International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 10 Issue 3, May-Jun 2026 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

From Reactive to Proactive: A Conceptual Framework for AI-Driven Predictive Analytics in K-12 Construction Risk and Cost Management

Denish Sonani

School of Business, Economics, and Technology, Campbellsville University, Campbellsville, USA

ABSTRACT

Purpose
This paper addresses the lack of practice-ready frameworks for integrating AI-driven predictive analytics into K-12 construction governance. It proposes the Proactive Program Intelligence (PPI) Framework specifically for public K-12 capital programs managed by owner's representatives.

Design/methodology/approach
This conceptual paper synthesizes eight peer-reviewed studies across decision theory, machine learning, and organizational adoption. It utilizes DECAS decision theory as a theoretical anchor and draws on empirical documentation of K-12 governance deficiencies.

Findings
The resulting PPI Framework features a three-layer architecture: data governance, predictive modelling, and decision activation. It provides a structured pathway to transition K-12 management from reactive judgment to proactive, data-informed governance.

Originality
This is the first framework to synthesize AI-driven cost and risk identification specifically for the owner's representative role in K-12 public construction.

Research limitations/implications
The framework requires future empirical validation through case studies and K-12-specific datasets.

Practical implications
The framework offers a staged, capability-first roadmap suitable for the governance constraints of public bond-funded programs.

KEYWORDS: *predictive analytics, AI-driven risk management, construction cost estimation, K-12 construction, owner's representative, proactive governance, machine learning, DECAS framework, program management, data-driven decision-making, organizational adoption, construction leadership.*

How to cite this paper: Denish Sonani "From Reactive to Proactive: A Conceptual Framework for AI-Driven Predictive Analytics in K-12 Construction Risk and Cost Management" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-10 | Issue-3, June 2026, pp.1-7, URL: www.ijtsrd.com/papers/ijtsrd125218.pdf

IJTSRD125218

1. INTRODUCTION
K-12 School Districts' Capital Construction Programs in the U.S. are among the most complex and publicly scrutinized infrastructure investments. Most of the funding for K-12 Capital Construction Programs is derived from voter-approved bonds, thus they represent significant accountability obligations to governing boards, taxpayers, and communities. However, even with these high accountability obligations, construction risk and cost management practices within K-12 are still predominantly reactive. In fact, construction risks are identified after they have impacted project performance, and cost overruns are managed as a result of using contingency drawdowns rather than taking the steps necessary to prevent them from happening in the first instance (Jayakannan, 2025).

The limitations of traditional project management approaches are well documented. Most of the estimating and risk identification processes rely upon the use of expert judgment; however, this type of judgment is subject to many cognitive biases such as optimism bias, anchoring, and scope insensitivity (Vilibić et al., 2026). Also, although parametric cost models provide consistency, they only consider historical averages for calibration. Parametric models also cannot account for the difficulty associated with predicting the non-linear interdependencies of various inputs such as inflation rates, construction program types, and construction program durations (Aung et al., 2023). The result of this reliance upon estimating by expert judgment, coupled with the ineffectiveness of traditional project management techniques, is a continuous pattern of traditional cost escalation, coupled with a reactive approach to construction risk, thereby resulting in the loss of confidence in school district leadership and diminished project outcomes.

Artificial intelligence and predictive analytics offer a meaningful path forward. For example, machine learning models have consistently outperformed traditional cost estimating methods (Zainab et al., 2022); AI-based frameworks expand and systematize risk identification (Vilibić et al., 2026); and data-driven decision frameworks result in improved organizational decision quality and timeliness (Elgendy et al., 2021). However, the translation of these capabilities into an integrated and practical framework for K-12 construction program managers and owners' representatives has not yet been explored.

This paper is meant to fill the above-mentioned gap. Specifically, it synthesizes three separate streams of research - decision theory, machine learning, AI-based risk identification and organizational adoption dynamics - into a unified framework called The Proactive Program Intelligence (PPI) Framework. Through this framework, predictive analytics will be integrated into K-12 construction program governance at a conceptual level (as a three-tiered framework). The primary contribution of this framework lies in the specificity of its definition; unlike existing studies which focus solely on algorithmic capabilities and provide no context for their application, the PPI Framework is geared towards addressing the institutional realities associated with public K-12 programs including the existence of bond accountability, board governance, and lean program management offices, which create limits that do not exist within the domain of commercial construction. The intended audience for this PPI Framework includes; owners' representatives and managers of K-12 programs, district leadership and researchers studying the incorporation of artificial intelligence within the governance of educational infrastructure.

The paper proceeds as follows. Section 2 presents a thematically organized literature review establishing the theoretical and empirical foundations. Section 3 introduces and elaborates the PPI Framework. Section 4 discusses implications for practice and research limitations. Section 5 concludes with a summary of contributions and directions for future empirical investigation.

2. Literature Review

2.1. The ongoing problem of managing risk and construction project costs.

Construction projects are characterized by multiple levels of complexity inherent in the sociotechnical system of construction projects. Each task depends on other tasks and each task has different demands for resources and is exposed to a variety of external risks. Therefore, when a strategy fails to address the needs associated with the planning, execution, and successful completion of the project, cost overruns and schedule delays are not an anomaly, but about how construction projects are traditionally delivered and managed. Jayakannan (2025) has identified the underlying systemic cause of this problem to be the pervasive reliance of the construction industry on reactive risk management approaches (or non-incremental risk reduction processes in general), where risk registers are compiled at the time of project initiation and rarely are updated subsequently on a project-specific basis; and where cost contingency funds are viewed as a safety net for unforeseen risks rather than tools used to proactively control risk.

The political and fiscal constraints of public bond financing have exacerbated these impacts within K-12 programs when scope changes or budget increases are needed, as they require board approval along with potential scrutiny from the community. In addition, Sonani and Fulford (2025) document directly the difficulties associated with K-12 programming in the United States through empirical analysis, identifying three structural factors which lead to the governance structures that create reactive governance. These include 1) Fragmentation-driven inefficiencies caused by the use of multiple layers of committees with very little clarity regarding who has decision rights; 2) The immutability of fixed budgets and deadlines for academic achievement creates late-stage cost premiums that arise from indecision made earlier in the project lifecycle; 3) A lack of formalized decision-making frameworks across district; as a result, every team essentially reinvented their own approach to delivering on a project at the earliest stage possible. Their results confirm that without a standardized governance structure in place, K-12 programs will typically exist as reactive regardless of each team member's competency.

Even if teams operate with superior capabilities, traditional estimation techniques further increase the likelihood of K-12 programs being reactive due to their reliance on parametric and analogical estimation methodologies which are based on the judgment of an expert utilizing historical averages to make an educated guess according to market conditions or specific risks associated with a project. Aung et al. (2023) illustrate that these methodologies typically struggle to accurately predict construction outcomes based on the correlation between variables within a project. They continue to perform poorly when compared to machine learning, and a multi-project data set compiled by Zainab et al. (2022) corroborates the assertion that inflation is the greatest single determinant when assessing construction costs in all applications for estimation. Traditional methods undervalue inflation rates and serve to diminish the validity of estimates by comparison.

2.2. Theoretical foundations: the DECAS framework

The theoretical anchor for integrating analytics into construction decision-making is provided by the Decision Context and Analytics Support (DECAS) framework (Elgendy et al., 2021). DECAS expands on classical decision-making theories with the idea that data and analytic capabilities should not only be thought of as information inputs but also as additional contributors to the decision-making process. DECAS provides an understanding of how human decision-makers and analytic systems can work together to help each other make better decisions through the use of analytics to enhance human cognitive abilities beyond what can be achieved through traditional rational thought processes.

DECAS redefines the role of the owner's representative within construction program management - not simply as the central place for expert judgment, but also as a decision executive with the aid of data-enhanced analytical capabilities and tools. By providing data-driven insight, analytics enhances the role of the owner's representative, while at the same time enabling the owner's representative to assess large project portfolios faster and more accurately than would be possible through the use of professional knowledge alone. This new understanding of DECAS has addressed the most prevalent concern associated with the use of AI in construction; namely, that AI tools replace the need for professional judgment.

2.3. Machine learning for construction cost prediction

The introduction of machine-learning methods to predict construction costs has been well received. In a study that compared three predictive machine-learning models (linear regression, support vector machines (SVM), and artificial neural networks (ANN)) against historical construction costs from 250 construction projects, Aung et al. (2023) demonstrated that all three machine learning models significantly outperform traditional methods for estimating construction costs. The model that employs artificial neural networks (ANN) exhibited exemplary performance as compared with expert judgment alone, with a mean absolute error (MAE) of 5.21%, a root mean square error (RMSE) of 6.79%, and improved on the previous expert judgment values of 12.34% for MAE and 15.80% for RMSE, as well as the third method being parametric estimation, which did lead to an estimated MAE of 9.67% and an estimated RMSE of 12.45%. The analysis of the attributes of costs was conducted by calculating the importance of the attributes, from which the top three predictors of cost overruns emerged to be the initially estimated costs, project type, and project duration. This indicates that the top three predictors of co-cost overruns can lead to establishing system data governance priorities for the program manager establishing predictive systems.

Through the use of an integrative data intelligence model developed by Zainab et al. (2022), AI expects the optimum predictive capability to develop by integrating data quality and data integration method with the algorithm used, in this case, the use of XGBoost and Random Forest (XGBoost = 0.87, MAPE = 0.25) to establish the accuracy of the data. They also confirmed that when analyzing K-12 projects, where data exists in contractor submittals, change order logs, budget systems, and scheduling tools, there will be less likelihood of a return from AI investment if prior to investing in AI, substantial work on data governance was performed.

2.4. AI-based risk identification

Risk identification in construction has historically been constrained by the cognitive limitations of individual practitioners. Vilibić et al.'s (2026) case study demonstrated that large language models can process extensive project documentation – over 225,000 words in their study – and generate structured, phase-specific risk logs with breadth and consistency that exceed typical expert-driven processes. Expert reviewers rated all three AI models tested as 'very useful' for initial risk identification while acknowledging that prioritization and contextual mitigation remain human responsibilities.

This finding has broader implications for the governance of program-level risk. With multi-project K-12 programs across a district's portfolio, it is not feasible to identify all potential risks via the use of manual processes. AI-driven identification of potential risks can provide a comprehensive first pass of numerous risk scenarios that require expert input, to convert from expert-initiated processes to those supported by AI, and to reduce the risk that an expert would overlook a major risk because of work overload or cognitive bias. The study also provided evidence that AI decreases optimism bias, which has been historically documented as a failure mode for estimating public infrastructure projects.

2.5. Organizational adoption dynamics

Ayinaddis (2025) performed a systematic review of 78 peer-reviewed studies discussing the dynamics of AI adoption, based on the Technology-Organization-Environment (TOE) framework. From this review, he found that the capacity of an organization to adopt AI innovations, as determined by the organization's size, has been shown to mediate the effect of organization size on the ability to adopt AI innovations. Larger organizations will benefit from pre-existing infrastructure, staff with technical expertise, and monetary resources, while smaller organizations will be constrained by the organizational structure and ability to implement and maintain AI tools. It is consistently noted across organizations of all sizes that the management support and commitment of the management team are the most significant factors that enable the successful adoption of AI tools.

Public K-12 school districts represent a unique subset within this typology. In some instances, large urban school districts are managing capital programs that exceed billions of dollars in value and may rival the capital budgets of some corporations. Conversely, many mid-sized or smaller districts manage programs and have limited technical capacity and resources to support program management offices, in turn providing only limited capabilities to their respective organizations. For these organizations, the pathway to the use of AI tools is through engagements with external program managers who provide analytics infrastructure as a service. This model of adoption has significant implications for the design of the program manager's tools, including ease of use for non-technical users, interoperability with existing platforms, and the incorporation of training and change management plans.

3. Proactive Program Intelligence (PPI) Framework

Based on the four streams of literature discussed in the preceding section, this research introduces the Proactive Program Intelligence (PPI) Framework, a conceptual model for K-12 construction program management which integrates AI-enabled predictive analytics. The PPI Framework is made up of three interdependent layers: (1) the Data Governance and Integration; (2) the Predictive Modelling; (3) the Decision Activation layer. Each layer has a unique set of activities and competencies associated with them. Collectively, the PPI Framework embodies the collaborative rationality (DECAS) principle by treating analytics as tools for supporting decision-making processes, not just replacing them. A key aspect of the structure of the PPI Framework is that it is built in stages, allowing organizations to implement Layer 1 first to realize value quickly through improved data governance, prior to investing in advanced analytic capabilities and working through subsequent stages as organizational capability evolves.

3.1. Layer 1: Data governance and integration

Data governance is the foundation of any predictive analytics implementation strategy for K-12 construction programs since access to structured high-quality project data serves as the basis for any analytic capability. Project data in K-12 construction programs generally occurs in a variety of formats, including vendor submittals, change order logs, inspection reports, budget management systems, and schedule management software, which do not exhibit uniformity regarding how projects are established or how they are managed between different project and/or vendor sources. The research findings of Zainab et al. (2022), which indicate that the quality of the data and the overall integration strategy of that data are equally as important as the choice of algorithm, as well as the findings of Ayinaddis (2025) that document the difficulties of data management as one of the primary barriers to implementation of analytics, support the idea that Layer 1 is not an optional component for the development of an analytics capability; it is a necessary condition for the development of any subsequent analytics capability. Sonani and Fulford (2025) came to similar conclusions independently from the perspective of practitioners, explicitly calling out the need for a governance charter to formalize decision rights and expectations around data quality as well as an ERP-grade standardized workbook to capture workflows and data requirements across each stage of a project's lifecycle. These represent two of the essential organizational constructs that comprise the foundation of Layer 1 of the PPI Framework.

Layer 1 consists of three tasks: data standardization; data integration; and data governance. Data standardization deals with how to ensure that there are consistent definitions of the same fields and project taxonomies between all projects and vendors, so that data for a given project can be aggregated from multiple sources. Data integration connects disparate data sources into a single, unified platform or data warehouse (the Program Controls Platform) to create a single source of truth for the Program's cost, schedule, risk, and contract data. Data governance includes the development of the processes for assuring the quality of data, controlling access to it, documenting the audit trail of the data, and maintaining the data over time. For the Owner's Representatives, Layer 1 represents the Program Controls Infrastructure's foundational deliverable and is the entry point into the PPI Framework for all organizations at all stages of AI Maturity.

3.2. Layer 2: Predictive Modelling

Once there is a Data Governance infrastructure in place, Layer 2 can activate two independent streams of predictive modelling (Cost Forecasting and Risk Identification). The Cost Forecasting stream is built using machine learning techniques as validated by Aung et al., and an integrated framework proposed by Zainab et al. (2022) that uses ensemble models, particularly Gradient Boosting, to create probabilistic forecasts of the costs for individual projects and on the Project Portfolio level. The literature identifies several features that are vital to the input of predictive models, including: the kind of project that you're undertaking, how much you expect to spend on the project, how long you expect it to take to complete the project, what is the prevailing inflation index within the area, and how the contract will be delivered.

The risk identification phase is informed by the AI-based framework demonstrated in a case study by Vilibić et al. (2026) using large language models to produce structured phase-specific risk logs by analyzing project documents. When applied to K-12 programs, you can use the AI-assisted approach at the start of your project to identify risks outside of those typically identified by expert teams, at design midpoints to indicate any emerging cost and schedule exposure with respect to contract documents, and at construction phase checkpoints to highlight any operational risk. The outputs from this phase feed directly into your program risk register, which the program managers and owner representatives will priorities and evaluate. By using this hybrid combination of human and AI resources, the automation-augmentation balance that the expert reviewers from Vilibić et al. (2026) determined was the best system for dividing labor is achieved.

3.3. Layer 3: Activating decisions

The purpose of this third layer is to put into practice the DECAS principle of collaborative rationality, and to structure how to take management decisions based on predictive model output. According to DECAS (Elgendy et al., 2021), just producing output from predictive analytics does not provide increased value for the organization; rather, the organization's ability to apply the analytics output in a coordinated and timely manner provides greater value than continuing to develop models.

Escalation protocols expressly identify when risk and cost variance flags will trigger an escalation review process. Escalation protocols serve to provide the structure that links predictive signals to the organization's response. The use of feedback loops to provide continual improvement to the accuracy of the predictive models via captured actual project outcomes allows for the ongoing assimilation of project-specific patterns into the evolving model, improving the predictive model's ability based on the actual outcomes of the projects.

The decision activation layer represents the most impactful area of organizational leadership development. According to Ayinaddis (2022), the two most significant success factors in the effective adoption of AI technologies within organizations are Management Support and Leadership Commitment (these are the only things he cites). For K-12 programs, this creates a very specific need for district leadership, the program director, and the owner's representative to actively advocate for the use of data-driven governance, as opposed to being a passive user of the analytics reports generated from the systems. Therefore, the PPI Framework positions the decision activation layer not as a task within a technical system, but as an organizational leadership function, thus linking the use of AI data to the K-12 Educational Administration body of research on data-informed leadership.

4. Discussion

4.1. Theoretical contributions

The PPI Framework provides two primary theoretical contributions in relation to existing literature. First, the PPI framework demonstrates an extension of the DECAS framework (Elgendy et al., 2021) into an architecture of governance for capital-intensive complex programs such as capital-intensive projects. The DECAS construct of collaborative rationalities is directly aligned with K-12 program management in the following way: 1) there is an inherent distinction between data and information; 2) the use of AI in conjunction with human judgment creates more accurate and effective decisions than the sum of either alone; and 3) the integration of conventional decision-making techniques and data allows K-12 programs to proactively position themselves for future success.

Then, the framework contributes to the educational administration literature by identifying AI-driven program governance as a leadership competency domain. The connection between Layer 3 decision activation and leadership commitment, grounded in Ayinaddis's (2025) finding that management support is the most critical organizational mediator of AI adoption – suggests that the adoption of predictive analytics in K–12 construction is ultimately a leadership challenge as much as a technical one. This positions the PPI Framework at the intersection of educational leadership theory and construction program management practice.

4.2. Practical Implications

For K-12 program practitioners, the PPI Framework provides a systematic implementation pathway that has been designed with the institutional realities of the K-12 public practices in mind, i.e. there are certain steps that must be followed, and there are regulations that apply to K-12 district's purchasing and purchasing processes, community accountability obligations and limitations that apply to K-12 district technology adoption and implementation processes, therefore the implementation processes of the PPI Framework stages must necessarily be slower than those of enterprise AI implementations in commercial companies. By first focusing on data governance (a step that can create a measure of immediate value) and building a data governance infrastructure, and for K-12 assemblies and their representatives, the PPI Framework will allow K-12 program managers to create an environment for predictive analytics infrastructure to be established. Therefore, the K-12 program managers responsible for K-12 program implementation will develop the ability to implement predictive analytics applications without committing to a complete technology installation upfront.

The PPI Framework's adoption's human elements are worthy of additional emphasis. Supporting evidence from adjacent governance contexts indicates that structured frameworks do not fail because of a lack of technical requirements; they fail because of implementation deficiencies due to organizational culture and their members' managerial behaviors. A study by Kuchhal et al. Utilizing Well-structured Performance Intervention Plan Studies in the Corporate World Determines the Most Significant Failure Modes Associated with Structured Performance Intervention Plans are Insufficient Managerial Support, Lack of Continuous Feedback Mechanisms, and Lack of a Genuine Commitment to Growth in the Organization's Culture, Rather Than Failures of the Technical Design of the Plans.

These results can be directly transferred to the PPI framework. Layer 3's ability to activate decisions will either succeed or fail based on how Authentically Program Directors and District Leaders Act as Champions of Data-Driven Governance by Establishing a Continuous Feedback Loop between Model-Generated Outputs and Decision Actions and Reframing Predictive Analytics as Tools for Programmed Improvement Instead of Audit or Surveillance Mechanisms.

The Owner's Representative Role is Uniquely Positioned within the PPI Framework. Owner's Representatives are the Primary Link between Layer 2 Predictive Outputs and Layer 3's Ability to Activate Decisions. They're the Infrastructure that Provides Smaller Districts with Access to Analytical Capabilities They Can't Develop Internally. The Owner Representative Role Represents the Critical Human Node of the PPI Framework by Being a Data-Informed Governance Partner Rather than Just a Contract Management Role.

4.3. Limitations

As a working paper focused on the development of a conceptual framework, the Primary Limitation of This Paper is That There Has Not Been Any Empirical Validation Thus Far. Although Grounded in and Supported with Existing Literature, The PPI Framework has not Yet Been Demonstrated to Be an Effective Program Management Approach. In addition, the Empirical Studies Used to Develop the Framework Were Conducted Regardless of the National or Sector Contexts [Iraq (Zainab et al., 2022), Croatia (Vilibić et al., 2026), and Malaysia (Aung et al., 2023)] and May Not Transfer Directly to the U.S. K-12 Context without Modifications.

Another Limitation Is That There Is No Empirical Evidence Supporting Leadership Behavior as a Moderator of AI Adoption Success in Construction. While Ayinaddis (2025) Discusses Management Support's Contribution to Successful AI Adoption, He Does Not Evaluate Leadership Behaviors or Competencies that Drive Adoption Success in Public Sector Infrastructure Organizations. This creates a significant disconnect between Constructed Theory and the Evidence Base Supporting the Theory.

5. Conclusion

Reactive risk management and recurring patterns of cost overruns are structural outcomes of construction project management systems developed during a pre-digital age. Construction project delivery has undergone significant transformation with the introduction of artificial intelligence (AI) as a tool for predictive analytics. Predictive analytics allow for a new governance model by enabling the identification of risks prior to their occurrence and continuously updating cost projections based on actual project data rather than relying on historical benchmarks that are no longer applicable.

This paper introduced the Proactive Program Intelligence Framework as a conceptual model to be employed within the specific governance context of K-12 public constructions programs in order to achieve such benefit. The framework combines multiple components of effective governance, including the formation of a robust, cohesive three-tiered structure that addresses the needs of K-12 public construction programs. The pillars of the framework include (1) data governance (including predictive modelling and automated decision-making); (2) the owner's representative as the central governance agent; and (3) a phased strategy to account for the unique institutional challenges associated with K-12 construction programs.

Further studies should focus on the empirical validation of the proposed framework via various avenues, including (1) case studies of K-12 construction programs that have implemented predictive analytics capabilities, (2) quantitative studies to assess the validity of machine learning (ML) cost models developed using K-12-specific datasets, and (3) leadership studies to identify the behaviors and skills of successful K-12 construction program leaders that are associated with effective governance. Ethical issues regarding AI-generated risk and cost assessments for public sector programs, including transparency, audit requirements, and accountability for algorithmically generated recommendations, require further research.

K-12 construction program professionals and K-12 school districts have an obligation to be good stewards of the trust and financial resources that are provided by the communities they serve. By implementing the PPI Framework as a starting point for K-12 program governance that leverages the power of AI, school districts will demonstrate their commitment to fulfilling this obligation.

References

[1] Ayinaddis, S.G. (2025), "Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: a systematic review and bibliometric analysis", *Journal of Innovation & Knowledge*, Vol. 10, p. 100682, doi:10.1016/j.jik.2025.100682.

[2] Aung, T., Liana, S.R., Htet, A. and Bhaumik, A. (2023), "Using machine learning to predict cost overruns in construction projects", *Journal of Technology Innovations and Energy*, Vol. 2 No. 2, doi:10.56556/jtie.v2i2.511.

[3] Elgendy, N., Elragal, A. and Päivärinta, T. (2021), "DECAS: a modern data-driven decision theory for big data and analytics", *European Journal of Information Systems*, Vol. 30 No. 5, pp. 508-528, doi:10.1080/12460125.2021.1894674.

[4] Jayakannan, S.M. (2025), "Predictive analytics for construction project risk management: leveraging AI for proactive mitigation strategies", *World Journal of Advanced Engineering Technology and Sciences*, Vol. 15 No. 2, pp. 2204-2209, doi:10.30574/wjaets.2025.15.2.0737.

[5] Ravi Kumar, K., Anush, H. and Sonani, D. (2024), "Catalyzing organizational evolution: a scholarly examination of performance improvement plans and their enhancement of employee transition experiences in corporate frameworks", *The Business & Management Review*, Vol. 15 No. 3, pp. 29-36, doi:10.24052/BMR/V15NU03/ART-04.

[6] Sonani, D. and Fulford, M.D. (2025), "The need for standardized decision-making in K-12 construction projects", *Computational Intelligence and Machine Learning*, Vol. 6 No. 2, pp. 35-40.

[7] Vilibić, K., Sigmund, Z. and Završki, I. (2026), "Intelligent risk identification in construction projects: a case study of an AI-based framework", *Buildings*, Vol. 16 No. 2, p. 409, doi:10.3390/buildings16020409.

[8] Zainab, H.A., Abbas, M.B., Murizah, K. and Zainab, A.K. (2022), "Developing an integrative data intelligence model for construction cost estimation", *Complexity*, Vol. 2022, p. 4285328, doi:10.1155/2022/4285328.