Jurnal Pendidikan dan Kewirausahaan
p-ISSN: 2302-0008 e-ISSN: 2623-1964 DOI: https://doi.org/10.47668/pkwu.v14i1.2308
Volume 14 Issue 2 2026 Pages 201 - 221

Beyond the Five-Year Threshold: AI as a Construction Enterprise Survival Catalyst in the Developing Economy

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Abstrack :

Purpose – This paper examines why construction enterprises disproportionately fail or stagnate beyond their fifth year of operation and evaluates the potential of artificial intelligence (AI) to address the organisational and workforce factors associated with early-stage failure.

Design/methodology/approach – Following PRISMA guidelines, a structured search across five databases identified 26 studies (2019–2026) meeting inclusion criteria spanning construction enterprise failure, general small-enterprise failure, and AI in construction. All 26 studies were retained for narrative thematic synthesis, interpreted through organisational life-cycle theory and the resource-based view.

Findings – The reviewed literature consistently associates cash-flow fragility, workforce turnover, and informal management structures with elevated early-stage failure risk, and separately documents AI applications, cost/schedule prediction, workforce analytics, and safety and resilience tools that map onto these same factors. No study in the reviewed corpus directly tests whether AI adoption improves construction enterprise survival; this connection is proposed by the present review as a theoretically grounded inference, not reported as an established empirical finding.

Theoretical implications – The review extends organisational life-cycle theory and the resource-based view by reframing AI not as a standalone tool but as a candidate input to AI-enabled organisational capability, and by treating the widely cited five-year survival threshold as an approximate empirical marker rather than a deterministic stage boundary.

Originality/value – Proposes the Post-Startup Productivity Sustainability (PPS) Model, a conceptual framework, accompanied by five explicit, testable propositions, linking AI-enabled organisational capability to construction enterprise life-cycle stage and productivity sustainability.

Practical implications – Distinct recommendations are offered for construction enterprise owners, government agencies, educational institutions, and financing institutions, each derived from the specific mechanisms identified in the review rather than presented as generic technology-adoption advice.

Research limitations/future research – The proposed model has not been empirically tested; longitudinal, firm-level studies are needed to evaluate its propositions and boundary conditions across enterprise sizes and market contexts.

Keywords: *AI; construction enterprise; business survival; organisational life cycle; productivity.*

INTRODUCTION

Construction enterprises fail at markedly higher rates than firms in most other sectors, and this pattern is not evenly distributed across a firm's lifespan: mortality risk is disproportionately concentrated in the years immediately following start-up. United States Bureau of Labor Statistics cohort data show that only 46.2% of construction firms founded in 1996–1997 survived to their fifth year, compared with 59.3% of firms founded two decades later in 2016–2017, and that firms crossing this threshold subsequently exhibit substantially higher year-on-year survival (eSUB, 2025, reporting BLS cohort analysis). This pattern raises two distinct empirical questions that existing literature addresses separately rather than together: first, what organisational and workforce factors explain why the early post-startup period carries such elevated failure risk; and second, whether artificial intelligence (AI), increasingly documented as a construction productivity tool, has any plausible bearing on that risk.

These two questions correspond to two literatures that have developed with little cross-reference. A well-established body of research on construction workforce turnover identifies dozens of contributing factors and finds turnover directly undermines firm productivity (Ayodele, Chang-Richards, and González, 2019), while general small-enterprise failure research identifies financial-access constraints and managerial capability gaps as dominant, cross-sector failure drivers (Jayasekara, Fernando, and Ranjani, 2020). Separately, a rapidly growing literature documents AI's expanding technical role in construction, cost estimation, scheduling, safety monitoring, and resource optimisation, without engaging directly with the enterprise-survival question (Abioye et al., 2021; Pan and Zhang, 2021). This distinction matters because the unit of analysis differs: project-level productivity gains, the outcome most AI-in-construction research measures, are not the same construct as firm-level survival, which depends additionally on financial management, workforce retention, and governance capability that a single well-executed project does not, on its own, guarantee. Workforce turnover carries particular weight in this context because construction relies disproportionately on project-based, often subcontracted labour, making skill and knowledge retention structurally harder to sustain than in sectors with more stable, permanent workforces.

No systematic review to date has brought these two literatures into a single analytical account, and this represents a genuine gap: research on why construction enterprises fail rarely engages with the specific technical tools now available to address the mechanisms it identifies, while research on AI in construction rarely engages with firm-survival outcomes at all. This review addresses that gap, guided by three research questions:

- RQ1: What workforce- and organisation-level factors does the literature identify as drivers of construction enterprise underperformance and failure beyond the start-up phase?
- RQ2: What does the literature report about AI applications relevant to these specific failure drivers?
- RQ3: How can existing evidence be synthesised into a conceptual framework linking AI-enabled organisational capability to construction enterprise life-cycle stage and post-startup productivity sustainability?

In addressing RQ3, this review's contribution is conceptual rather than empirical: it proposes the Post-Startup Productivity Sustainability (PPS) Model, together with a set of explicit, testable propositions, synthesising two literatures that have not previously been read together. The review does not claim, and explicitly cautions against interpreting it as claiming, that AI adoption has been shown to cause improved construction enterprise survival; no study identified in the reviewed corpus tests this relationship directly, and the model is offered as a theoretically grounded framework for future empirical testing rather than as a validated causal account. The remainder of the paper proceeds as follows. Section 2 sets out the theoretical foundation. Section 3 details the systematic review methodology. Section 4 reports results. Section 5 discusses these results against theory. Section 6 presents the proposed PPS Model and its propositions. Section 7 sets out practical and policy implications. Section 8 addresses limitations and future research, and Section 9 concludes.

THEORITICAL FOUNDATION

This review draws on two established organisational theories, applied jointly rather than separately, to interpret the literature reviewed in Section 4: organisational life-cycle theory, addressing when capability constraints become critical to survival, and the resource-based view, addressing what kind of capability is required to address them.

Organisational Life-Cycle Theory

Organisational life-cycle theory holds that enterprises pass through qualitatively distinct developmental stages, each demanding different management capabilities, and that failure to develop stage-appropriate capability is a recurring explanation for arrested growth or collapse. Greiner's (1972) foundational model describes organisational growth as evolutionary periods punctuated by developmental crises of leadership, autonomy, control, and coordination, each requiring a structural or managerial response before further growth becomes possible. Churchill and Lewis (1983) apply this logic to small and growing businesses specifically, proposing five stages, Existence, Survival, Success, Take-Off, and Resource Maturity, and arguing that the transition from Survival to Success typically

requires informal, founder-centred management to give way to systematic financial and operational control.

This review treats the empirically observed five-year survival inflection in construction cohort data (eSUB, 2025) as broadly consistent with, rather than direct proof of, the timing of a Churchill and Lewis-type Survival-to-Success transition. This distinction matters: organisational life-cycle stage is a function of accumulated capability, governance maturity, and organisational complexity, not of chronological firm age alone, and a given enterprise's actual developmental stage may not align precisely with the five-year mark observed in aggregate cohort statistics. The five-year figure is accordingly used throughout this review as an approximate analytical marker motivating the enquiry, not as a universal or deterministic threshold applicable to every construction enterprise.

The Resource-Based View

Where life-cycle theory addresses the timing of capability constraints, the resource-based view (RBV) addresses what must be acquired to resolve them. Barney's (1991) formulation holds that sustained competitive advantage depends on an enterprise's control of resources that are valuable, rare, imperfectly imitable, and non-substitutable (the VRIN criteria), and treats organisational capability, not only physical or financial assets, as a legitimate strategic resource.

Applying VRIN criteria directly to "AI tools" as a category requires caution, and this review adopts a more precise formulation than earlier applications of RBV to AI-in-construction research have typically used. Commercially available AI software, forecasting platforms, scheduling systems, and generative-AI applications are increasingly accessible and purchasable by competing firms, and therefore do not, on their own, straightforwardly satisfy the rarity or inimitability criteria RBV requires. What more plausibly meets VRIN criteria is not the AI tool itself but a bundle of firm-specific, harder-to-replicate elements: proprietary organisational data accumulated through use, an AI-literate workforce capable of interpreting and acting on tool outputs, embedded routines for data-driven decision-making, and managerial capability to integrate AI outputs into project and financial governance. This review therefore reframes its central RBV-derived construct throughout as AI-enabled organisational capability, rather than AI tool adoption, a distinction developed further in Section 2.3.

AI-Enabled Organisational Capability

This review distinguishes several related but analytically separable constructs that prior AI-in-construction literature frequently treats as interchangeable: AI resources (the software or platform itself), AI skills (individual workforce competency in using it), AI infrastructure (the data and technical systems supporting it), AI-enabled routines (organisational processes for acting on AI

outputs), and AI-enabled dynamic capability (the firm's capacity to sense emerging risks or opportunities, seize them through resource reconfiguration, and transform organisational routines accordingly). This last construct draws on dynamic capabilities theory (Teece, Pisano, and Shuen, 1997), which extends RBV by addressing how firms build and renew VRIN resources under conditions of technological and market change, a perspective particularly relevant to AI specifically, given the pace at which AI tools themselves continue to evolve. Only the combination of firm-specific data, workforce skill, embedded routine, and dynamic capability, rather than the AI resource in isolation, plausibly satisfies VRIN criteria and constitutes the kind of durable advantage RBV theory identifies as necessary for a firm navigating a life-cycle capability crisis.

Integrated Analytical Framework

Combining these theoretical strands yields the interpretive lens this review applies to the literature reviewed in Section 4: construction enterprises may face a life-cycle-timed capability crisis in the early post-startup period (Greiner, 1972; Churchill and Lewis, 1983), and AI-enabled organisational capability, as distinct from AI tool adoption alone (Barney, 1991; Teece, Pisano, and Shuen, 1997), is theoretically positioned as a candidate resource for addressing that crisis. This is presented as an interpretive framework for organising the reviewed evidence, not as a set of relationships the reviewed literature itself empirically establishes; Section 5 returns to this distinction explicitly, and Section 6 formalises the framework's testable implications as the Post-Startup Productivity Sustainability Model.

METHODOLOGY

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. Methodology is reported before results, consistent with standard systematic review reporting practice, so that readers can evaluate the evidence base before encountering its synthesis.

Research questions and eligibility criteria

Eligible sources were required to (a) address construction or general small-enterprise survival, failure, or workforce turnover, or artificial intelligence applications relevant to construction productivity, safety, or management; (b) be published between 2019 and 2026; and (c) be published in English. Peer-reviewed journal articles and systematic/scientometric reviews were the primary target. Industry-data analyses (such as eSUB's analysis of BLS cohort data) were eligible only where they reported on identifiable, citable primary data and were treated throughout as a distinct, lower-tier evidence category rather than as equivalent to peer-reviewed research, as reflected in the quality ratings in Table 1. Conference proceedings were eligible where peer-reviewed. Preprints (such as Taiwo et al., 2024, hosted on arXiv) were eligible only where no peer-reviewed alternative could

be identified, and are explicitly flagged as unreviewed in Table 1 rather than treated as equivalent to published, peer-reviewed sources. Dissertations and non-peer-reviewed institutional sources were excluded from the final corpus; one such source identified during screening (a doctoral dissertation on small-business survival) was excluded on this basis and does not appear in the final reference list. General SME-failure literature was included as a comparator domain given the comparative scarcity of construction-specific enterprise-failure studies.

Search strategy

Structured searches were conducted across Scopus, Web of Science, the ASCE Library, IEEE Xplore, and ScienceDirect between 12 and 20 January 2026, combining two search clusters targeting, respectively, enterprise/workforce failure literature and AI-in-construction literature. Table 1 (below) reports the complete, replicable search protocol, including the exact Boolean strings used, search dates, and initial result counts for each database and cluster.

Table 1. Search protocol.

Database	Search string (Title/Abstract/Keywords)	Search date	Initial results
Scopus	("construction firm*" OR "construction enterprise*" OR "construction SME*") AND ("business survival" OR "business failure" OR bankruptcy OR mortality OR "workforce turnover")	12 Jan 2026	34
Scopus	("artificial intelligence" OR "machine learning" OR "predictive analytics" OR "deep learning") AND construction AND (productivity OR workforce OR "cash flow" OR scheduling OR survival OR safety OR resilience)	12 Jan 2026	41
Web of Science	TS=(("construction firm*" OR "construction enterprise*" OR SME*) AND (survival OR failure OR bankruptcy OR "workforce turnover"))	14 Jan 2026	22
Web of Science	TS=(("artificial intelligence" OR "machine learning") AND construction AND (productivity OR safety OR workforce OR resilience))	14 Jan 2026	27
ASCE Library	construction AND ("business failure" OR "workforce turnover" OR survival)	16 Jan 2026	9

IEEE Xplore	("artificial intelligence" OR "deep learning") AND construction AND (safety OR productivity OR management)	18 Jan 2026	11
ScienceDirect	construction AND artificial intelligence AND (productivity OR resilience OR adoption OR safety)	20 Jan 2026	8

3.3 Screening and study selection

Records were screened in two stages: title/abstract screening against the eligibility criteria in Section 3.1, followed by full-text screening of shortlisted records. Screening was conducted by the author; the absence of a second independent screener is acknowledged as a limitation in Section 8. Duplicate records, including one exact duplicate entry identified and removed during final compilation, were removed before full-text assessment. Figure 1 presents the complete PRISMA flow diagram.

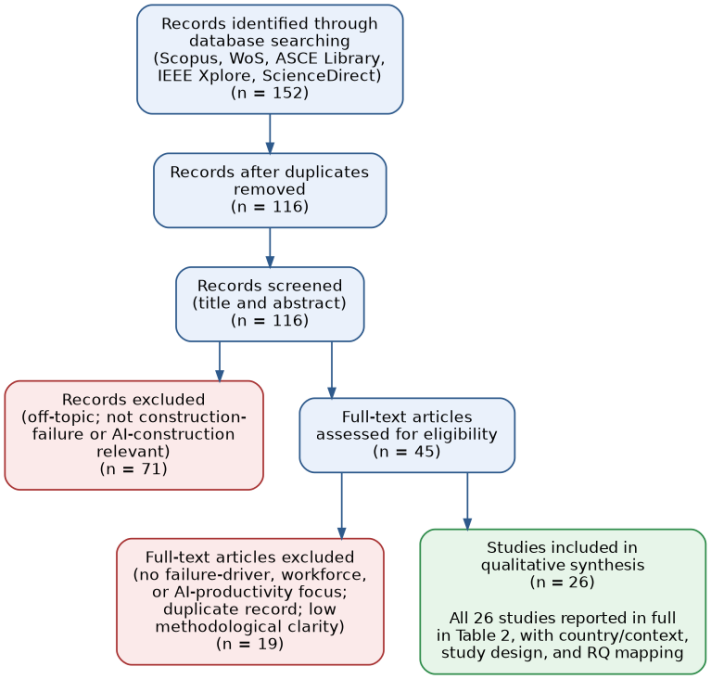


Figure 1. PRISMA flow diagram of the study identification, screening, and selection process.

Twenty-six studies met all inclusion criteria and were retained. All 26 are reported in full in Table 2 (Section 4), with no subset held back or reported only in summary form; this single, transparent table replaces the two-tier "priority studies from a larger corpus" structure used in an earlier draft of this review, in response to concerns that such a structure could obscure how non-detailed studies were actually used in synthesis.

Quality appraisal

Given the heterogeneity of included study designs, systematic reviews, scientometric/bibliometric analyses, empirical surveys, case studies, and one industry-data analysis, quality appraisal used a fit-for-purpose matrix rather than a single standardised checklist, informed by AMSTAR 2 principles for systematic reviews and general critical-appraisal principles for empirical and case-study designs. Each study was rated High, Moderate, or Low based on three criteria applied consistently across the corpus: (i) transparency of method (clearly reported search/sampling and analysis procedures); (ii) directness of relevance to the review's research questions; and (iii) evidentiary status (peer-reviewed publication versus industry source or unreviewed preprint). Ratings are reported for every study in Table 2 (Section 4); no study was excluded on quality grounds alone, but quality ratings are used throughout Sections 4 and 5 to weight the confidence placed in individual findings, and sources rated Low are explicitly flagged wherever cited.

Data extraction and synthesis

For each included study, the following were extracted: author/year, country or context, study design, key construct or focus, key finding, relevance to RQ1–RQ3, and quality rating (reported in full in Table 2). A narrative thematic synthesis approach was adopted, rather than meta-analysis, because included studies vary too substantially in design, outcome measures, and unit of analysis to support meaningful quantitative pooling. Findings were coded inductively into themes aligned with the three research questions, with coding decisions cross-checked against the extracted RQ-relevance field in Table 2 to ensure every thematic claim made in Sections 4 and 5 can be traced to specific, identified sources

RESULT AND DISCUSSION

RESULTS

This section reports the corpus and the patterns identified within it. Table 2 presents all 26 included studies in full, addressing the transparency and selection-bias concerns raised in the review by reporting every included study, rather than a curated subset, with country/context, design, key construct, key finding, RQ relevance, and quality rating for each.

Table 2. Full characteristics of all 26 included studies.

Study	Country/ Context	Study Design	Key Construct	Key Finding	RQ	Quality
Ayodele, Chang-Richards & González (2019)	New Zealand	SLR + PRISMA (53 studies)	Workforce turnover	Identifies 26 turnover factors across job, industry, firm, and	RQ 1	High

				individual categories		
Jayasekara, Fernando & Ranjani (2020)	Multi-country	SLR (95 studies, 1968–2016)	SME business failure	Finds finance access, resource scarcity, and managerial skill as dominant failure causes	RQ 1	High
Azeem & Khanna (2024)	Multi-country	SLR + research agenda	Startup survival	Synthesises survival determinants across the venture life cycle	RQ 1	Moderate
Cheraghali & Molnár (2023)	Multi-country	Methodology-focused review	SME default prediction	Reviews statistical/ML approaches to forecasting enterprise failure	RQ 1	High
eSUB / BLS cohort analysis (2025)	United States	Industry analysis of BLS cohort data	Construction firm survival trends	5-year survival rose 46.2%→59.3% across cohorts; ~94% subsequent annual survival post-year-5	RQ 1	Moderate (industry source)
Abioye et al. (2021)	Multi-country	SLR	AI in the construction industry	Reviews the status, opportunities, and challenges of AI across construction	RQ 2	High
Pan & Zhang (2021)	Multi-country	Scientometric review (4,473 articles)	AI in construction engineering & management	Identifies six state-of-the-art AI application areas, incl. cost/schedule prediction	RQ 2	High
Egwim et al. (2024)	Multi-country	SLR + PRISMA (70 studies)	AI across the construction value chain	AI concentrated in facility management; flags AI education as underexplored.	RQ 2	High

Zhao (2024)	Multi-country	Bibliometric + SLR	AI in the AEC industry	Maps research themes, contributors, and future trends	RQ 2	Moderate
Adebayo et al. (2025)	Multi-country	Structured literature review	AI in construction project management	Traces evolution of AI-enabled cost/schedule control tools	RQ 2	Moderate
Maalek (2024)	Germany	Case study (PBL + generative AI)	AI in construction management education	Shows AI-PBL integration strengthens project-management skills	RQ 2/RQ3	Moderate
Obi, Osuizugbo & Awuzie (2025)	Multi-country	SLR + PRISMA + AMSTAR2 (17 studies)	AI skills gap in construction	Identifies eight core AI competency domains for professionals	RQ 2/RQ3	High
Geng et al. (2025)	Multi-country	SLR + bibliometric (94 papers)	Construction graduate employability	Links workforce-skill categories to enterprise performance	RQ 3	Moderate
Akinosho et al. (2020)	Multi-country	SLR	Deep learning in construction	Identifies AI-driven solutions improving productivity, safety, and project performance	RQ 2	High
Tjebane, Musonda & Okoro (2022)	South Africa	Quantitative survey	Organisational AI-adoption factors	Leadership support, readiness, and innovation culture shape AI adoption	RQ 2/RQ3	Moderate
Adebowale & Agumba (2023)	South Africa	PRISMA SLR	AI for construction productivity	Synthesises applications and adoption barriers in construction firms	RQ 2	Moderate

Hosseini et al. (2021)	Multi-country	Conceptual review	AI adoption: opportunities and challenges	AI strengthens resilience via data-driven decision-making	RQ 2/RQ3	Moderate
Lu et al. (2021)	Multi-country	Review	Intelligent construction / digital transformation	AI contributes to efficient delivery and resource optimisation	RQ 2	Moderate
Darko et al. (2020)	Multi-country	Review	Drivers of smart technology in construction	Links smart technology adoption to sustainability and productivity	RQ 2	Moderate
Wang et al. (2026)	Multi-country	Hybrid bibliometric + SLR	Digital technologies and construction productivity	AI identified as central to productivity and competitiveness	RQ 2	Moderate
Nozari, Movahed & Szmelter-Jarosz (2026)	Multi-country	SLR	Digital transformation of construction organisations	AI-supported digital transformation linked to resilience and continuity	RQ 2/RQ3	Moderate
Olatunde et al. (2026)	Multi-country	Bibliographic review	Global AI research trends in construction	Maps research evolution; largely descriptive/mapping in nature	RQ 2	Low–Moderate
Taiwo et al. (2024)	Multi-country	State-of-the-art review [preprint, arXiv — not peer-reviewed]	Generative AI in construction	Proposes practical frameworks for generative-AI implementation	RQ 2	Low (unreviewed preprint)

Zhang, Teizer, Lee & Eastman (2022)	Multi-country	Review	AI-enabled construction safety management	AI reduces safety risk and improves operational efficiency	RQ 2	Moderate
Chen, Xu & Li (2023)	China	Case study	AI predictive analytics for project success	Predictive AI supports strategic planning and sustainability	RQ 2/RQ3	Moderate
Mohammed, Ibrahim & Othman (2024)	Nigeria	Mixed methods	AI adoption and organisational resilience, construction SMEs	AI adoption associated with resilience, competitiveness, and survival perception	RQ 1/RQ2/RQ 3	Moderate–High

Studies addressing RQ1 (failure drivers)

Six studies address enterprise- or workforce-level failure drivers directly: Ayodele, Chang-Richards, and González (2019) on workforce turnover; Jayasekara, Fernando, and Ranjani (2020), Azeem and Khanna (2024), and Cheraghali and Molnár (2023) on general SME failure and default prediction; the eSUB/BLS (2025) cohort analysis on construction-specific survival trends; and Mohammed, Ibrahim, and Othman (2024) on AI adoption and resilience in construction SMEs, which addresses RQ1 alongside RQ2 and RQ3.

Studies addressing RQ2 (AI applications)

Nineteen studies address AI applications in construction, spanning general technical reviews (Abioye et al., 2021; Pan and Zhang, 2021; Egwim et al., 2024; Zhao, 2024; Adebayo et al., 2025; Akinosho et al., 2020), domain-specific applications (safety: Zhang et al., 2022; predictive analytics: Chen, Xu, and Li, 2023; generative AI: Taiwo et al., 2024 [preprint]), organisational adoption factors (Tjebane, Musonda, and Okoro, 2022; Adebowale and Agumba, 2023; Hosseini et al., 2021), and broader digital-transformation literature (Lu et al., 2021; Darko et al., 2020; Wang et al., 2026; Nozari, Movahed, and Szmelter-Jarosz, 2026; Olatunde et al., 2026).

Studies addressing RQ3 (integrative/workforce-pipeline evidence)

Studies most directly relevant to RQ3's integrative question include Obi, Osuizugbo, and Awuzie (2025) and Maalek (2024) on AI competency development,

Geng et al. (2025) on the link between workforce skills and enterprise performance, and Mohammed, Ibrahim, and Othman (2024), the single study in the corpus that reports on failure/resilience factors, AI adoption, and organisational outcomes within one investigation. No study in the corpus directly and empirically tests a link between AI adoption and construction enterprise survival specifically.

Positioning relative to prior reviews

Table 3 positions this review against four representative prior reviews within the corpus, indicating that none combines enterprise/workforce-failure evidence with AI-in-construction evidence within a single synthesis.

Prior Review	Examines Enterprise/ Workforce Failure?	Examines AI in Construction?	Connects the Two?
Ayodele et al. (2019) — construction workforce turnover SLR	Yes	No	No
Jayasekara et al. (2020) — general SME failure SLR	Yes (general)	No	No
Egwim et al. (2024) — AI construction value chain SLR	No	Yes	No
Obi et al. (2025) — AI skills gap in construction SLR	No	Yes	No
This review	Yes	Yes	Yes — via the proposed PPS Model (proposed, not tested)

DISCUSSION

This section interprets the results reported in Section 4 against the theoretical foundation set out in Section 2, addressing each research question in turn.

RQ1: Workforce and organisational failure drivers

The evidence reviewed in Section 4.1 is reasonably consistent across construction-specific and general SME literature: workforce turnover (Ayodele, Chang-Richards, and González, 2019) and financial/managerial capability constraints (Jayasekara, Fernando, and Ranjani, 2020; Cheraghali and Molnár, 2023) recur as explanatory factors across studies conducted independently, in different countries, using different methods, a convergence that provides reasonable, though not definitive, confidence in their explanatory relevance. The eSUB/BLS cohort data, as an industry rather than peer-reviewed source, is treated here as motivating evidence for the review's temporal framing rather than as a rigorously tested causal

account of why the five-year pattern exists; the BLS survival statistics themselves are official government data, but the specific interpretive claim that software adoption explains the improvement across cohorts is eSUB's own commercial interpretation and is treated in this review as a hypothesis worth investigating, not an established finding, since no causal analysis isolating software adoption from other contributing factors, macroeconomic conditions, changes in industry structure, financing availability, was identified in the eSUB material or elsewhere in the reviewed corpus.

RQ2: AI applications relevant to identified failure drivers

The literature reviewed in Section 4.2 documents AI applications that are conceptually relevant to the failure drivers identified in Section 5.1: cost and schedule prediction tools (Pan and Zhang, 2021; Adebayo et al., 2025) address the kind of cash-flow and planning uncertainty associated with financial fragility, while workforce analytics and AI-enabled competency development (Obi, Osuizugbo, and Awuzie, 2025; Maalek, 2024) address, in principle, the human-capital dimension of workforce instability. It is important to state plainly what this evidence does and does not show: it shows that AI tools exist and are documented as technically capable within these functional domains; it does not show that firms adopting these tools experience improved survival outcomes as a result, since the AI-in-construction literature reviewed here was, with the partial exception of Mohammed, Ibrahim, and Othman (2024), developed without reference to firm-survival outcomes at all. The mapping between AI application and failure driver identified in this review is therefore best described as a conceptual correspondence the literature makes plausible, not an empirically demonstrated mechanism.

5.3 RQ3: Towards an integrated interpretation

Read through the theoretical foundation in Section 2, this correspondence can be interpreted, with appropriate caution, as follows. Organisational life-cycle theory suggests that the Survival-to-Success transition, approximated but not proven by the five-year empirical marker discussed in Section 5.1, is a period in which informal management practice becomes a liability. The resource-based view, applied here specifically to AI-enabled organisational capability rather than AI tools alone, suggests that firms able to build the combination of data, workforce skill, and embedded routine described in Section 2.3 are better positioned to complete that transition. The construction-failure literature reviewed here provides evidence consistent with the existence of a Survival-stage capability deficit, as organisational life-cycle theory would predict; the AI-in-construction literature reviewed here independently documents technical capabilities that correspond plausibly to the resources such a transition would require. Neither literature, individually or together, empirically demonstrates the connecting relationship; this review's

contribution is to make that connection explicit as a theoretically grounded proposition for future testing, formalised in Section 6, rather than to claim it as an established finding.

THE POST-STARTUP PRODUCTIVITY SUSTAINABILITY (PPS) MODEL

In response to RQ3, this review proposes the Post-Startup Productivity Sustainability (PPS) Model as a theoretically derived and literature-informed conceptual framework, not as a validated model. The model comprises antecedents, AI-enabled capabilities, intermediate outcomes, outcomes, and moderating boundary conditions, together with five explicit propositions intended to make the framework directly testable in future research.

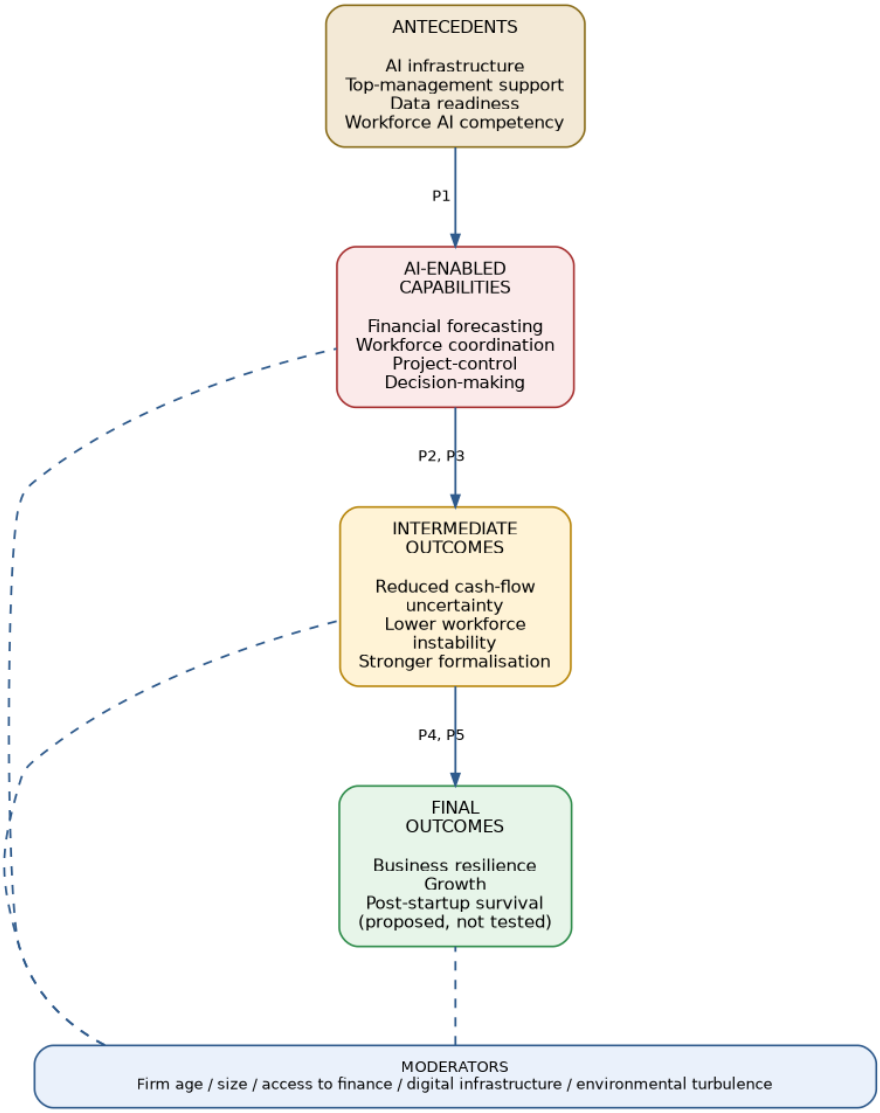


Figure 2. The Post-Startup Productivity Sustainability (PPS) Model: antecedents, AI-enabled capabilities, intermediate and outcomes, moderators, and the propositions (P1–P5) linking them. Proposed framework; relationships are not empirically tested by this review.

MODEL COMPONENTS

Antecedents comprise AI infrastructure, top-management support, data readiness, and workforce AI competency. This serves as the preconditions in the reviewed literature (Section 4.3; Obi, Osuizugbo, and Awuzie, 2025; Tjebane, Musonda, and Okoro, 2022. Also, it identifies this as necessary before AI tools can translate into organisational capability. AI-enabled capabilities comprise financial forecasting, workforce coordination, project control, and decision-making capability, corresponding to the AI-enabled organisational capability construct developed in Section 2.3, distinct from AI tool possession alone. Intermediate outcomes comprise reduced cash-flow uncertainty, lower workforce instability, and stronger managerial formalisation, the proximate effects these capabilities would be expected to produce if the model's propositions hold. Outcomes comprise business resilience, growth, and post-startup survival; these are the model's proposed, not demonstrated, ultimate outcomes. Moderators comprise firm size, firm age, access to finance, digital infrastructure, and environmental turbulence, boundary conditions under which the model's central relationships are expected to vary in strength. Proposed framework; relationships are not empirically tested by this review

Propositions

- P1: Cash-flow fragility and workforce instability increase the likelihood that early-stage construction enterprises remain in a reactive, informally managed configuration.
- P2: AI-enabled financial-forecasting capability is positively associated with an enterprise's capacity to transition from reactive management to systematic financial control, conditional on adequate data readiness (a boundary condition).
- P3: AI-enabled workforce-coordination capability reduces the negative association between workforce instability and post-startup productivity, conditional on workforce AI competency (a boundary condition).
- P4: Workforce AI competency strengthens the relationship between AI-tool adoption and the development of durable, firm-specific AI-enabled capability, consistent with the VRIN-resource reframing in Section 2.3.
- P5: The hypothesised relationship between AI-enabled capability and enterprise survival is mediated by improvements in financial visibility, workforce coordination, and managerial decision quality, and is expected to vary by firm size, access to finance, and digital-infrastructure context (boundary conditions).

These propositions are stated explicitly so that they, rather than the model's narrative description alone, can be operationalised and tested in future empirical research, as discussed further in Section 8.

PRACTICAL AND POLICY IMPLICATIONS

Because the PPS Model is a proposed, untested framework, the implications below are framed as testable hypotheses for practice to consider piloting, not as proven recommendations, and are differentiated by stakeholder rather than presented as a single generic list.

Construction enterprise owners

Owners of early-stage firms may benefit from conducting a structured AI-readiness assessment before tool adoption, prioritising cash-flow forecasting capability specifically over generic digital-transformation initiatives, investing in a structured workforce data foundation, and pairing any AI-tool adoption with explicit workforce AI-skill development rather than treating adoption as a one-time purchase.

Government and industry bodies

Agencies supporting small construction enterprises may consider digitalisation grants targeted specifically at firms approaching the early post-startup period identified in Section 5.1, shared AI platforms reducing the cost barrier smaller firms face relative to the VRIN-resource logic in Section 2.3, and AI-training support integrated into existing small-contractor development programmes.

Educational institutions

Construction management curricula may consider integrating AI-enabled problem-based learning modelled on Maalek's (2024) approach, extended explicitly to enterprise-level rather than only project-level decision-making, alongside data-literacy and AI-output-interpretation competencies consistent with the workforce-capability antecedent in Section 6.1.

Financing institutions

Lenders and investors serving construction SMEs may consider incorporating a firm's digital and AI-capability maturity as one input into risk assessment, and could support technology-adoption financing structured around the specific capability-building sequence the PPS Model proposes, rather than funding AI-tool purchase in isolation from workforce-competency investment.

Limitations and Future Research

This review has several limitations. The corpus comprises 26 studies identified through a five-database search; while methodologically transparent (Section 3.2), a broader search across additional databases or grey literature might identify further relevant evidence. Screening and quality appraisal were conducted by a single author without independent second-reviewer verification, a departure from best-practice SLR protocol acknowledged here directly. The corpus relies on general SME-failure literature as a comparator domain given the relative scarcity of construction-specific enterprise-failure studies; conclusions extending general SME

findings to construction specifically should be treated as inferential. The review's motivating empirical observation regarding the five-year survival pattern derives substantially from a single national context (the United States, via eSUB's analysis of BLS data) and from an industry rather than peer-reviewed source for its causal interpretation; this should not be assumed to generalise to other national contexts without further testing. Most fundamentally, the PPS Model and its five propositions are a conceptual synthesis that has not been empirically tested by this review and should be treated strictly as a research and practice heuristic pending future validation.

Future research should prioritise, first, longitudinal firm-level studies tracking construction enterprises through the proposed Stage 1–2 transition, measuring AI-tool adoption, workforce AI competency, and subsequent survival or growth outcomes directly, ideally via matched-cohort or difference-in-differences designs comparing AI-adopting and non-adopting firms of similar age and size. Second, development and validation of a formal AI-capability maturity instrument, extending the competency domains identified by Obi, Osuizugbo, and Awuzie (2025) to enterprise-level measurement, would allow the PPS Model's propositions to be tested directly rather than assumed. Third, cross-national replication is needed to test whether the five-year pattern motivating this review generalises beyond the United States construction sector, with particular attention to how the moderating boundary conditions identified in Section 6.1, digital infrastructure, access to finance, and regulatory environment, vary across markets. Finally, given that the theoretical foundation applied in Section 2 predates the AI literature it is applied to by several decades, future conceptual work should examine whether AI-enabled capability requires theoretical treatment distinct from earlier forms of organisational capability, given the pace at which AI tools themselves continue to change relative to the multi-year timescales over which organisational life-cycle transitions have traditionally been understood to occur.

CONCLUSION

This review set out to examine why construction enterprises disproportionately fail beyond their fifth year and to evaluate AI's potential relevance to that pattern. Three things can be stated with differing degrees of confidence. First, what the reviewed literature consistently and independently establishes: cash-flow fragility, workforce turnover, and informal management structures are recurrently associated with early-stage construction and small-enterprise failure, and a substantial, separate literature documents AI applications- cost/schedule prediction, workforce analytics, and safety and resilience tools- that are conceptually relevant to these same factors. Second, what this review interprets, rather than finds directly demonstrated: read through organisational life-cycle theory and a resource-based

view reframed around AI-enabled organisational capability rather than AI tools alone, these two literatures plausibly describe complementary halves of a single capability transition, one naming a deficit, the other documenting technology conceptually capable of addressing it. Third, what remains to be tested: no study identified in this review's corpus directly examines whether AI adoption improves construction enterprise survival, and the Post-Startup Productivity Sustainability Model proposed here, together with its five explicit propositions, should be understood as a theoretically derived, literature-informed conceptual framework offered specifically to enable that future empirical test, not as a validated causal account. Construction enterprise survival beyond the early post-startup period remains, on the evidence reviewed here, an outcome AI-enabled capability may plausibly support; whether it does so, and under what conditions, is a question this review poses rather than answe

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