Economic Sciences

UDC 658.5:69

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DOI: https://doi.org/10.25313/2520-2057-2026-9-12145

A DATA-ORIENTED PERFORMANCE MANAGEMENT MODEL FOR A CONSTRUCTION ENTERPRISE: LINKING PROCESS OPTIMIZATION, INDIVIDUAL PERSONNEL EFFICIENCY, WORK QUALITY, AND PROFITABILITY

Summary. *The construction industry remains one of the slowest-growing major sectors in productivity terms: global construction labor productivity improved by only 0.4% annually between 2000 and 2022, compared with 2.0% for the total economy [15]. This paper examines the structural relationship between data-oriented management practices, workforce performance, construction quality control, and enterprise profitability. The study combines a structured literature review, comparative analysis of published sector statistics, case-study synthesis, and author-developed conceptual modeling. The resulting four-layer performance management model treats traceable data flows as the connective mechanism among process control, personnel performance, quality management, and financial decision-making. Evidence from Kazakhstan, the Asia-Pacific region, Ukraine, and the United States is used to illustrate the model's components. The reviewed evidence supports associations between more structured measurement, quality-management practices, and improved operational or financial outcomes, but it does not establish a universal causal effect size. The framework is intended for mid-size and owner-led construction* *enterprises seeking a scalable performance-management architecture that can be tested empirically in future research.*

Key words: *construction performance management, data-driven decision-making, labor productivity, quality management, key performance indicators, process optimization, financial discipline, profitability, reinvestment strategy, owner-led enterprise.*

Introduction. The global construction market reached US$11.39 trillion in 2024 and is projected to expand to US$16.11 trillion by 2030 [7]. Yet output growth coexists with a persistent productivity problem. Mischke et al. [15] report that global construction productivity improved by only 0.4% annually between 2000 and 2022, compared with 2.0% for the total economy. In the United States, the latest BLS construction-industry measures show marked variation even within residential construction: single-family labor productivity increased by 6.1% in 2024, whereas multiple-family residential productivity declined by 12.8% [22]. This divergence illustrates why sector-level averages can conceal materially different performance trajectories across subsectors.

The more actionable management issue is not simply whether firms possess digital tools, but whether data are captured consistently, integrated across functions, and converted into timely decisions. In a 2024 study of 933 construction and engineering businesses in the Asia-Pacific region, Autodesk and Deloitte Access Economics [3] reported that each additional digital technology used was associated with 1.4 percentage points higher annual revenue growth and 1.0 percentage point higher annual profit growth. These are associations rather than causal estimates, but they demonstrate the financial relevance of digital maturity. The RICS Construction Productivity Report 2026, based on responses from nearly 3,000 professionals across five regions, likewise documents fragmented productivity definitions, low benchmark adoption of only 5%-16%, and substantial differences in measurement frequency; respondents rated workforce skills as the strongest productivity lever across regions [19]. Together, these findings point to measurement discipline, workforce capability, and data integration as complementary management priorities.

Scholarly attention to construction performance management has expanded substantially. Abdelhameed et al. [1] identified 7,358 Scopus-indexed records on construction project performance published between 1989 and 2023 and retained 276 publications for scientometric and qualitative analysis, documenting exponential growth in the field. At the project level, Ibrahim et al. [11] argue that conventional financially oriented measurement is insufficient and should be complemented by non-financial performance measures. At the productivity level, the umbrella review by Gutierrez-Bucheli et al. [10], which synthesized 46 reviews published between 2013 and 2025, highlights persistent inconsistency in terminology and measurement and calls for standardized, lifecycle-oriented metrics. A gap therefore remains in translating these strands into an operational framework that links process, personnel, quality, and financial data in a form usable by mid-size and owner-led firms.

The present study addresses that gap. The research **objective** is to analyze the structural links among process optimization, individual employee performance, quality management, and enterprise profitability in the construction sector, and to propose a data-oriented management model that formalizes those links as an actionable management instrument. **The scientific novelty** of the study lies in the original synthesis of a four-layer performance management framework that treats continuous data flows as the connective tissue among process, personnel, quality, and financial domains in construction enterprises.

The working hypothesis is that construction enterprises with consistent performance-data collection, structured quality management, and explicit capital-allocation rules will exhibit more stable long-run operational and financial performance than comparable firms without those practices. Because the present study is a synthesis and conceptual-modeling exercise rather than a longitudinal firm-level test, the hypothesis is evaluated for consistency with the reviewed evidence rather than treated as causally confirmed.

The study has three principal limitations. First, the review emphasizes English-language publications and therefore may underrepresent evidence from non-Anglophone regions. Second, the empirical material is drawn from published studies and sector reports rather than primary fieldwork, which limits the comparability and granularity of firm-level observations. Third, the proposed four-layer model and the reinvestment extension are conceptual; their causal pathways, threshold values, and effect sizes require prospective validation. These limitations are material to interpretation and are reflected in the cautious wording of the conclusions.

The findings are relevant to construction enterprise owners and managers, project commissioners, investors, and researchers working at the intersection of operations management and organizational performance. The United States provides a useful scale reference: construction spending exceeded US$2 trillion in 2024, while sector employment reached 8.3 million in July 2024, above the previous 2006 peak of 7.7 million [14]. At this scale, management systems that improve the traceability of process, quality, workforce, and financial information have practical significance even when their firm-level causal effects remain to be established.

Materials and Methods. The methodology of this study combines four complementary approaches: a systematic literature review, comparative analysis of sector statistics, case-study synthesis, and author-developed conceptual modeling. Together, these approaches allow the study to triangulate between theoretical frameworks, quantitative sector data, and practice-based evidence.

A structured search of Scopus and Web of Science was conducted using combinations of the terms "construction performance management," "data-driven construction," "construction labor productivity," "construction key performance indicators," "quality management construction profitability," and "process optimization construction." The academic search focused on English-language peer-reviewed journal articles and conference proceedings published from 2020 through 2026. Full texts were retrieved from publisher platforms including SpringerLink, the ASCE Library, MDPI, Emerald, Taylor & Francis, Elsevier, and IOP. Authoritative industry and government reports were included selectively when they supplied sector statistics or benchmarking evidence not available in the academic corpus; these sources were treated as contextual evidence rather than substitutes for peer-reviewed research.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) logic guided screening and selection. The initial search and deduplication process produced 312 candidate items; relevance, date, language, publication type, and direct connection to the study's four core constructs were then assessed, resulting in a final evidence corpus of 22 sources used in the article. Each retained source was coded by research method, geographic scope, performance dimension, and type of measurement or data instrument. Because the study combines academic and authoritative gray literature, claims are reported with attention to the evidentiary strength of the underlying source.

Quantitative sector statistics were taken from sources with transparent methodology and identifiable publication records. The U.S. Bureau of Labor Statistics [22] provides construction labor-productivity measures through 2024. Meisels et al. [14] provide U.S. construction output, spending, and employment indicators for 2024, while Deloitte [7] provides the global construction-market size and 2030 projection. Mischke et al. [15] are used for the global 2000-2022 productivity comparison and construction return-on-invested-capital trend. The RICS [19] report is used for cross-regional evidence on productivity definitions, measurement frequency, benchmarking, and perceived productivity drivers. Autodesk and Deloitte Access Economics [3] provide the digital-adoption benchmark used in the introductory and implementation analyses.

Three publications provide particularly direct anchors for the model. Cheirkhanova et al. [5] analyze 2023 financial and operational data from 23 Kazakhstani construction companies using regression, multivariate analysis, and clustering to examine relationships among quality-management variables, sales, profitability, and customer satisfaction. Gutierrez-Bucheli et al. [10] synthesize 46 construction-productivity reviews and identify standardization, lifecycle measurement, and dashboard-based benchmarking as major needs. Breuling et al. [4] develop 14 application-specific KPIs for data-based construction project management and describe their potential for digital tracking of site status and optimization opportunities, while noting the need for further validation. These studies are supplemented by the wider review corpus in the comparisons and implementation recommendations that follow.

The four-layer data-oriented performance management model was developed by inductively organizing recurring constructs in the reviewed literature into a sequential decision architecture. The model layers are: data inputs; process optimization and workforce performance; integrated KPI analytics; and management decision output. The architecture is intended to make the provenance of each KPI visible from source data through management action. The separate reinvestment cycle introduced later is an author-developed extension intended to connect operational performance with capital-allocation discipline. It is presented as a testable managerial proposition, not as an empirically validated causal model.

Results and Discussion. Across the reviewed literature, low construction productivity is associated with several interacting constraints rather than a single root cause. These include workforce skills, logistics and coordination, rework, inconsistent measurement, and delayed feedback [2; 19). The management implication is that performance systems should capture both outcome measures and the operational conditions that precede them. Retrospective reporting of cost overruns, schedule delays, or defect totals remains useful for accountability, but it is less useful for intervention when the underlying event has already propagated through the project. This distinction motivates the model's emphasis on traceable, higher-frequency data flows.

Fig. 1 uses the latest BLS residential construction measures to illustrate the heterogeneity hidden by aggregate construction statistics. In 2024, labor productivity increased by 6.1% in single-family residential construction as output rose by 5.9% and hours worked were essentially unchanged (-0.1%). In multiple-family residential construction, labor productivity declined by 12.8% as output fell by 12.2% while hours worked increased by 0.7% [22]. The opposing directions within closely related subsectors support the use of disaggregated performance measures rather than a single sector-wide productivity signal.

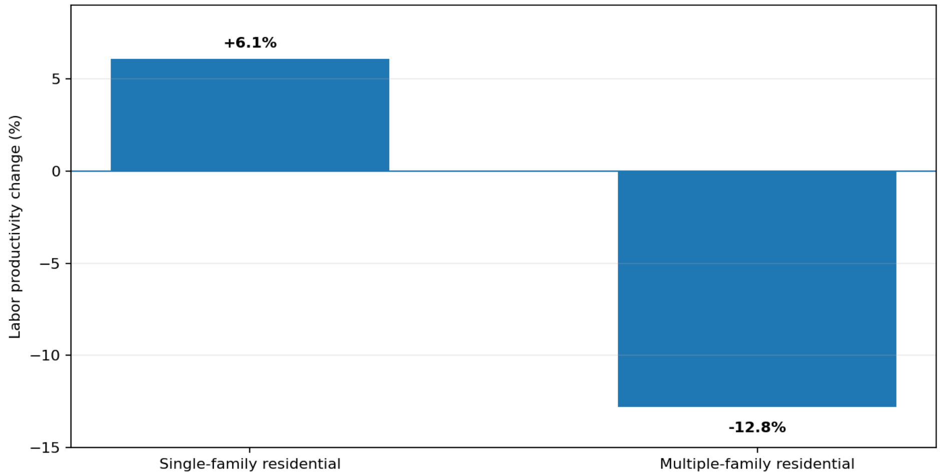

Fig. 1. U.S. Residential Construction Labor Productivity Change in 2024

Source: compiled by the author based on [22]

The U.S. contrast sits within a wider structural productivity gap. Mischke et al. [15] report that global construction productivity improved by only 10% in total, or 0.4% annually, between 2000 and 2022, compared with 50% in the total economy, or 2.0% annually. RICS [19] shows why cross-firm comparison remains difficult: no single productivity definition reaches 30% adoption in any surveyed region, and external benchmark use ranges from 5% to 16%. The same RICS survey identifies workforce skills as the only productivity constraint rated as high impact across all five regions. These findings suggest that data governance must be developed alongside workforce and site-management capability rather than treated as a technology-only intervention.

The financial context reinforces the need to connect operational measures with economic outcomes. Meisels et al. [14] report that U.S. construction nominal value added increased by 10% and gross output by 12% in 2024. At the same time, Mischke et al. [15] show that post-tax return on invested capital for construction companies and raw-material suppliers decreased by 0.5 percentage points globally between 2008 and 2023, whereas product suppliers gained 9.2 percentage points. Rising output can therefore coexist with pressure on capital returns. A performance-management system should consequently show how schedule, productivity, and quality deviations flow through to margin and capital-allocation decisions.

The principal contribution of this paper is the four-layer data-oriented performance management model shown in Fig. 2. The model is presented as a data-flow architecture rather than an organizational chart. Its design premise is that site-level measurements become more useful when they can be traced through process, workforce, quality, and financial domains to an explicit management response. The framework therefore emphasizes vertical traceability from operational data to decision-making and horizontal integration across performance domains.

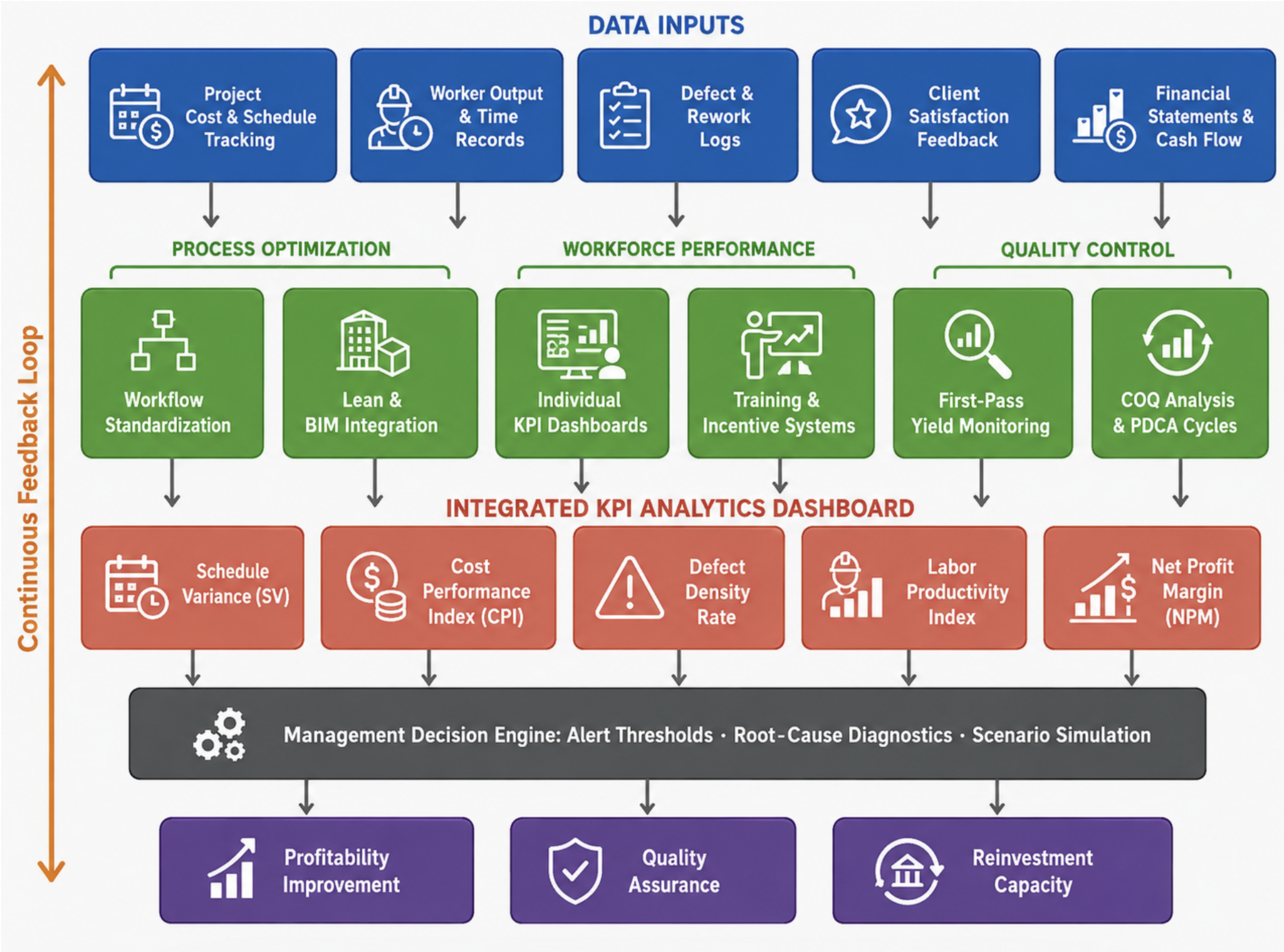

Fig. 2. Data-Oriented Performance Management Model for a Construction Enterprise

Source: compiled by the author based on [4; 10; 16; 5]

Layer 1 (Data Inputs) captures five primary streams: project cost and schedule tracking, worker or crew output and time records, defect and rework logs, client-satisfaction feedback, and financial statements and cash-flow data. The purpose is not to maximize data volume, but to establish ownership, frequency, and traceability for each stream. Murguia et al. [16] demonstrate the practical value of a data-to-dashboard strategy that aligns metrics, digital tools, and analyses, while also identifying multi-source integration and conversion of information into decisions as implementation challenges. Gutierrez-Bucheli et al. [10] similarly emphasize the need for standardized measurement frameworks that enable comparison across projects and the broader value chain.

Layer 2 (Process Optimization and Workforce Performance) receives Layer 1 data and applies them in two parallel tracks. Process optimization uses standardized workflow information and, where appropriate, Lean- or BIM-enabled monitoring to identify recurring bottlenecks and deviations. The workforce track uses task-appropriate worker- or crew-level indicators to identify training, coordination, or allocation needs without assuming that every construction activity can be fairly attributed to an individual. Breuling et al. [4] developed 14 application-specific KPIs for data-based construction project management and argue that such KPIs can support digital tracking of site status, weak points, and optimization potential; the authors also note that further validation is required. The proposed model therefore treats KPI-based workforce feedback as a management mechanism whose effectiveness must be verified in implementation.

Layer 3 (Integrated KPI Analytics Dashboard) consolidates the data streams into a compact set of indicators: schedule variance (SV), cost performance index (CPI), defect density or rework rate, labor productivity, and net profit margin. The exact dashboard composition can vary by project type. Ibrahim et al. [11] emphasize that financial measures alone are insufficient for construction performance assessment and should be complemented by non-financial indicators, while Abdelhameed et al. [1] show the centrality of KPI-based performance assessment in the broader construction-project-performance literature. The design rule in this model is therefore traceability: every dashboard measure should be linked to an identifiable source stream and to a defined management response when a threshold is crossed.

Layer 4 (Management Decision Engine) converts monitored deviations into documented management responses. It combines alert thresholds, root-cause investigation, and scenario analysis so that managers can examine the operational and financial implications of a proposed intervention before committing resources. This layer is likely to be organizationally demanding because it requires clear decision rights, data ownership, and response protocols. The model does not require a single automated platform; its essential requirement is a traceable link between a KPI deviation, the diagnostic process, the selected action, and subsequent performance review.

Performance management is weakened when KPIs are read in isolation. A cost-performance deterioration may reflect rework, skills, logistics, coordination, scheduling, or other operating conditions rather than a purely financial cause. Cross-domain analysis is therefore used here to generate plausible upstream explanations before management selects an intervention.

Fig. 3 presents the author-developed KPI Interaction Matrix as a structured diagnostic map across the four core performance domains. The 16 cells include four within-domain feedback relationships and twelve cross-domain links. The matrix is intended to help managers generate and test candidate upstream explanations for an observed deviation; it does not assign causal probabilities or estimate effect sizes.

	Process Optimization	Workforce Performance	Quality Management	Financial Performance
Process Optimization	Workflow feedback and standardization	Work design shapes measured output	Process deviations may precede defects	Schedule/cost variance affects project economics
Workforce Performance	Skill/coordination data informs workflow review	Task/crew performance feedback	Training/experience are candidate quality drivers	Labor productivity affects cost exposure
Quality Management	Rework data flags process bottlenecks	Defect patterns inform training review	COQ and defect monitoring	Failure costs affect margin
Financial Performance	Budget constraints shape process investment	Training/resources depend on allocation	Quality investment depends on allocation	Margin and capital-allocation review

Fig. 3. Proposed KPI Interaction Matrix for Construction Enterprise Performance Management

Source: compiled by the author based on [9; 5; 20; 4]

The matrix should be interpreted as a conceptual map of management pathways rather than as an estimated causal network. Quality can influence financial performance through failure and rework costs, while workforce capability can affect both process reliability and quality outcomes. Shafiei et al. [20], using a system-dynamics case model, show that additional training and more experienced labor can reduce failure costs while increasing prevention costs, with an overall reduction in cost of quality under the modeled conditions. Assaad et al. [2] independently rank errors, omissions, rework, inadequate training, and insufficient coordination among the most important adverse labor-productivity factors in offsite construction. The matrix formalizes these cross-domain relationships so that managers can trace a KPI deviation upstream before selecting an intervention.

Cheirkhanova et al. [5] provide construction-specific empirical evidence for the quality-finance linkage. Their analysis of 23 Kazakhstani construction companies reports statistically significant relationships between quality-management variables and sales performance; the study identifies customer satisfaction, product profitability, and the economic efficiency of the QMS as important positive predictors, while emphasizing that quality-related expenditure must be optimized rather than increased indiscriminately. This evidence supports the model's decision to connect quality indicators to financial outcomes, but it does not by itself establish the magnitude or direction of every pathway shown in the KPI Interaction Matrix.

Table 1 presents an ideal-typical comparison of three performance-management configurations synthesized from the reviewed literature. The categories are analytical constructs rather than mutually exclusive industry classes, and the entries should not be read as estimated performance effects. The comparison focuses on data granularity, feedback cadence, KPI scope, workforce visibility, financial linkage, and implementation burden - the dimensions most directly related to the proposed model's architecture.

Table 1

Ideal-Typical Comparison of Construction Performance Management Configurations

Criterion	**Retrospective Reporting**	**Project-Level KPI Tracking**	**Data-Oriented Integrated Model (Proposed)**
Data granularity	Aggregated project or firm data	Project-level data with limited disaggregation	Project-, process-, crew/worker-, quality-, and finance-linked data where valid
Feedback cadence	Monthly or quarterly reporting	Periodic project-control cycle	Higher-frequency updates with defined exception thresholds
KPI scope	Primarily financial and completion outcomes	Cost, schedule, and selected quality indicators	Cost, schedule, quality, productivity/workforce context, and margin
Workforce visibility	Indirect or limited	Mostly team/project level	Worker-, crew-, or task-level only where attribution is valid
Financial linkage	Project accounting separated from operating feedback	Financial review tied to project control	Operational KPIs linked to margin and explicit capital-allocation decisions
Implementation burden	Low	Moderate	Moderate to high; depends on data integration and governance maturity

Source: author synthesis based on [11; 16; 4; 5]

The principal distinction in Table 1 is architectural. Retrospective reporting is primarily designed for periodic accountability, whereas integrated KPI systems are designed to shorten the interval between observation and response and to make operational-financial linkages explicit. Murguia et al. [16] illustrate the value and difficulty of moving from dispersed digital measurements to a coherent dashboard, and Breuling et al. [4] show how application-specific KPIs can make site status and weak points visible. The proposed model extends this logic by requiring each operational metric to have a documented data source and a management response, while treating capital allocation as a separate, explicit decision rule rather than as an assumed consequence of better project performance.

Construction labor productivity is shaped by heterogeneous and interacting factors, which makes individual performance difficult to isolate from task design, logistics, coordination, and site conditions. Qi et al. [18] extracted 591 construction labor-productivity articles published between 1973 and 2023 and used hierarchical topic modeling to demonstrate the breadth and fragmentation of the research domain. For management purposes, this means that worker-level indicators should be used only where attribution is technically and organizationally defensible; otherwise, crew- or task-level measures may provide a more valid basis for intervention.

Table 2 summarizes evidence that can be translated into measurable interventions within the proposed model. The table deliberately distinguishes observed findings from proposed management responses so that the model does not convert measurement studies or context-specific cases into unsupported universal effect claims.

Table 2

Published Evidence on Labor Productivity and Corresponding Model Implications

Evidence area	Published finding	Evidence base	Model implication
Skills and training	Unskilled labor and improper training were the highest-priority adverse productivity factor.	Assaad et al. (2023): 100 completed survey responses; offsite construction.	Layer 2 should connect productivity deviations with training and skill data before assigning individual accountability.
Logistics, rework, coordination	Poor logistics, errors/omissions/rework, and insufficient coordination were among the five highest-priority adverse factors.	Assaad et al. (2023): ranking of 20 labor-productivity risk factors.	Layer 1 should capture rework and coordination events; Layer 2 should use them in root-cause analysis.

Evidence area	Published finding	Evidence base	Model implication
Workforce scheduling	In the reported COVID-19 case, adding employees increased extra-hours cost by up to 104.25%, illustrating material cost sensitivity to scheduling choices.	Corral et al. (2023): multi-objective scheduling model; context-specific case.	Use scheduling analytics as decision support; do not generalize the case percentage as a universal effect size.
Data-to-dashboard measurement	Digital measurement can improve the timeliness and organization of performance information, but multi-source data integration remains a practical challenge.	Murguia et al. (2022): construction data-to-dashboard strategy.	Layers 1-3 should use common definitions, ownership, and data provenance.
Kinematic work measurement	Best activity-recognition model achieved 90% accuracy and F1 = 0.876 for automated work sampling.	Jacobsen et al. (2023): sensor-based study of construction work activities.	Layer 1 may automate work sampling where justified; measurement accuracy is not equivalent to a productivity gain.
KPI-based site tracking	Fourteen application-specific KPIs were developed to support data-based project management and digital tracking of site status and weak points.	Breuling et al. (2025): construction KPI framework; further validation required.	Layers 2-3 can use application-specific KPIs, with local validation before performance incentives are attached.

Source: author synthesis based on [2; 6; 16; 12; 4]

The evidence in Table 2 supports two design choices. First, productivity measurement should include upstream conditions such as skills, logistics, rework, and coordination rather than only output per labor hour. Second, digital monitoring should be treated as measurement infrastructure, not as proof of productivity improvement. Jacobsen et al. [12], for example, achieved 90% activity-classification accuracy and an F1 score of 0.876 in a kinematic monitoring study, demonstrating the technical feasibility of automated work sampling; the study does not claim that the monitoring system itself raises labor productivity. This distinction is important when translating research prototypes into management KPIs.

Assaad et al. [2] provide a useful empirical benchmark for the workforce layer. Based on 100 completed industry survey responses and 20 labor-productivity risk factors in offsite construction, the five highest-priority adverse factors were unskilled labor and improper training, poor logistics, errors/omissions/rework, work-area congestion and overcrowding, and insufficient coordination. Eighty percent of the assessed factors fell into the high-overall-risk cluster. These findings support a performance system that combines labor-output measures with training, logistics, rework, and coordination data instead of interpreting low output as an individual-worker problem by default.

Quality management in construction is better treated as an economic optimization problem than as a compliance cost alone. The Cost-of-Quality (COQ) framework separates conformance costs, such as prevention and appraisal, from failure costs, such as rework and warranty-related losses. Shafiei et al. [20] model these categories as an interrelated system and show in a construction case simulation that greater training and labor experience can increase prevention expenditure while reducing failure costs and total COQ. The implication is not that prevention spending always produces a fixed return, but that the balance between prevention and failure costs should be measured explicitly.

Cheirkhanova et al. [5] reinforce this cost-benefit perspective with firm-level data. Their regression and multivariate analysis of 23 Kazakhstani construction companies links QMS-related variables with sales, profitability, and customer satisfaction and shows that the economic efficiency of the QMS is financially relevant. The study also cautions against poorly optimized quality expenditure. For the proposed model, the practical requirement is therefore to combine defect or rework indicators with a COQ account so that management can distinguish productive prevention expenditure from cost growth that does not generate commensurate performance benefits.

A systematic review by Sharma and Laishram [21] further shows that construction COQ implementation is hindered by inconsistent and insufficiently measurable cost factors. Their PRISMA-based review synthesizes the literature into a structured COQ framework and argues for clearer quantitative classification of quality costs. Embedding a COQ module in Layer 2 and linking it to margin indicators in Layer 3 addresses this measurement gap without implying that one universal optimal COQ ratio applies across projects.

The proposed framework includes an explicit capital-allocation extension because operational gains do not automatically translate into durable enterprise value. The literature reviewed here provides evidence on financial management and real-estate development outcomes, but it does not directly validate a universal reinvestment cycle for owner-led construction firms. The cycle in Fig. 4 is therefore presented as an author-developed governance mechanism: a firm defines in advance how a portion of distributable profit may be retained for productive assets or business capability after liquidity, debt-service, tax, and project-risk requirements are satisfied.

Fig. 4 presents this reinvestment mechanism as a closed management loop. Quality execution and cost control protect project economics; retained earnings create investment capacity; selected productive assets or business capabilities can generate future cash flows; and the resulting cash flows may support further reinvestment. The model is deliberately non-numeric because appropriate allocation rates depend on firm risk, leverage, liquidity, market conditions, and investment opportunity. Its empirical value should be tested using longitudinal firm-level data rather than inferred from illustrative percentages.

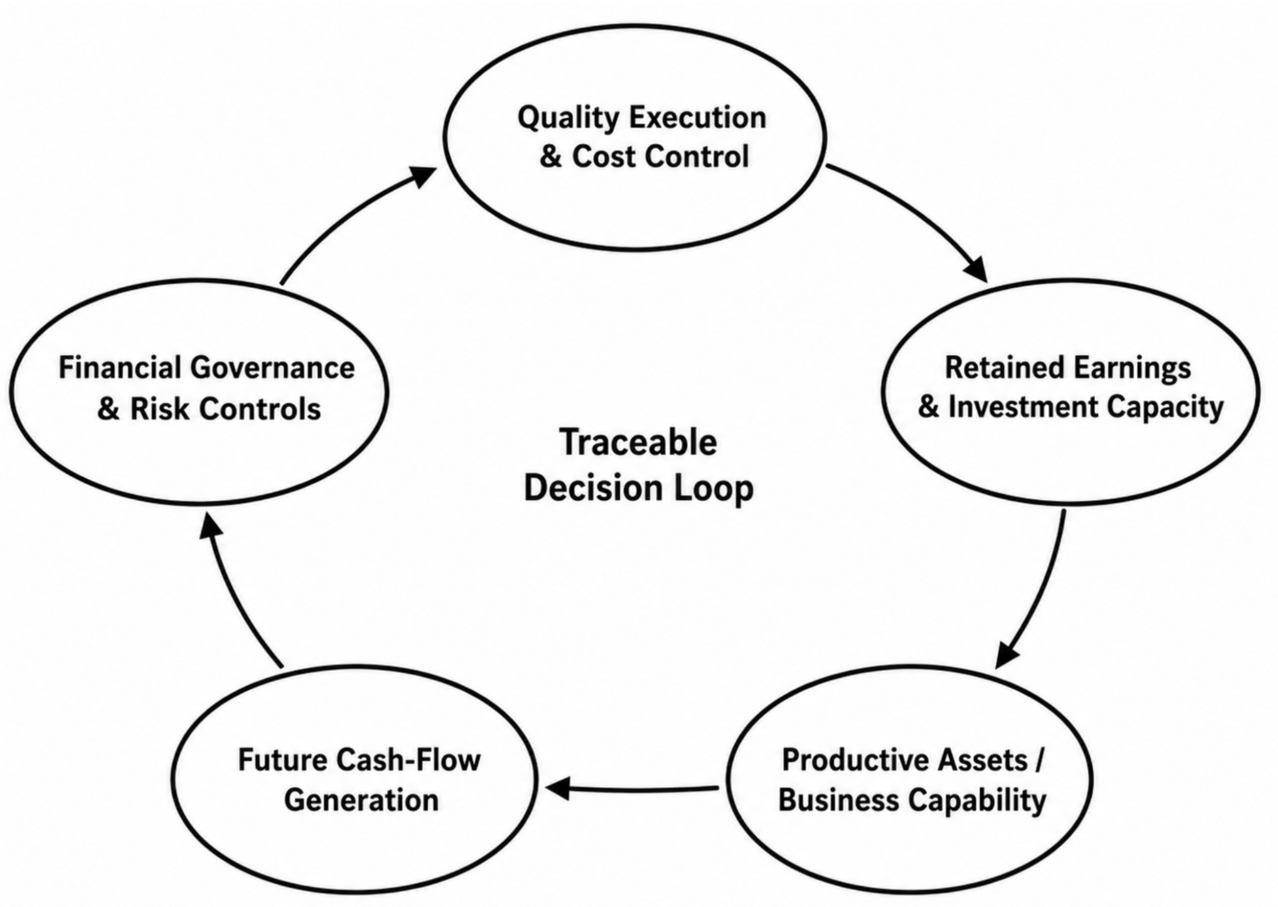

Fig. 4. Illustrative Profit Reinvestment Cycle for a Construction Enterprise

Source: conceptual synthesis informed by [8; 13; 17]

The available literature offers partial support for the components of this extension, but not for the full cycle as a causal mechanism. Geltner et al. [8] identify a positive relationship between REIT valuation indicators and the share of development assets, showing that development activity can be connected to firm value under specific real-estate market conditions. Majaham et al. [13] identify financial management, project-management competency, and human-resource capability among the internal determinants of construction-firm growth. These findings justify treating capital allocation and organizational capability as management variables, while remaining insufficient to prescribe a fixed reinvestment percentage.

For implementation, the reinvestment rule should be defined as a governance process rather than a target return assumption. Management can establish a hierarchy in which operating liquidity, committed project obligations, taxes, and prudent debt service are funded first; only residual distributable cash is then considered for reinvestment. Candidate investments should be evaluated using the same data discipline as project operations - documented cash-flow expectations, downside scenarios, decision thresholds, and post-investment review. This preserves the conceptual link between operational performance and capital allocation without introducing unsupported market-value or return estimates.

Evidence from volatile construction markets reinforces the importance of disciplined financial management, while also underscoring the need for caution in causal interpretation. Prokopenko and José [17] examine financial statements from ten Ukrainian construction companies over 2019-2023 and discuss revenue growth, profitability, cost management, and operational efficiency as components of financial-potential management. Majaham et al. [13] similarly identify financial management as a core internal growth factor. In the present model, these findings support formalizing capital-allocation controls at the management-decision layer; whether systematic reinvestment improves long-run firm performance is retained as a proposition for future longitudinal testing.

Based on the evidence synthesis, four implementation recommendations follow. They are presented as sequenced management practices rather than guaranteed performance interventions, because the reviewed studies vary substantially in context, measurement, and research design.

Recommendation 1: Begin with the data inventory, not the dashboard. Before purchasing analytics software, the firm should document which Layer 1 streams are captured, who owns each stream, how frequently it is updated, and how data quality is checked. Low-cost digital logs, standardized defect records, structured client feedback, and consistent financial coding can create a usable baseline before more sophisticated analytics are introduced. This sequence is consistent with the data-to-dashboard logic described by Murguia et al. [16].

Recommendation 2: Match performance accountability to the level at which work can be validly measured. Where individual task output is observable and comparable, worker-level indicators can support targeted training and feedback. Where work is interdependent, crew- or task-level metrics are more defensible. Assaad et al. [2] show that training, logistics, rework, congestion, and coordination are major productivity risks, so a fair workforce dashboard should make these contextual factors visible rather than attributing every variance to the worker.

Recommendation 3: Formalize a COQ account within the management accounting system. Prevention and appraisal costs should be distinguishable from internal and external failure costs, allowing managers to test whether additional quality expenditure is reducing total quality-related cost. Shafiei et al. [20] and Sharma and Laishram [21] provide the conceptual basis for this separation, while Cheirkhanova et al. [5] demonstrate the relevance of QMS economics to construction-firm performance.

Recommendation 4: Treat reinvestment as a pre-defined governance rule subject to liquidity and risk constraints. Rather than selecting an arbitrary percentage after profit is reported, management should specify the decision hierarchy, eligibility criteria for investment, approval thresholds, and conditions under which cash must be retained. This recommendation is an author-developed extension of the performance model and should be evaluated prospectively; it is not presented as a benchmark established by the cited literature.

Table 3 translates the conceptual model into a phased implementation roadmap. The timelines are indicative planning windows rather than empirically estimated durations, and the expected outcomes are operational milestones rather than unsupported forecasts of percentage improvement.

Table 3

Implementation Roadmap for the Data-Oriented Performance Management Model

Phase	Indicative Duration	Key Actions	Data Requirements	Expected Operational Milestone
Phase 1: Data Infrastructure	0-3 months	Audit data gaps; deploy basic digital logging; assign data ownership and validation rules	Five Layer 1 streams: cost/schedule, output/time, defect/rework, satisfaction, financial	Documented data owners, update frequencies, definitions, and baseline KPI values
Phase 2: KPI Dashboard	3-6 months	ConFig. core KPIs; define thresholds; train managers to investigate exceptions	Validated Layer 1 outputs feeding dashboard indicators	Recurring KPI review with traceable exceptions and documented management actions
Phase 3: Workforce Integration	6-12 months	Add worker-, crew-, or task-level views where attribution is valid; connect deviations to training, logistics, and rework	Disaggregated output plus contextual workforce/process data	Performance feedback uses both output and root-cause context; attribution rules are documented
Phase 4: Quality and Financial Integration	12-24 months	Formalize COQ account; connect quality indicators to margin; define capital-allocation governance	COQ categories, margin trend, liquidity and reinvestment decision records	Quality costs are separately visible and capital-allocation decisions follow explicit approval criteria
Phase 5: System Optimization	24+ months	Run scenario reviews; benchmark externally; recalibrate thresholds and definitions	Layers 1-3 plus validated external benchmarks	Annual model review with documented revisions, benchmark comparisons, and data-quality checks

Source: author synthesis based on [16; 2; 4; 20; 5]

The roadmap reflects a recurring finding in the digital-construction literature: technology adoption is useful only when measurement practices, organizational routines, and decision processes develop with it. Autodesk and Deloitte Access Economics [3] report statistically significant associations between broader digital-tool use and revenue/profit growth in a survey of 933 Asia-Pacific construction and engineering businesses, while Murguia et al. [16] emphasize the challenge of integrating multiple data sources into decision-ready dashboards. Breuling et al. [4] likewise frame KPIs as instruments for data-based project control rather than as outcomes in themselves. The phased sequence therefore starts with data ownership and baseline measurement, then adds dashboards, workforce integration, COQ and capital-allocation rules, and finally recurring model review.

The framework's most distinctive element is the explicit connection between operational measurement and capital allocation. Existing performance frameworks commonly end at project or firm financial indicators, whereas the proposed decision layer asks what management should do with the resulting financial capacity. The evidence reviewed from Prokopenko and José [17], Majaham et al. [13], and Geltner et al. [8] supports the relevance of financial management and investment decisions, but it does not prove the proposed reinvestment loop. Accordingly, the reinvestment component should be understood as a testable extension whose value lies in making the decision rule visible and auditable.

Conclusion. This paper investigated the structural relationships among process optimization, individual workforce performance, quality management, and enterprise profitability in the construction sector, and proposed an original four-layer data-oriented performance management model that formalizes those relationships as an actionable management framework.

The evidence is consistent with, but does not causally confirm, the study's working hypothesis. Mischke et al. [15] document a long-run construction productivity gap and pressure on construction-company returns; RICS [19] demonstrates fragmented measurement and low benchmark use; Cheirkhanova et al. [5] provide firm-level evidence that QMS-related variables are associated with sales and profitability; and Autodesk and Deloitte Access Economics [3] report positive associations between digital-tool adoption and financial growth indicators. Taken together, these sources justify a management architecture that connects operational data, quality, workforce conditions, and financial decisions, while leaving the magnitude of firm-level performance effects for prospective testing.

The research objective - to analyze structural links among process, personnel, quality, and financial domains and translate them into an integrated management model - was addressed through three author-developed instruments: the four-layer data-oriented performance model, the KPI Interaction Matrix, and the illustrative Profit Reinvestment Cycle. The first two organize measurement and feedback pathways supported by the reviewed literature; the third extends the framework into capital-allocation governance and is explicitly identified as a proposition requiring longitudinal validation.

The practical significance of the work lies in its modularity. A construction enterprise can begin with a small number of traceable data streams and gradually add KPI integration, workforce feedback, COQ accounting, and capital-allocation controls as data quality and management capability improve. This is particularly relevant in large and competitive markets such as the United States, where construction spending exceeded US$2 trillion and employment reached 8.3 million in 2024 [14]. The framework does not require a single software platform; it requires consistent definitions, ownership, traceability, and decision rules.

Future research should prospectively test the proposed model in defined firm-size and geographic settings, compare worker-, crew-, and project-level measurement validity, and develop standardized instruments for the five Layer 1 data streams. Longitudinal studies should estimate whether changes in feedback frequency, COQ visibility, and capital-allocation discipline produce measurable effects on productivity, quality, margin stability, and asset growth. Such studies are also needed to determine whether the proposed pathways hold across different construction subsectors and macroeconomic conditions.

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