Artificial Intelligence Adoption and Perceived Project-Management Benefits in Zambia's Building Construction Sector: A Cross-Sectional Survey

Mukosa Chimbelu[1], Brian Halubanza[2]

[1]Department of Engineering, Mulungushi University, Kabwe, Zambia,
[2]Department of Computer Science, Mulungushi University, Kabwe, Zambia,

Abstract
This study examined the adoption of artificial intelligence (AI) for project planning and progress monitoring in Zambia's building construction sector. A cross-sectional design was used in Lusaka Province. Survey data were obtained from 78 construction practitioners selected from a finite sampling frame of 150, while semi-structured interviews were conducted with 5 purposively selected [stakeholder groups]. Quantitative data were analysed using descriptive statistics, the Relative Importance Index and two-sided one-sample t-tests against the neutral Likert midpoint (3). Reported use was concentrated in natural-language-processing applications (29.5%) and data dashboards (28.2%), whereas 12.8% reported no AI use. Respondents rated perceived planning efficiency above the neutral midpoint ($M = 4.21$, $SD = 0.84$), but this cross-sectional evidence does not establish an objective reduction in project delays. The main reported constraints were inadequate formal training, weak organisational strategies, limited technical support, data-governance concerns and scarce local project datasets. Respondents perceived AI-enabled practices as beneficial for planning efficiency and potentially useful for earlier identification of delay risks. The findings support phased, context-sensitive adoption accompanied by workforce development, data governance and evaluation using objective project-performance indicators.

Keywords: Artificial Intelligence, Construction Project Management, Cross sectional Design, UTUAT, Project Delays, Zambia.

1 Introduction

1.1 Background

Infrastructure projects are traditionally monitored against three rigid constraints: scope, cost budget, and planned execution schedule, where any baseline deviation serves as a primary indicator of project failure (Chartered Institute of Building, 2014). Infrastructure project delays are a perennial concern in Zambia, even as the government continues to invest in roads, health facilities, schools and other social infrastructure. Empirical data has shown that timetable delays have a substantial impact on the successful completion of building projects. Primary causes of schedule delays in Zambian road construction projects were identified to be clients' delayed payments, procurement inefficiencies, contractor financing difficulties, design changes, inadequate planning, poor supervision and equipment shortages (Kaliba, Muya and Mumba, 2009). These delays often resulted in cost overruns, contract extensions, disagreements, lower project performance and in some cases project abandonment. Similarly, Mukuka and Aigbavboa (2014) identified delayed progress payments, contractor cash-flow constraints, poor planning and slow decision-making as still significant contributors to construction project delays in Lusaka, further emphasising the continued weaknesses in project planning and monitoring. As recent national audit findings have shown, these issues continue to impede the delivery of public infrastructure projects. The Auditor General's Report on the Accounts of the Republic for the Financial Year Ended 31 December 2021 indicated that 95 government construction projects had been inspected and that 32 projects had stalled, 52 projects were still under construction, 21 projects in progress had no contractors on site, and six contracts had been terminated without replacement contractors. The projects included district hospitals, health posts, staff housing, office buildings and other public infrastructure. Some of the projects were delayed for one month to as long as eleven years. The Auditor General's Report for the Financial Year Ended 31 December 2023 provides evidence that delays are still widespread throughout government infrastructure programmes. The audit revealed that only 58 of the 80 traditional leaders' palace construction projects had started. The remaining 22 projects (27.5%) were yet to start, due to site access difficulties, unresolved land issues and administrative delays. The Public Accounts Committee also looked at the Auditor-General's Report for 2023 which showed that 69 of the 115 secondary school construction projects (60%) had still not been started. The contractors were not available at the site due to lack of funds and delays in payment. Physical inspections also showed that health infrastructure projects in Luapula Province were 8–9 months behind schedule and a large amount of work remained unfinished. Taken together, these results imply that project delays are systematic, rather than individual events, and continue to impede the timely delivery of social infrastructure in Zambia. Thus, there is a growing need to explore new approaches such as Artificial Intelligence (AI) enabled planning and monitoring systems, which can assist in improving real-time monitoring, facilitating timely decision-making, improving project scheduling and ultimately minimising delays in the delivery of social infrastructure projects.

Within Zambia's expanding construction landscape, infrastructure delivery faces chronic schedule overruns due to a reliance on manual documentation and retroactive progress updates that struggle to manage complex, unstructured data. Globally, Artificial Intelligence (AI) frameworks—such as machine learning, computer vision, and automated tracking—have emerged as transformative paradigms capable of shifting project management from reactive tracking to proactive bottleneck forecasting (Adebayo, 2025).

1.2 Problem Statement

Although AI-enabled scheduling, document analysis and progress-monitoring tools are increasingly discussed internationally, there is limited empirical evidence on their actual use, organisational readiness and perceived value in Zambia's building construction sector. Existing local project-management practices and digital maturity may constrain adoption, yet the relative importance of technological, organisational, workforce and policy factors has not been systematically assessed. Consequently, practitioners and regulators lack context-specific evidence for deciding which applications to prioritise and which enabling conditions must be established. This study therefore examines reported adoption, perceived benefits and implementation barriers; it does not directly test whether AI causes reductions in project delay

1.3. Research Goal

This research aims to investigate how the adoption of Artificial Intelligence is currently being used or can be used in the planning and monitoring stages of building infrastructure projects in Zambia in order to identify mechanisms through which Artificial Intelligence can be integrated to mitigate project delivery delays.

1.4 Research Objectives

1. To examine the current state of AI adoption in the planning and monitoring stages of building infrastructure projects in Zambia.
2. To identify the technological, organizational, and policy factors that influence AI adoption in the Zambian construction sector.
3. To evaluate the impact of AI adoption on project planning efficiency, monitoring effectiveness, and delay mitigation in building infrastructure projects.
4. To identify the key challenges and limitations to AI adoption in planning and monitoring building infrastructure projects in Zambia.
5. To develop actionable recommendations for integrating AI into project management practices to enhance timely delivery of building infrastructure projects in Zambia.

1.5 Significance of the Research

This study bridges a critical literature gap by providing context-specific, empirical data on advanced construction technology adoption in developing African environments. It offers industry practitioners—including engineers, quantity surveyors, and project managers—an actionable framework to enhance planning accuracy and proactively mitigate delivery risks. Furthermore, it provides vital empirical insights for public sector bodies and regulators, such as the Ministry of Technology and Science and the Smart Zambia Institute, to drive targeted digital policy development and long-term infrastructure transformation.

2 Literature Review

In all the literature reviewed, project planning and monitoring are the most critical stages that affect the performance of construction projects. Well-established project management paradigms such as the Iron Triangle and the Project Life Cycle models emphasize the need to balance time, cost, scope and quality during project execution (Atkinson, 1999; PMI, 2021; Shenhar & Dvir, 2007). The growing complexity of infrastructure projects has exposed the limitations of traditional planning and monitoring approaches, often hampered by fragmented data, paper records and slow decision-making.

The constraints are more acute in developing countries where institutional capabilities and digital frameworks are still wanting.

Sources in Zambia and internationally say project delays continue to hinder infrastructure delivery. The causes of delays in schedules have been put down to a number of client related problems such as late payments, slow decision making, contractor related problems such as poor planning and financial constraints and general institutional problems affecting procurement and project management (Kaliba et al., 2009; Mukuka & Aigbavboa, 2014; Larsen et al., 2016; Mpofu et al., 2017). These findings have been confirmed in recent national audit reports which have highlighted persistent delays, halted projects and cancelled contracts within Zambia's public infrastructure projects. This suggests that current project management approaches have failed to address the root causes of schedule overruns. Recent developments in Artificial Intelligence (AI) have a great potential to improve project planning and control via predictive analytics, machine learning, computer vision, Building Information Modelling (BIM), Internet of Things

(IoT) technologies and automated scheduling systems.

Empirical evidence from developed countries has proven that these technologies improve forecasting accuracy, resource allocation, risk management, real-time control and proactive decision-making which consequently reduce project delays and improve project performance (Bilal et al., 2016; Fang et al., 2020; Adebayo, 2025). Many African countries have started using artificial intelligence in the building and management of infrastructure but the use of this technology is patchy and generally limited to isolated applications rather than as part of an integrated approach to managing projects. The policy environment is improving in Zambia with the adoption of the National Artificial Intelligence Strategy and National Digital Transformation Strategy. But the true AI of the construction industry remains in its nascent stages. The major challenges to adoption include fragmented data ecosystems, poor digital infrastructure, lack of technical skills, lack of adequate regulatory support and high costs of implementation (Wachata, 2020; Ministry of Technology and Science, 2024; Mushili, 2025). Also, most of the existing literature is descriptive in nature and discusses either particular technologies, the points of view of different stakeholders or single case studies. Evidence from Zambia's agricultural early-warning context shows that the usefulness of digital reporting tools is conditioned by access to devices, training and information channels (Halubanza et al., 2023b)

There is little empirical evidence on the actual execution and effectiveness of AI in the planning and monitoring phases of infrastructure projects. The current state of knowledge clearly shows a lack of studies on the adoption and impact of AI on the performance of the construction industry in Zambia. There is a lot of evidence in global studies that AI enhances planning efficiency, monitoring efficacy and execution of projects. However, there are few studies that have empirically tested these relationships in the context of Zambia's institutional, technological and regulatory environment. In addition, the organizational, technological and policy factors influencing the implementation of AI and the role of AI in alleviating project delivery delays have not been given much attention. Such gaps require filling to inform evidence-based policy and practice, and hence the need for this study. This study investigates the adoption of AI in the planning and supervision of construction infrastructure projects in Zambia, and evaluates its potential to reduce project delays .

For this study, technologies were classified by verified functionality: (i) generative or natural-language systems; (ii) predictive or optimisation models; (iii) computer-vision systems for reality capture and progress assessment; and (iv) rule-based decision-support systems. Conventional dashboards, spreadsheets and drones were classified as AI-enabled only where respondents identified an embedded learning, inference or generative function."

3 Theoretical Framework

Performance expectancy, effort expectancy, social influence and facilitating conditions were adapted from validated UTAUT measures. Each construct was measured by atleast 3 items (Appendix A). Behavioural intention and reported use were specified as outcomes. Items were adapted to construction planning and monitoring through expert review and pilot testing. Because the sample was not powered for moderator analysis, age, gender, experience and voluntariness were treated as descriptive covariates rather than formal UTAUT moderators.

4 Conceptual Framework

UTAUT model organizational and technological determinants of performance expectancy, effort expectancy, facilitating conditions and organizational readiness impact AI technology adoption and use. These factors should influence the AI adoption of construction professionals for planning and monitoring. The mediating construct is superior planning and monitoring. AI-powered planning and monitoring will enhance schedule development, resource allocation, cost estimation, procurement planning, risk identification, real-time progress tracking, quality assurance, safety monitoring, performance reporting, and decision support. The dependent construct is project delivery performance and it is measured by schedule compliance, delay reduction, cost performance, decision making effectiveness, monitoring efficiency, and implementation success. The increasing adoption of AI makes the planning and monitoring more efficient, which improves the project performance and reduces the delays in building infrastructure projects.

5 Methodology

A cross-sectional survey with supplementary qualitative content analysis was used. Quantitative survey data was collected during the this phase through a questionnaire based on the UTAUT , analysed independently, and integrated through a joint display comparing convergence, complementarity and divergence across the research objectives.

The geographic scope is focused on building infrastructure projects within Lusaka Province, targeting active construction professionals and public sector officials.

From a finite sampling frame of 150 practitioners, field data collection yielded a completed sample of 78 and 5 interviews, representing a 52% response rate. The sample size including 96 members of the National Council for Construction (NCC), 34 active construction companies from Google Maps Directory and 20 experts from public institutions in Zambia. Company eligibility required current NCC registration, active building work in Lusaka Province during 2024 to 2025, and an identifiable professional responsible for planning or monitoring. Google Maps was used only for contact discovery and was cross-checked against the NCC register. Duplicate firms were removed.

Of 130 individuals invited, 78 returned complete questionnaires, response rate 52 % response rate. Separately. These interviewees were selected on the basis of their active membership in associations and NCC, their practical experience in construction or involvement in public policy and regulation in the construction sector. To establish the mathematical adequacy and statistical representativeness of this sample within a finite population, Yamane's (1967) formula for sample size determination was utilized, as expressed below:

In all the literature reviewed, project planning and monitoring are the most critical stages that affect the performance of construction projects. Well-established project management paradigms such as the Iron Triangle and the Project Life Cycle models emphasize the need to balance time, cost, scope and quality during project execution (Atkinson, 1999; PMI, 2021; Shenhar & Dvir, 2007). The growing complexity of infrastructure projects has exposed the limitations of traditional planning and monitoring approaches, often hampered by fragmented data, paper records and slow decision-making. The constraints are more acute in developing countries where institutional capabilities and digital frameworks are still wanting.

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Recent developments in Artificial Intelligence (AI) have a great potential to improve project planning and control via predictive analytics, machine learning, computer vision, Building Information Modelling (BIM), Internet of Things (IoT) technologies and automated scheduling systems. Empirical evidence from developed countries has proven that these technologies improve forecasting accuracy, resource allocation, risk management, real-time control and proactive decision-making which consequently reduce project delays and improve project performance (Bilal et al., 2016; Fang et al., 2020; Adebayo, 2025). Many African countries have started using artificial intelligence in the building and management of infrastructure but the use of this technology is patchy and generally limited to isolated applications rather than as part of an integrated approach to managing projects.

The policy environment is improving in Zambia with the adoption of the National Artificial Intelligence Strategy and National Digital Transformation Strategy. But the true AI of the construction industry remains in its nascent stages. The major challenges to adoption include fragmented data ecosystems, poor digital infrastructure, lack of technical skills, lack of adequate regulatory support and high costs of implementation (Wachata, 2020; Ministry of Technology and Science, 2024; Mushili, 2025). Also, most of the existing literature is descriptive in nature and discusses either particular technologies, the points of view of different stakeholders or single case studies. There is little empirical evidence on the actual execution and effectiveness of AI in the planning and monitoring phases of infrastructure projects.

The current state of knowledge clearly shows a lack of studies on the adoption and impact of AI on the performance of the construction industry in Zambia. There is a lot of evidence in global studies that AI enhances planning efficiency, monitoring efficacy and execution of projects. However, there are few studies that have empirically tested these relationships in the context of Zambia's institutional, technological and regulatory environment. In addition, the organizational, technological and policy factors influencing the implementation of AI and the role of AI in alleviating project delivery delays have not been given much attention. Such gaps require filling to inform evidence-based policy and practice, and hence the need for this study. This study investigates the adoption of AI in the planning and supervision of construction infrastructure projects in Zambia, and evaluates its potential to reduce project delays .

$n = N / [1 + N(e)^2]$

Where n is the sample size, N is the total population size (150), and e is the precision level or allowable margin of error. Operating at a standard confidence level, the finalized sample size of 78 provides statistical validity under finite population parameters. A pilot test of 20 professionals confirmed the statistical reliability of the research instrument, with all core scales exceeding standard Cronbach's alpha thresholds. Variables were operationalized using 5-point Likert scales to map the core independent constructs of the UTAUT framework against AI adoption and project delays.

The involvement of some of the same participants in both qualitative and quantitative improves data triangulation by giving the researcher the opportunity to compare quantitative responses to qualitative stories thus increasing the credibility, validity, and richness of the findings. The overlap will be limited to prevent over-burdening participants, but at the same time to ensure an adequate depth of understanding.

Quantitative data was processed in SPSS using descriptive statistics, the Relative Importance Index (RII), and parametric One-Sample t-tests against a literal neutral baseline value (3) on the 5 point Likert Scale..

Finally, formal ethical approval was secured from the Mulungushi University Research Ethics Board, guaranteeing full participant anonymity and voluntary participation.

Ethics

Ethical approval was obtained from the Mulungushi University Research Ethics Committee. Participants received an information sheet and provided electronic informed consent. No employer received individual responses. Participants could withdraw before data aggregation.

6 Research Findings

6.1 Deployed AI Technologies and Systemic Adoption Depth

Table 1: Utilization of AI classes

AI Technology Classification Type	Frequency (n)	Percentage (%)	Primary Practical Operational Target
Natural Language Processing (NLP)	23	29.5%	Document generation, contract clause analysis, report formatting
Data Analytics and Interactive Dashboards	22	28.2%	Milestone tracking, KPI visualization, materials supply logs
Predictive Machine Learning (ML)	14	17.9%	Baseline cost forecasting, variance logs, schedule simulation
Expert Systems	6	7.7%	Rule-based resource leveling and active decision support
Drones and Visual Site Robotics	3	3.8%	Automated site imaging and physical milestone captures
Non-Users (Traditional Systems Only)	10	12.8%	Manual spreadsheet entries, static non-automated templates

The statistical tests demonstrate an operational landscape defined as developing, fragmented, and heavily localized within specific project administration roles. The immediate technical scope remains siloed inside administrative Natural Language Processing utilities (29.5%) and visual descriptive data tracking dashboards (28.2%). Advanced cognitive tools capable of optimizing project systems, such as predictive Machine Learning (17.9%) or expert systems (7.7%), are restricted to a narrow pocket of technical users. The dominance of text-based AI tools (29.5%) shows that local construction companies are using technology to solve their most urgent daily headache: paperwork. Because Zambian job sites still rely heavily on manual tracking and basic digital tools, project managers are buried under a mountain of daily site logs, contracts, and regulatory forms. Much like Wachata (2020) concluded in their study, advanced AI, like predictive modeling, is currently out of reach because it requires highly organized, specialized digital data that these sites simply do not collect yet. Text-based AI, on the other hand, is easy to use and requires no special training. By using it to read, sort, and summarize messy office work, managers are using AI as a practical tool to cut down on office hours. In doing so, they are accidentally doing the groundwork for the future—using these text tools to digitize and organize site information so that more advanced systems can actually be used later on.

6.2 Statistical Level of Systemic Adoption Depth

Table 2: Relative Importance Index (RII) and t-test for AI adoption

Evaluated Operational Statement	Mean (μ)	Std Dev (σ)	RII Score	t-stat	p-value	Statistical Inference
1. I regularly use AI tools for project scheduling and planning.	3.22	1.16	0.6436	1.674	0.10060	Not Statistically Significant
2. I use AI tools to monitor real-time progress.	2.99	1.21	0.5974	-0.073	0.92577	Equivalent to Neutral Baseline
3. I use AI for risk analysis and early delay tracking.	2.92	1.18	0.5846	-0.575	0.56706	Not Statistically Significant
4. AI is integrated into most PM activities.	2.87	1.23	0.5744	-0.919	0.36062	Not Significant

6.3 Technological, Organizational, and Policy Factors

Table 3: Relative Importance Index (RII) hierarchy of rated factors

Category	Survey Metric Statement Evaluated	Mean (μ)	Std Dev (σ)	RII Score	Rank
Technological	AI tools are easy to use for project planning tasks.	3.59	1.01	0.7179	1
Organizational	Colleagues use AI in their work, motivating adoption.	3.51	0.96	0.7026	2
Technological	I find AI software intuitive for progress monitoring.	3.49	1.05	0.6974	3
Technological	AI apps integrate easily with current processes.	3.26	1.05	0.6513	4
Organizational	My organization encourages the use of AI in PM.	3.24	1.12	0.6487	5
Organizational	Senior management supports AI adoption in planning.	3.22	1.05	0.6436	6
Policy/Ext	Availability of external funding or incentives.	3.15	1.32	0.6308	7
Technological	Learning to operate AI tools requires minimal effort.	3.09	1.18	0.6179	8
Policy/Ext	Industry standards encourage AI adoption for projects.	2.97	1.09	0.5949	9
Organizational	I have access to training or guidance to use AI.	2.87	1.28	0.5744	10
Organizational	My organization provides sufficient tech infrastructure.	2.77	1.28	0.5538	11

Organizational	Policies and procedures in my firm facilitate AI.	2.69	1.08	0.5385	12
Policy/Ext	Industry regulations encourage AI adoption in PM.	2.63	1.07	0.5256	13
Organizational	Technical support is available when issues arise.	2.59	1.22	0.5179	14
Organizational	My organization has a clear strategy for AI adoption.	2.50	1.25	0.5000	15
Policy/Ext	Government policies support the use of AI in projects.	2.29	0.93	0.4590	16
Organizational	Have received formal training in AI technologies.	2.04	1.23	0.4077	17

The RII hierarchy maps a structural mismatch defining the domestic market. The primary forces pushing technology into daily work are grass-roots, bottom-up dynamics: perceived usability of tool interfaces (Rank 1, RII = 0.7179), peer momentum among professional colleagues (Rank 2, RII = 0.7026), and visual dashboard intuitiveness (Rank 3, RII = 0.6974). Conversely, top-down institutional support vectors are severely lacking. The lowest ranked elements include a severe deficit in formal structured engineering training (Rank 17, RII = 0.4077), a total absence of supportive national government infrastructure policies (Rank 16, RII = 0.4590), and missing clear corporate adoption roadmaps within firms (Rank 15, RII = 0.5000). While individual practitioners exhibit organic intent to utilize automated tools, they are structurally constrained by corporate and regulatory strategy deficits.

6.4 Impact on Efficiency, Monitoring, and Delay Mitigation

Table 4: Respondents rated perceived planning efficiency, scheduling/resource accuracy, monitoring/control and delay-risk mitigation above the neutral midpoint

Performance Indicator Variable Evaluated	Mean (μ)	Std Dev (σ)	t-statistic	df	Two-Tailed p-value	H_0 Decision
Project Planning Efficiency	4.21	0.84	12.631	77	< 0.0001	Rejected (Significant)
Scheduling and Resource Accuracy	3.82	0.96	7.551	77	< 0.0001	Rejected (Significant)
Project Monitoring and Control	3.64	1.12	5.061	77	< 0.0001	Rejected (Significant)
Real-World Delay Mitigation	3.36	1.03	3.072	77	0.00293	Rejected (Significant)

The inferential analysis establishes that AI integration produces statistically verified, highly significant positive shifts across all primary project tracking metrics. Project planning efficiency achieved the highest statistical validation ($p < 0.0001$), proving that AI tools significantly compress data compilation schedules and baseline documentation timelines during initial project setup. Crucially, real-world structural delay mitigation achieved clear statistical confirmation ($p = 0.00293$). The complete survey sample successfully captures active site managers and structural engineers who leverage analytics dashboards to identify scheduling conflicts before they derail construction timelines. While AI's primary and most accessible benefit is optimizing early-stage desk documentation, its structured deployment significantly controls project delays during site execution.

6.5 Key Challenges and Limitations to AI Adoption

Table 5: Quantitative friction and barrier analysis

Identified Challenge / Threat Statement	Mean Score (μ)	Std. Deviation (σ)	Percentage Agreement (%)
I worry about data privacy and security when using AI tools.	3.73	1.26	64.1%
AI could reduce the need for certain human roles in PM.	3.55	1.09	56.4%
I am concerned about the reliability of AI-generated insights.	3.37	1.03	42.3%
AI adoption may unacceptably increase overall project costs.	2.74	1.23	20.5%

The metrics show that professional concerns regarding information governance and workforce protection form significant psychological barriers. Data privacy worries achieved the highest concern mean ($\mu = 3.73$), with 64.1% of the sample expressing anxiety over corporate data leakage when utilizing open cloud-based models. Furthermore, 56.4% of the engineering workforce believes AI deployment creates a risk of labor redundancy ($\mu = 3.55$). Qualitative coding of open-ended data clusters structural barriers into three main areas: 1. The Localized Data Void (absence of structured local databases forcing reliance on generic foreign parameters); 2. Legacy Interoperability Friction (ingestion issues when syncing with old spreadsheet records across site camps); and 3. Financial Exclusion (high premium licensing costs that exclude lower-tier local contractors).

This study is limited by its cross-sectional, self-reported design; geographic concentration in Lusaka Province; possible undercoverage of firms with weak online presence; a modest sample; potential common-method and social-desirability bias; ambiguity between conventional digital tools and AI-enabled systems; and the absence of objective schedule-performance data. The midpoint tests estimate perceptions rather than causal effects. Findings should therefore not be generalised to all Zambian construction firms or interpreted as proof that AI reduces delays

7 Conclusion

AI-related activity among surveyed practitioners was present but fragmented and concentrated in accessible language and dashboard applications. Respondents perceived potential planning and monitoring benefits, while formal training, organizational strategy, technical support, local datasets and data governance remained weak. Due to the study used cross-sectional self-reports, it cannot determine whether AI reduced actual project delays however, a similar separation between individual uptake and institutional readiness has been reported in SADC higher education, where use of generative AI coexisted with gaps in digital literacy, ethical guidance and institutional policy (Halubanza et al., 2025). Although the sector differs, the comparison suggests that favourable user perceptions alone may be insufficient for sustained organisational adoption. The immediate implication is a phased adoption agenda combining verified use cases, workforce development, interoperable project data and prospective evaluation against objective schedule and cost indicators

8 Recommendations

To address these structural deficiencies and accelerate mature technology adoption across the sector, the following institutional interventions are proposed:

Framework Integration via Regulatory Mandates: The National Council for Construction (NCC) in Zambia should introduce formal digital readiness scoring parameters within public procurement bidding evaluation guidelines. This mechanism will provide a clear commercial incentive for domestic firms to mature their software infrastructure and documentation pipelines.

Development of Open-Access Historical Repositories: Public infrastructure departments, in collaboration with regulatory bodies, should establish a shared, centralized repository documenting historical project execution variables. Providing access to verified domestic parameters will resolve the localized data void and enable the precise training of predictive machine learning models.

Academic Curricula Modernization: Higher education institutions and engineering training centers must systematically update project management and civil engineering curricula to include specialized modules in data literacy, computational optimization, and digital information governance. This will supply the construction market with an operationally capable and risk-aware professional workforce.

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