_27

16) Jackson, M. (2026). Beyond metrics: Utilizing AI agents for construction schedule quality analysis, AACE ConEx 2026, DSAA-4875. https://web.aacei.org/docs/default-source/annual-conference/2026-conex---technical-sessions.pdf?sfvrsn=bc991a46_1
17) Jang, S., & Lee, G. (2023). Interactive design by integrating a large pre-trained language model and building information modeling, arXiv. https://arxiv.org/abs/2306.14165
18) Kanner, J. (2023). Observe and report: AI makes the jobsite safer, Construction Executive, 3 December. https://constructionexec.com/article/observe-and-report-ai-makes-the-jobsite-safer/
19) Khalifi, H., Caers, J., Taha, Y., Benzaazoua, M., & Elghali, A. (2026). Adaptive mine planning under geological uncertainty: A POMDP framework for sequential decision-making, arXiv. https://arxiv.org/abs/2605.13702
20) Kouhi, R. M., Najeeb, A. T., Taherdangkoo, R., Ardejani, F. D., & Butscher, C. (2025). A survey study on the adoption and perception of artificial intelligence in the mining industry, Discover Applied Sciences, 7, 713. https://link.springer.com/article/10.1007/s42452-025-07342-1
21) Kusumadjaja, P. (2023). Leveraging BIM, automation, and machine learning for future cost assessment of energy conservation measures, AACE International Transactions 2023, BIM-4057. https://web.aacei.org/docs/default-source/toc/toc_2023Trans.pdf
22) Kögel, D., Meile, S., & Canós-Darós, L. (2026). Who's steering whom and in what direction? An experiment on AI versus top management decision-making in projects, Project Management Journal, 57(2). https://doi.org/10.1177/87569728251379338
23) Lagutin, K. (2026). From PMO to AI-powered investment protection system, PM World Journal, Vol. XV, Issue VII, July. https://pmworldjournal.com/article/from-pmo-to-ai-powered-investment-protection-system
24) Leitão, F. N., Holanda, L. C. de, & da Silva, A. G. (2024). Industrial goods cost estimating using machine learning techniques, AACE International Transactions 2024, DSAA-4395. https://web.aacei.org/docs/default-source/toc/toc_2024Trans.pdf
25) Leung, R., Hill, A. J., & Melkumyan, A. (2023). Automation and AI technology in surface mining with a brief introduction to open-pit operations in the Pilbara, arXiv. https://arxiv.org/abs/2301.09771
26) Lozada, J. (2025). Leveraging computer vision AI to drive cost efficiency, AACE International Transactions 2025, DSAA-4646. https://web.aacei.org/docs/default-source/toc/toc_2025Trans.pdf
27) Lozada, J., Mickelsen, K., Sayed, H., & Zerkel, S. (2024). A case study on the usage of data analytics and machine learning to measure schedule health, AACE International Transactions 2024, DSAA-4328. https://web.aacei.org/docs/default-source/toc/toc_2024Trans.pdf
28) Malla, V., Pulla, T., & Poolla, C. (2025). AI applications in the AEC industry: A systematic literature review, AACE International Transactions 2025, DSAA-4629. https://web.aacei.org/docs/default-source/toc/toc_2025Trans.pdf
29) Meltser, S. (2026). Balancing AI and human judgment for better project management, PM World Journal, Vol. XV, Issue VII, July. https://pmworldjournal.com/article/balancing-ai-and-human-judgment
30) Patel, A., & Kumbharathi, V. (2026). False confidence – The risk of AI hallucinations, AACE ConEx 2026, DSAA-4843. https://web.aacei.org/docs/default-source/annual-conference/2026-conex---technical-sessions.pdf?sfvrsn=bc991a46_1
31) Phillips, R. B., & Amratia, D. (2026). Embedding predictive AI in capital project portfolios: A case study from over 3000 projects, AACE ConEx 2026, RISK-4890. https://web.aacei.org/docs/default-source/annual-conference/2026-conex---technical-sessions.pdf?sfvrsn=bc991a46_1

32) Pirozzi, M. (2026). AI agent for PMO: An exploration of n8n orchestration and prompt engineering applied to a project's communications, PM World Journal, Vol. XV, Issue V, May. https://pmworldjournal.com/article/ai-agent-for-pmo
33) Project Management Institute. (2026). The standard for artificial intelligence in portfolio, program, and project management. Project Management Institute.
34) Scarpati, P. (2026). Building the future: Construction at the center of technological innovation at CES 2026, Construction Executive, 6 April. https://constructionexec.com/article/building-the-future-construction-at-the-center-of-technological-innovation-at-ces-2026/
35) Schneider, M., & Barbosa, W. F. (2025). Turn around on the future of construction: The power of AI in construction planning and scheduling, AACE International Transactions 2025, DSAA-4501. https://web.aacei.org/docs/default-source/toc/toc_2025Trans.pdf
36) Schwartz, A., Dembert, E., Albritton, S., Schoenbrun, E., Kelly, T., Thrailkill, J., Coslett, R., & Wood, J. (2024). Supercharging asset longevity with IoT sensors and AI, AACE International Transactions 2024, DSAA-4300. https://web.aacei.org/docs/default-source/toc/toc_2024Trans.pdf
37) Schwartz, A., Dembert, E., Kaplan, B., Johannsen, J., & Minnoor, N. (2026). Building smarter: Harnessing artificial intelligence for construction oversight, AACE ConEx 2026, DSAA-4821. https://web.aacei.org/docs/default-source/annual-conference/2026-conex---technical-sessions.pdf?sfvrsn=bc991a46_1
38) Simard, M., & Aubry, M. (2025). The project management office's active participation in a digital transformation: A trajectory full of twists and turns, Project Management Journal, 56(1). https://doi.org/10.1177/87569728241242029
39) Taiwo, R., Bello, I. T., Abdulai, S. F., Yussif, A.-M., Salami, B. A., Saka, A., & Zayed, T. (2024). Generative AI in the construction industry: A state-of-the-art analysis, arXiv. https://arxiv.org/abs/2402.09939
40) Weaver, P. (2025). AI-enhanced project estimating, monitoring, and forecasting, PM World Journal, Vol. XIV, Issue I, January. https://pmworldjournal.com/article/ai-enhanced-project-estimating-monitoring-and-forecasting
41) Zvarivadza, T., Grobler, H., Rajpurohit, S. S., Moyo, S., Onifade, M., & Khandelwal, M. (2025). Advanced machine learning for pillar stress prediction and design optimisation in hardrock platinum mining, Geomechanics and Geophysics for Geo-Energy and Geo-Resources. https://link.springer.com/article/10.1007/s40948-025-00990-y

About the Author

Konstantin Lagutin

Tel Aviv, Israel

Konstantin Lagutin is an international PMO and capital-project management leader with 25+ years of experience across mining, metals, chemicals, oil and gas, and industrial transformation programs in the GCC, EMEA, Russia, CIS, Europe, and the United States. He holds an MBA and an MSc in Data Business Analytics and is a certified Project Management and MIT Digital Transformation professional.

Konstantin has built PMOs and project management systems from scratch for major Mining & Metals companies, supporting capital-project portfolios from $1 billion to $7.5 billion. His work spans stage-gate governance, digital PMOs, lean construction, BIM-enabled, Agile, and 4D construction management. Most recently, he has focused on AI-supported PMO transformation, integrating schedule, cost, risk, document control, and executive dashboards to improve capital discipline and decision quality.

Konstantin can be contacted at lagutin.ki@gmail.com | +972 54 756-7868