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What Works Now in AEC in the Post-ChatGPT Era: A Phase Aligned Evidence Map of AI Startup Value

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This study presents an evidence map of AI-startup activity across the architecture, engineering, and construction (AEC) lifecycle in the post-ChatGPT period (2023–2025). Peer-reviewed literature and auditable public implementations were synthesized and coded by project phase, task, AI modality, integration touchpoint, and reported evaluation approach. Activity is concentrated in design and construction, with comparatively fewer offerings in feasibility and operations where data are sparse or heterogeneous. Reported use cases cluster around design optioneering and model checking, preconstruction quantity takeoff/estimating and schedule-risk analytics, and construction safety and progress monitoring. Across modalities, generative and language-model tools dominate design and document intelligence, computer vision dominates progress and safety workflows, and predictive analytics supports select operations use cases. The review identifies five recurring barriers, data readiness and integration, industry culture and trust, scalability versus customization, regulatory/liability posture, and workforce capability, and translates them into actionable evaluation guidance. Specifically, we provide phase-aligned decision aids for procurement and pilots, including a startup screening rubric and a pilot scorecard that pairs technical validity with operational KPIs and integration readiness. The findings inform practitioner adoption strategies and support research and education agendas emphasizing standardized reporting, reproducible evaluation protocols, and multi-site validation.

Keywords: Construction technology startups, Generative AI in AEC, AI adoption and governance, AI pilot evaluation framework, ChatGPT

Introduction

The AEC industry has seen a surge of AI experimentation since late 2022 advances in large language models (LLMs), reflected in enterprise deployment intent and workflow redesign reported in global surveys (McKinsey & Company, 2025). Scholarly analyses indicate that near-term benefits are most consistently observed in design alternatives and verification, construction progress and safety analytics, and task-specific automation that augments, rather than replaces, professional judgment (Adebayo et al., 2025; Sami Ur Rehman et al., 2022; Zhuang et al., 2025). In contrast, early-phase feasibility remains constrained by sparse, context-specific data, which favors decision support over decision automation (Bagasi et al., 2025). Recurring adoption barriers such as information fragmentation, explainability/trust, and workflow fit align with ISO 19650 / UK BIM Framework guidance emphasizing lifecycle information requirements, common data environments, and auditability (UK BIM Framework, 2020; Kulinan et al., 2024). For safety analytics, referred studies related to stress reporting model validity (e.g., precision/recall/F1) alongside environmental dependencies (e.g., occlusion, lighting, camera placement), motivating evaluation that links model metrics to operational KPIs (Kulinan et al., 2024; Lee & Lee, 2023). Market analyses similarly highlight scaling pressures for construction-technology solutions and continued investment momentum post-2022 (Blanco et al., 2023).

Prior studies often treat "AI in AEC" broadly spanning internal tools, incumbents, and emerging vendors while offering limited phase-wise synthesis for the post-ChatGPT period and limited reporting of deployment constraints and neutral validation metrics usable by practitioners (Alwashah, 2025). In this study, an AI startup is defined as a venture-stage company whose AEC offering is AI-first i.e., AI/ML (including LLMs, computer vision, or predictive analytics) is central to the product value proposition such that the offering would be materially degraded without it; tools where AI is only an ancillary feature are excluded unless AI drives measurable workflow impact. This study addresses these gaps through a startup-focused, phase-wise review of evidence reported from January 2023 to December 2025. We examine: (1) which project phases show the most substantive AI-startup impact from 2023–2025, and (2) which delivery constraints and validation indications are consistently reported. "Post-ChatGPT" is used as a capability/adoption inflection point reflecting late-2022 LLM mainstreaming and rapid platform embedding rather than as a founding-date criterion; accordingly, earlier-founded firms (e.g., ALICE Technologies, Togal.ai) are included when post-2023 sources document material AI-enabled workflow changes and/or measurable impacts.

The Pre-ChatGPT Landscape

Before generative AI (pre-2023), AI adoption in AEC was uneven and concentrated in narrow, BIM-enabled workflows where structured inputs were available (e.g., clash detection and computer-vision–based safety/progress analytics), with performance sensitive to site conditions (Sami Ur Rehman et al., 2022). Commercial milestones included Spacemaker's generative site-layout optimization (acquired by Autodesk in 2020) and Smartvid.io/Newmetrix safety analytics later integrated into Oracle's construction platform (Autodesk, 2020; Oracle, 2021). By the late 2010s, contractors piloted tools such as Togal.ai (takeoff), OpenSpace and Buildots (progress verification), and ALICE Technologies (schedule optimization), yet by 2022 fewer than one-third of contractors reported using AI/ML, reflecting persistent barriers related to data readiness, uncertain ROI, and workforce capability (Regona et al., 2022; Ghimire et al., 2024).

The Post-ChatGPT Catalyst

The late-2022 introduction of ChatGPT lowered experimentation barriers by enabling non-technical users to interact with AI via natural language and accelerated embedding of LLM-based capabilities into incumbent AEC platforms. Examples include Procore's AI assistants and Togal.AI's "TogalGPT," which apply GPT-4 for submittal/RFI support and drawing/spec interpretation within existing workflows rather than as standalone analytics (Procore, 2025; Togal.AI, 2025). In design, contemporary reviews emphasize generative optioneering and automated checking as augmentative aids under professional control (Li et al., 2025; Xiong et al., 2025). Market analyses report robust ConTech investment and continued confidence post-2022, alongside enterprise surveys indicating rising day-to-day AI use (Blanco et al., 2023; McKinsey & Company, 2025).

Despite this momentum, durable impact remains constrained by information quality, lifecycle governance, and human-in-the-loop validation in a distributed, high-liability project environment (Adebayo et al., 2025). In computer-vision safety applications, studies emphasize reporting technical validity (precision/recall/F1) and deployment dependencies (e.g., lighting, occlusion, camera placement) as prerequisites for credible operational claims (Lee & Lee, 2023). Overall, the post-

ChatGPT shift is less a single "killer app" than accelerated experimentation within incumbent workflows and a broadened readiness for structured human–AI collaboration in AEC.

Methodology

A structured evidence evaluation of AI startups in AEC (January 2023–December 2025) was conducted using Web of Science and Scopus as primary academic databases and Google Scholar as a supplemental search engine, complemented by targeted online sources. Search strings combined lifecycle phases with AI modalities and startup indicators (e.g., "AEC OR construction" AND "AI OR LLM OR computer vision OR generative" AND "startup OR venture" AND "feasibility OR design OR preconstruction OR construction OR operations"). Following de-duplication and screening (title/abstract followed by full-text eligibility review), the final evidence corpus used to populate the phase-aligned synthesis comprised 37 sources (15 peer-reviewed and 22 industrial/grey).
In addition to peer-reviewed journals and conferences, industrial/grey sources (vendor documentation and case studies, platform documentation, industry and VC reports, standards guidance such as ISO 19650/UK BIM Framework, and reputable trade press) were treated as evidence only when auditable, defined as providing: (i) a described workflow and deployment context, (ii) integration touchpoints and/or data requirements, and (iii) at least one traceable outcome measure (technical metric and/or operational KPI) and/or a baseline comparator. Inclusion required AEC relevance, explicit AI functionality, and a startup-developed or startup-integrated application with sufficient detail to code project phase and implementation constraints (data/workflow/governance). Exclusion removed patents, opinion articles, marketing-only claims lacking verifiable methods/metrics, and duplicates. To mitigate grey-literature bias, peer-reviewed sources were prioritized for constraints and evaluation measures; archived web pages were used where relevant; and sensitivity checks excluded single-site vendor-only reports to confirm that high-level patterns were not driven by unverifiable claims.

Findings: Key Trends by Project Stage

All phases of the AEC lifecycle are currently targeted by AI startups. Activity is observed to be most concentrated in design and construction, while fewer offerings are identified in the areas of feasibility and operations as detailed in Table 1. The observed phase trend aligns with areas where digital data are prevalent and inefficiencies incur significant costs, as indicated by market analyses and phase-specific scholarly syntheses(Chew et al., 2024; Reja et al., 2022).

Feasibility Stage

Feasibility workflows increasingly blend generative exploration with early constraint checks (e.g., massing, yield studies, zoning/code interrogation, and test-fits), but outputs remain decision-support because entitlement, cost, and risk remain context-sensitive. Public implementations illustrate the trajectory: the City of Austin announced integration of Archistar's eCheck for AI-powered residential plan "pre-checks" (early 2025), and Archistar markets compliance assessment "from weeks to minutes" as a pre-review accelerator (Archistar, 2025). To address feasibility's evidence gap, pilots should report phase-appropriate metrics: (i) time-to-first-feasible option (hours), (ii) severity of zoning/code issues flagged per submission, (iii) % of generated options meeting key constraints (setbacks, FAR, height), and (iv) handoff friction to BIM (e.g., % geometry requiring rework after export). Peer-reviewed studies emphasize that data sparsity and model-to-context mismatch constrain predictive accuracy in conceptual stages, reinforcing the need for human-in-the-loop review and ISO 19650-aligned information requirements (Chew et al., 2024; UK BIM Framework, 2020).

Design Stage

Post-2023 activity in design concentrates on two major trajectories: generative optioneering at the concept level, and automation of repetitive detailing in later design stages. Different review recommend evaluating design tools using time-to-solution, solution diversity/quality, and downstream clashes/coordination outcomes with AI positioned to augment designer judgment(Chew et al., 2024; Khan et al., 2025). Startups and established companies are increasingly providing tools for fast layout generation and design exploration, leading to shorter cycle times and expanded solutions for clients. (Axeleo Capital, 2025; Laiout, 2025). For instance, Augmenta claims substantial cycle-time reductions and prefab readiness, typically via Revit/IFC round-trips; we treat these as vendor evidence unless independently replicated (Augmenta, 2024). The emerging "AI copilot" pattern where LLM-based assistants query models and specifications while engineers retain decision control aligns with academic guidance that AI should augment designer cognition and automate checking, rather than replace human designers entirely (Bagasi et al., 2025; Li et al., 2025). This is especially true for code compliance and complex edge-case engineering, where human judgment remains crucial.

Pre-Construction Stage

Estimating, scheduling, and procurement show visible adoption. Togal.AI cites up to 80% of time reduction in case studies (Togal.AI, 2025). Generative scheduling and AI schedule-risk tools (e.g., ALICE, nPlan) provide multi-scenario optimization and risk forecasts, with technical documentation and case material published through professional venues (AACE) and academic teaching studies(Hall et al., 2022; Phillips et al., 2024). Bid procurement and contract review are becoming increasingly automated, as highlighted by Parspec's 2025 Series A funding, which reflects investor interest in automating submittals and specification parsing. Additionally, contract risk tools like Document Crunch are now integrating with project management platforms to facilitate legal reviews (Parspec, 2025; Document Crunch, 2025). Trunk Tools has emerged as a notable player in submittal/spec processing and document triage. Its agent suite parses specifications, checks compliance, drafts responses, and routes items to reviewers within incumbent workflows. Workflows in AI applications remain human-in-the-loop, with suggestions vetted by professionals. Integration into existing platforms like Procore and Autodesk is crucial for user adoption, as closer alignment with established software encourages acceptance (UK BIM Framework, 2020).

Construction Stage

On site, AI is most mature capture to progress analytics, safety monitoring, and targeted robotics. Vendor platforms such as Buildots, OpenSpace align with systematic reviews describing end-to-end CV progress pipelines following the pattern acquisition, retrieval, estimation, visualization and common constraints (occlusion, capture cadence) (Reja et al., 2022). For safety, refereed studies recommend reporting precision/recall/F1 and explicitly documenting environment dependencies; this provides model-level validation that can be paired with operational KPIs on site (Lee & Lee, 2023). Beyond progress and safety analytics, contractors are piloting LLM-driven field assistants for on-site Q&A, RFI drafting, and retrieval of drawings/specs/SOPs. Trunk Tools positions its agents as a "jobsite copilot" that accelerates document interpretation while keeping approvals with superintendents and project engineers. Across construction use-cases, adoption correlates strongly with how well these technologies integrate into existing project controls and workflows. Successful implementations pair advanced tech with change management efforts around data capture cadence and crew processes. Reported benefits stress earlier variance detection, reduced rework, and improved leading indicators when tools are embedded in existing project controls and accompanied by change-management on data capture.

Table 1. Examples of AI Startup Focus by Project Phase (2023–2025)

Phase	**High-value tasks automated**	**Representative startups**	**Dominant AI modalities**	**Primary integration touchpoints**
Feasibility	Site feasibility analysis; early massing & yield studies; permit/code checking; climate risk screening	Archistar; Hypar; Pantheon AI; Laiout; Jupiter Intelligence	Generative design; NLP for zoning/codes; geo-AI risk modeling	GIS/parcel data; planning portals; BIM (conceptual massing exports)
Design	Rapid concept generation to BIM; automated discipline detailing (e.g. MEP layouts); code/spec compliance review; layout optimization	Snaptrude; Augmenta; Higharc; Autodesk Forma/Revit Copilots	Generative design (optioneering); constraint-based AI; LLM document Q&A	BIM platforms (Revit, Rhino); cloud design tools; spec libraries
Pre-Construction	Quantity takeoff & estimating; schedule generation & risk analysis; bid procurement assistance; contract/submittal review	Togal.AI; Kreo; ALICE Technologies; nPlan; Parspec; Scalera.ai; Document Crunch; Volve; Reconstruct	CV on plans; LLM retrieval/QA; generative scheduling; predictive risk analytics	Common data environments (Procore, Autodesk Construction Cloud); P6/MS Project; cost databases; ERP systems
Construction	Reality capture & progress tracking; safety monitoring; field QA/QC assistance; site logistics and robotics	Buildots; OpenSpace; Disperse.io; Smartvid.io/Newmetrix ; Everguard.ai; Trunk Tools; Kwant.ai; Reconstruct; Dusty Robotics; Built Robotics; BotBuilt	Computer vision (image/video analytics); “agentic” LLM assistants; sensor fusion (IoT wearables); autonomous robotics	Project management platforms (Procore, ACC); BIM/Navisworks models; scheduling software; IoT gateways; equipment APIs
Operations / Facility	Digital twin-based monitoring; fault detection & diagnostics (FDD); energy optimization; portfolio maintenance analytics; occupancy and space utilization	Willow; BeamUP; Facilio; BrainBox AI; 75F; Cityzenith; (spatial analytics AI)	Predictive analytics; computer vision-to-twin integration; reinforcement learning for controls; portfolio-level LLM Q&A	Building management systems (BMS); CMMS maintenance systems; IoT/twin platforms (e.g. Azure Digital Twins)

Operation/ Facility Management Stage

In operations, AI adoption has focused on portfolio-scale optimization and digital-twin–enabled monitoring and diagnostics. Public case evidence provides measurable (vendor-reported) outcomes: BrainBox AI reports a 15.8% reduction in HVAC-related electricity consumption over an 11-month period in one case study; 75F reports average HVAC energy-use reduction of 41.8%; and Willow's DFW Airport case study describes a published goal to reduce maintenance costs 20–25% by 2030 through digital-twin operational efficiencies (BrainBox AI, 2025; 75F, 2025; Willow, 2025). To standardize evaluation beyond individual claims, operations pilots should report neutral KPIs recommended in digital-twin literature, EUI, comfort compliance hours, and MTTR, and document integration readiness (BMS/CMMS connectivity, sensor data quality, override governance). Consistent with peer-reviewed evidence, an augmentation model dominates: AI proposes setpoints and diagnostics while facilities managers retain override authority (Cespedes-Cubides & Jradi, 2024).

Discussion

The phase-wise synthesis indicates that AI startups are concentrated in areas where structured digital inputs and repeatable workflows are already established, such as design and construction. In contrast, there are comparatively fewer offerings in feasibility and operations, where data are sparse or heterogeneous.

Table 2. Pilot Evaluation Scorecard (Technical + Operational + Integration Readiness)

Dimension	**Minimum Reporting Items**	**Examples (choose phase-appropriate)**
Technical validity	Performance on representative project data + baseline comparator	CV: precision/recall/F1; MAE/MAPE; LLM retrieval/ QA
Deployment robustness	Context dependencies + failure modes + exception log	CV: lighting/occlusion/camera; Docs: drawing/spec quality; Models: discipline/region variability
Operational impact KPI #1	KPI linked to time/cost/quality/safety	Cycle time; variance lead time; rework rate; safety leading indicators
Operational impact KPI #2	Second KPI from a different category	Ops: EUI, comfort hours, MTTR; Field: RFI turnaround; install productivity proxy
Integration readiness (gate)	Touchpoints + interoperability evidence + data access approvals	CDE/PM/BIM/BMS/CMMS connectors; APIs; IFC/COBie support
Governance & auditability	Human approval, traceability, security	Approval gates; versioning; audit trail; permissions; data retention
Adoption & workflow fit	Training + usage evidence	Training hours; active users; task completion rate; user acceptance notes

Notes: Score each row 1–5; require Integration readiness ≥ 3 and Governance ≥ 3 to proceed beyond pilot.

The observed pattern aligns with findings from peer-reviewed literature: in design contexts, generative and checking tools are noted to decrease iteration time and broaden the option space while maintaining human oversight. In construction, vision-based progress and safety analytics align with an augmentation model, where technical validity must be interpreted alongside deployment constraints and jobsite process effects. By contrast, feasibility remains constrained by model-to-context mismatch and sparse early-phase data, supporting AI as decision support rather than decision maker. In operations, digital-twin literature emphasizes neutral outcome metrics tied to energy, comfort, and maintenance performance. Table 2. provides a minimal, auditable pilot scorecard combining technical validity, operational key performance indicators (KPI)s, and integration readiness to enable consistent comparisons across phases and vendors.

In addition to pilot measurement (Table 2), AEC decision-makers require a consistent method to shortlist AI startups prior to procurement or pilots. Table 3 proposes a screening rubric emphasizing technical credibility, domain fitness, integration posture, and validation strength.

Table 3. Startup Evaluation Rubric (Pre-Pilot Screening)

Criteria	What to assess	Minimum evidence
Technical credibility	Clear task definition; reported performance; disclosed limitations	Model/feature documentation; metrics on representative data; known failure modes
AEC domain fit	Specific phase/task + end-user role; workflow realism; compliance awareness	Use-case mapping (phase/task); SME involvement; example workflows (RFI/submittal/QTO, etc.)
Integration posture (gate)	Connectors/APIs; interoperability standards; implementation effort	Supported platforms (CDE/PM/BIM/BMS/CMMS); API docs; data requirements list
Validation strength	Baseline comparison; multi-site/third-party references; transparent KPIs	Case study with baseline; client references; pilot report or independent evaluation

Comparison with Prior State of Art

Relative to the pre-ChatGPT era, 2023–2025 shows broader accessibility through LLM-based assistants embedded in incumbent platforms and increased day-to-day experimentation. Persistent barriers, information fragmentation, explainability/trust, and workflow fit, remain, reinforcing the importance of governance practices (e.g., ISO 19650-aligned information requirements, auditability, and role clarity). Accordingly, credible startup value increasingly depends on workflow-embedded integrations and transparent reporting of both technical validity and operational KPIs (Table 2).

Challenges and Future Outlook

Recent ConTech scholarship indicates that adoption and scaling barriers are not purely technical: institutional misalignments between construction technology ventures and venture capital (e.g., time horizons, risk postures, and product/market expectations) can suppress diffusion even when tools perform well (Walzer et al., 2025). Investor-focused evidence further suggests that familiarity, entrepreneur characteristics, and environmental factors shape ConTech investment decisions, reinforcing the need for transparent validation evidence and integration posture in startup screening (Yücel & Comu, 2025). The rapid diffusion of AI across AEC is real, yet durable impact depends on solving five structural issues that repeatedly surface in the literature, industry surveys, and case evidence.

1. Data readiness and integration: Scaling beyond pilots depends on structured, accessible project data and reliable integration with enterprise systems; without this, model performance and automation break across phases.
2. Industry culture and trust: Adoption requires human-in-the-loop governance, transparency about limitations, and change management that earns field confidence through measurable “quick wins.”.
3. Scalability and customization: Project heterogeneity drives the need for configuration and retraining, creating tension between generalizable products and context-specific performance.
4. Regulatory and liability posture: High-liability decisions remain with licensed professionals; AI must support auditability, explainable outputs, and defensible oversight workflows.
5. Workforce capability and training: Sustained impact requires upskilling to interpret AI outputs, manage exceptions, and integrate tools into production workflows, not simply software deployment.

Limitations

This review is bound to the post-ChatGPT window till current date and may under-represent longer-running AI approaches and path-dependent adoption patterns. Evidence is drawn from peer-reviewed studies and publicly documented deployments (vendor case studies, industry reports, product documentation); consequently, results are vulnerable to publication and survivorship bias, selective reporting, and geographic/sector skew toward English-language, web-visible commercial projects. Much of the analysis depends on secondary sources, which may introduce bias, and verified data on AI performance is scarce. Moreover, as a qualitative review, the study does not offer a quantitative ranking of success factors or statistical outcome analysis. Insights are derived from expert commentary and reported experiences rather than quantitative data, which is currently sparse. The absence of comparable data, such as AI impact on project ROI across numerous projects, highlights a significant limitation in understanding what works in AI implementation within the AEC industry. These limitations emphasize the necessity for ongoing research, including more case studies, experiments, and longitudinal surveys, to establish a solid evidence base for AI adoption in the AEC.

Conclusion

This review offers a lifecycle map of post-ChatGPT startup activity and implementation guardrails organizations can apply immediately: prioritize high-readiness pilots, require integrations up front, instrument evaluations, and publish baselines and exception logs. The findings translate into concrete priorities for key audiences. For AEC educators and professional bodies, curricula and guidance should emphasize AI evaluation literacy (e.g., precision/recall/F1 and error metrics, failure modes), data readiness and interoperability (CDE concepts and ISO 19650-aligned information requirements), and human-in-the-loop governance (auditability, liability posture, and adoption measurement). For practitioners, the review informs standardized decision aids: a pre-pilot startup screening rubric (technical credibility, domain fit, integration posture, validation strength) and a pilot scorecard that pairs model metrics with operational KPIs and integration readiness using phase-appropriate measures. For researchers, multi-site replications should report both technical validity and operational outcomes under documented deployment constraints, including data quality, workflow embedding, and integration touchpoints. With disciplined information management, transparent validation, and workforce development, assistive AI can deliver faster, safer, and more resource-efficient projects while preserving professional judgment.

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