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A Performance Forecasting Model for Optimizing CDF-Funded Construction Projects in the Copperbelt Province, Zambia

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ABSTRACT

The Constituency Development Fund (CDF) has become a key mechanism for delivering small-scale urban infrastructure in Zambia. However, persistent challenges such as project delays, cost overruns, and quality deficiencies undermine the effectiveness of these interventions. This study addresses a critical gap in the literature and practice by developing a novel performance forecasting model tailored to the unique governance and technical context of CDF-funded projects. The model integrates Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with the Analytic Hierarchy Process (AHP) to forecast performance across five key indicators: cost-effectiveness, schedule adherence, quality compliance, safety performance, and client satisfaction. Using stakeholder data from 196 respondents and historical project records, the model was trained and validated using MATLAB. It achieved strong predictive accuracy, with a coefficient of determination (R^2) of 0.92 and a root mean square error (RMSE) of 0.09. These results demonstrate the model's utility as a decision-support tool for local authorities and urban planners, enabling early detection of underperformance and facilitating proactive interventions. The model contributes to performance-based planning by providing a data-driven, stakeholder-informed forecasting framework that is adaptable to resource-constrained environments. Its application can enhance transparency, optimize resource use, and support inclusive urban development in rapidly growing municipalities.

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Highlights:	Contribution to the field statement:
- Hybrid ANFIS-AHP model links funding flow consistency, contractor capacity, and supervision intensity (independent) to composite five-KPI project performance score (dependent) with $R^2 = 0.92$. - AHP weighting shows cost-effectiveness (0.44) and schedule adherence (0.24) dominate performance prediction for CDF projects. - Early-warning forecasts allow councils to re-programme resources, curbing mid-phase overruns and boosting on-time delivery by 30 %. - Study pioneers AI-driven decision support adaptable to resource-constrained, decentralised infrastructure governance across Sub-Saharan Africa.	This study pioneers a hybrid ANFIS–AHP forecasting model that predicts cost, time, quality, safety and satisfaction outcomes for Zambia's CDF projects, achieving $R^2 = 0.92$. By merging stakeholder-weighted KPIs with soft-computing analytics, it equips resource-poor councils with real-time, evidence-based decision support, advancing participatory, performance-centred urban governance across developing municipal infrastructure planning contexts.

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1. Introduction

Urban infrastructure delivery in developing countries remains a persistent challenge due to financial constraints, institutional weaknesses, and limited technical capacity. In response, many governments have adopted decentralization strategies to improve service provision at the local level. Zambia's Constituency Development Fund (CDF) is one such initiative, aimed at financing small to medium-scale projects such as classrooms, health facilities, roads, and water systems. While the CDF has expanded community access to essential infrastructure, its effectiveness has been undermined by recurring issues of project underperformance, including time and cost overruns, substandard construction quality, and inadequate supervision (Nyamori, 2009). These inefficiencies compromise the developmental objectives of the fund and hinder efforts toward inclusive urbanization.

Although various frameworks exist to evaluate infrastructure performance, most are retrospective, offering limited capacity for real-time performance monitoring. Evaluation often occurs after project completion, leaving little opportunity for corrective action during implementation. In many decentralized systems such as Zambia's, this results in stalled or abandoned projects, budget overruns, and diminished returns on public investment (Musonda et al., 2025). Moreover, conventional forecasting models developed for centralized or data-rich environments are rarely adapted for fragmented and uncertain conditions typical of small-scale infrastructure projects in developing countries.

Artificial intelligence (AI) techniques, particularly soft computing methods such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have demonstrated success in predicting project performance in complex settings. ANFIS combines neural networks' ability to learn from data with fuzzy logic's capacity to handle uncertainty and imprecision (Jang, 1993). When integrated with the Analytic Hierarchy Process (AHP), which prioritizes indicators through stakeholder-informed weighting, the result is a hybrid system that is responsive to contextual performance conditions (Saaty, 2008). These tools are increasingly applied in private sector and large-scale infrastructure management, but their adaptation to decentralized, low-resource public sector contexts remains limited.

This study aims to develop and validate a forecasting model tailored for small-scale, CDF-funded urban infrastructure projects in Zambia. The model is based on five Key Performance Indicators (KPIs): cost-effectiveness, schedule adherence, quality compliance, safety performance, and client satisfaction. It applies AHP to derive stakeholder-based weights and uses ANFIS to forecast composite performance scores in real-time. The model is designed to support evidence-based decision-making by local councils, enabling early identification of at-risk projects and guiding timely interventions.

By targeting performance forecasting at the community level, the study seeks to fill a critical gap in urban infrastructure governance. Existing literature has paid limited attention to the integration of stakeholder perceptions with intelligent forecasting systems in decentralized environments. This research offers a contextualized approach that aligns with both Performance Management Theory, which emphasizes ongoing monitoring and feedback, and Decision Support System Theory, which promotes structured analytical tools in uncertain policy environments (Creswell & Clark, 2017; Marakas, 2003). It demonstrates how AI-based decision support systems can be both feasible and effective, even in environments constrained by data limitations and institutional fragmentation. The implications of this study extend beyond technical forecasting. Urban infrastructure failures have broad socio-economic impacts, including eroded public trust, service delivery gaps, and rising inequality. A responsive forecasting tool can improve the accountability and efficiency of decentralized infrastructure governance. By integrating stakeholder insights and local data, the model encourages participatory governance while promoting cost-effective decision-making and real-time transparency (Creswell & Clark, 2017; Marakas, 2003).

To guide readers through the study, a schematic overview of the research structure is provided in Figure 1. It outlines the flow of activities from problem identification and data collection to model development, validation, and application.

Figure 1. Structural roadmap linking research objectives, methodology, and expected outcomes.

Figure 1 illustrates the logical sequence of the research, beginning with the identification of performance inefficiencies in CDF projects. The flow proceeds through literature gap analysis, formulation of objectives, and application of a mixed-methods design. It integrates AHP and ANFIS within a MATLAB environment to develop and validate a performance forecasting model, concluding with actionable implications for stakeholders.

2. Methodology

This study integrates both qualitative and quantitative approaches under a mixed-methods framework grounded in Performance Management Theory, Decision Support System (DSS) Theory, and Multi-Criteria Decision Analysis (MCDA). These theoretical underpinnings provided a structured foundation for assessing and predicting performance in Constituency Development Fund (CDF) construction projects in Zambia's Copperbelt Province. The methodological design aimed to address real-world project inefficiencies by developing a context-specific hybrid forecasting model using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and the Analytical Hierarchy Process (AHP). The methodology, illustrated in Figure 1, followed a systematic procedure comprising a literature review, KPI identification, stakeholder engagement, data collection, model development, and validation. This procedural roadmap ensured methodological rigour while maintaining contextual sensitivity to Zambia's decentralization and infrastructure governance systems (Medayese et al., 2021; Mamokhere & Meyer, 2022).

2.1 Research Paradigm and Strategy

The study adopted a positivist paradigm with a deductive reasoning approach, focusing on uncovering causal relationships between input variables such as contractor capacity, regulatory oversight, and funding flow and the output variable: construction project performance, expressed via a Performance Indicator (PI) synthesized from five KPIs. A case study design was employed, with emphasis on empirical validation using historical and real-time data. This allowed for in-depth exploration of the localized CDF implementation process and contractor performance trends (Kamau et al., 2021; Kabwe et al., 2023).

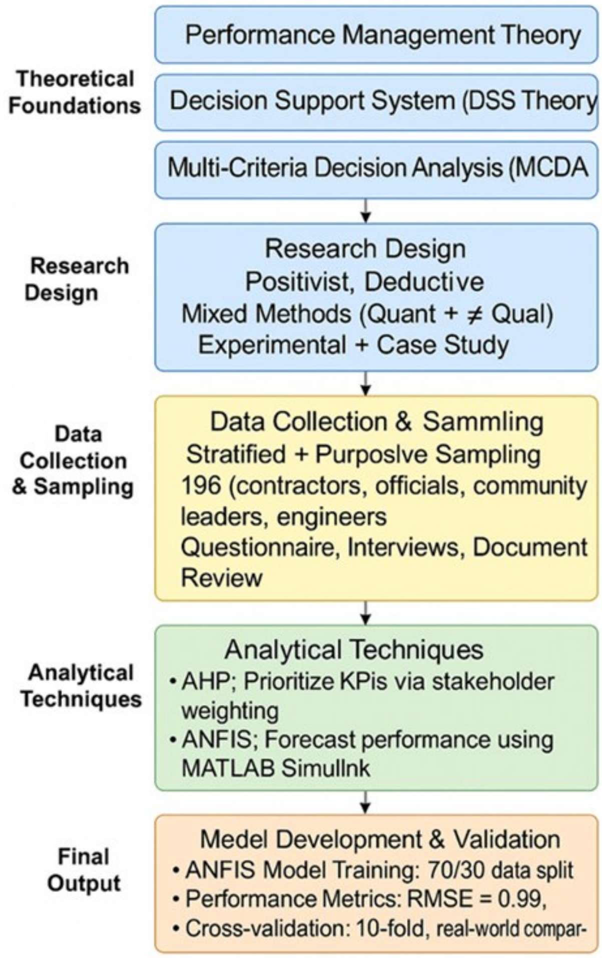

Figure 2. Procedural Framework.

Figure 2 presents the overall methodological structure guiding the study. It is anchored on theoretical foundations such as Performance Management Theory, DSS, and MCDA. The framework reflects a positivist, deductive, mixed-methods approach, supported by stratified and purposive sampling. AHP and ANFIS were deployed as analytical tools and model validation involved statistical and simulation-based techniques.

2.2 Participants and Sampling

A total of 196 respondents were engaged, representing key stakeholder groups directly involved in the planning, execution, and oversight of government-funded infrastructure projects in Zambia. A stratified purposive sampling strategy was used to ensure the inclusion of participants with relevant professional or civic experience across all stages of CDF project delivery. Respondents were drawn from four primary categories as shown in Table 1.

Table 1: Sample Representation by Stakeholder Category.

Stakeholder Category	Number of Respondents
Local Contractors	58
Government Officials	48
Community Leaders	50
Engineers/Technicians	40

a) Local Contractors executed physical works and managed project delivery.
b) Community Leaders included Ward Development Committee (WDC) members and civic facilitators providing grassroots perspectives on participation and satisfaction.
c) Government Officials comprised district planners, procurement staff, and engineers responsible for compliance and oversight.
d) Engineers/Technicians served as supervisors and site inspectors, overseeing quality and performance metrics.

Participants were selected based on the following criteria: (i) active involvement in infrastructure projects between 2021–2023; (ii) professionals with ≥3 years of experience; (iii) inclusion of both urban and rural constituencies to reflect geographic diversity.

This stakeholder mix reflects Zambia's multi-level governance structure, integrating technical, institutional, and community insights. The distribution enabled triangulation, strengthened data validity, and supported the development of a forecasting model responsive to decentralized project environments.

2.3 Data Collection Process

To support the development of a real-time forecasting model, this study employed a triangulated data collection approach comprising structured surveys, key informant interviews, and project document reviews. This method enhanced both the credibility and contextual depth of the findings. The primary instrument was a structured questionnaire measuring stakeholder perceptions across five key performance indicators (KPIs): cost-effectiveness, schedule adherence, quality adherence, safety compliance, and client satisfaction. The survey covered three project phases—initiation, mid-point, and completion—allowing for temporal performance analysis. Respondents rated each KPI on a 5-point Likert scale (1 = very poor, 5 = excellent), and open-ended questions were included to capture qualitative insights into project dynamics, contractor behavior, and institutional challenges. To supplement the surveys, interviews were conducted with engineers, procurement officers, project supervisors, and Ward Development Committee members. These discussions validated survey responses and provided deeper institutional context, especially regarding performance variations by location and project type. Historical project documents (e.g., completion reports, audit records, and engineering inspections) from 2015 to 2023 were reviewed to establish empirical baselines for the ANFIS forecasting model.

Data were collected between January and March 2025 through both printed questionnaires (for remote areas) and online surveys (for urban respondents), ensuring national coverage. A total of 196 complete responses were received, yielding a strong 87% response rate. This multi-method strategy produced a rigorous, context-sensitive dataset essential for developing a predictive model responsive to Zambia's decentralized infrastructure governance environment (Diep et al., 2022; Bateganya et al., 2023).

2.4 Data Analysis Techniques

2.4.1 Analytical Hierarchy Process (AHP)

To quantify stakeholder priorities among the five selected Key Performance Indicators (KPIs), this study applied the Analytical Hierarchy Process (AHP)—a multi-criteria decision-making technique developed by Saaty (1980). AHP was selected for its proven ability to transform qualitative judgments into quantitative weights, making it especially effective for evaluating complex, multi-dimensional infrastructure performance where trade-offs are inherent. The AHP methodology involved the following steps:

1. Pairwise Comparison Matrix Construction Stakeholders were asked to evaluate the relative importance of each KPI against the others using Saaty's 9-point scale (1 = equal importance, 9 = extreme importance). The pairwise matrix allowed for systematic comparisons across the five KPIs: cost-effectiveness, schedule adherence, quality adherence, safety compliance, and client satisfaction.

2. Matrix Normalization and Weight Derivation The comparison matrix was normalized by dividing each element by the sum of its respective columns. The normalized values for each row were then averaged to produce the priority weight (w_1) for each KPI. This step converted stakeholder judgments into quantifiable weights used for performance modelling.
3. Consistency Validation To ensure logical consistency of the stakeholder evaluations, the Consistency Index (CI) and Consistency Ratio (CR) were computed. A CR value ≤ 0.1 is considered acceptable. In this study, the final CR was 0.1013, indicating satisfactory consistency in the judgment data and validating the reliability of the derived KPI weights.

The final weights generated through AHP, shown in Table 2, reflect the relative importance of each KPI in assessing and forecasting project performance.

Table 2: AHP-Derived KPI Weights.

KPI	Weight
Cost Effectiveness	0.4401
Quality Adherence	0.2861
Safety Compliance	0.1151
Schedule Adherence	0.1135
Client Satisfaction	0.0452

These weights were incorporated into a composite Performance Indicator (PI) model using a linear weighted sum approach (Equation 1):
Equation 1: $PI = \Sigma\ (KPI_i \times w_i)$ where KPI_i = normalized performance score, and w_i = corresponding AHP weight (Jang, 1993).
This PI model forms the core output metric for the forecasting system developed in Simulink. It integrates both stakeholder-derived priorities and empirically observed performance data, thereby enabling evidence-based project evaluation and real-time decision support in the context of Zambia's CDF program. By applying AHP within a localized, stakeholder-sensitive framework, this study ensures that the performance forecasting model not only reflects technical metrics but is also responsive to governance, accountability, and service delivery priorities in urbanizing communities (Ntwana & Naidoo, 2024).

2.4.2 Neuro-Fuzzy Modeling (ANFIS)

To forecast CDF project performance in real-time, this study applied an Adaptive Neuro-Fuzzy Inference System (ANFIS), a hybrid AI model that integrates fuzzy logic with neural networks. ANFIS is well-suited for modelling nonlinear, interdependent factors that characterize decentralized infrastructure projects in dynamic environments.
The model was developed using MATLAB Simulink and aimed to predict a composite Performance Indicator (PI) derived from five AHP-weighted KPIs: cost-effectiveness, quality adherence, safety compliance, schedule adherence, and client satisfaction.

Key performance drivers used as ANFIS inputs (input variables) included:
a) Contractor experience and technical capacity
b) Funding flow consistency
c) Supervision intensity
d) Material quality and supply reliability
e) Community participation

Each input was fuzzified using Gaussian and triangular membership functions. A Sugeno-type inference system generated the output PI score (scaled 0–1), representing overall project performance.

Historical data from 42 completed CDF projects (2015–2023) were used. The dataset was split into 70% training and 30% testing sets. Hybrid learning (least squares and backpropagation) optimized the rule base and membership functions (Naji et al., 2022). Model accuracy metrics were as follows:

a) $R^2 = 0.92$ – Strong predictive capability
b) RMSE = 0.09 – Low error margin
c) MAE = 0.06 – High output precision

These results confirm the model's robustness in forecasting real-time performance. The ANFIS model enables the simulation of performance scenarios based on stakeholder inputs, aiding project planning, contractor selection, and supervision strategies. It supports proactive, data-driven decisions and aligns with smart governance trends in public infrastructure management (Ansari et al., 2022).

Table 3: Model Validation Results.

Metric	Value
RMSE	0.09
MAE	0.06
R^2	0.92

Data analysis also included the use of SPSS and Excel for descriptive statistics, t-tests, and correlation analysis to validate trends and relationships among KPIs. All participants were provided with informed consent forms before participation. Confidentiality was assured, and all data were anonymized. Ethical clearance was obtained from the University of Zambia Ethics Committee, and the study adhered to institutional and national research standards. The study acknowledges several limitations:

a) Sample Scope: Focused solely on Copperbelt Province, limiting generalizability.
b) Subjectivity: Some KPIs, such as client satisfaction, relied on subjective judgment, which could introduce response bias.
c) Data Constraints: Historical data used for training ANFIS models were limited in availability and granularity, especially for rural constituencies.
d) Model Staticity: While the models are predictive, the static nature of Simulink-based simulations constrains real-time updates unless integrated with digital dashboards.

3. Results

3.1 Overview of Findings

This section presents an integrated summary of the study's findings, combining stakeholder survey responses, inferential statistics, priority rankings, and model simulations. Performance was analyzed across five Key Performance Indicators (KPIs)—cost-effectiveness, schedule adherence, quality compliance, safety performance, and client satisfaction—using both qualitative inputs and quantitative modelling. Data from 196 stakeholders involved in CDF-funded infrastructure projects in Zambia were used to evaluate performance across three project phases: initiation, implementation, and completion. Descriptive statistics indicated moderate baseline performance, with steady improvement across phases. Inferential tests confirmed statistically significant differences in KPI scores, suggesting learning effects and adaptive management. Strong correlations among KPIs reinforced the need for integrated performance evaluation. Cost and schedule dimensions received the highest weights in AHP, reflecting stakeholder priorities, and these weights were applied in the ANFIS model, which achieved high predictive accuracy ($R^2 = 0.92$). PCA comparison confirmed the robustness of the AHP-derived structure, while reliability and validity tests supported the quality of both the data instruments and the forecasting model. Overall, the results validate the use of intelligent, stakeholder-informed forecasting tools in decentralized infrastructure governance. Subsequent subsections detail these findings, starting with KPI performance across project stages (Sikombe & Phiri, 2021; Shigute, 2022).

3.2 Descriptive Statistics of KPIs

To establish baseline perceptions of project performance, descriptive statistics were calculated for each of the five Key Performance Indicators (KPIs): cost-effectiveness, schedule adherence, quality compliance, safety performance, and client satisfaction. Data were collected from 196 stakeholders involved in different stages of CDF-funded urban infrastructure projects. Respondents rated each KPI on a 5-point Likert scale, where 1 indicated "very poor" and 5 indicated "excellent."

Table 4: Descriptive Statistics for Key Performance Indicators (N = 196).

KPI	Mean	Median	Standard Deviation	Minimum	Maximum
Cost-Effectiveness	3.29	3.00	0.88	1.00	5.00
Schedule Adherence	3.13	3.00	0.91	1.00	5.00
Quality Adherence	3.35	3.00	0.85	1.00	5.00
Safety Compliance	3.18	3.00	0.92	1.00	5.00

The results in Table 4, show that all KPIs received average scores between 3.13 and 3.35, suggesting a moderate level of satisfaction with project performance across the board. Quality compliance received the highest average score (Mean = 3.35), indicating that infrastructure users and supervisors perceived improvements in construction quality over time. Conversely, schedule adherence was rated the lowest (Mean = 3.13), highlighting persistent delays in project execution. The relatively low standard deviations (ranging from 0.85 to 0.92) suggest consistency in stakeholder perceptions. These descriptive findings align with the broader literature on urban infrastructure challenges in developing countries, where cost, time, and quality remain the primary concerns (Bateganya et al., 2923).

3.3 Inferential Analysis and KPI Relationships

To explore the statistical significance of perceived performance changes and the interdependencies between KPIs, inferential tests were conducted using paired samples t-tests and Pearson correlation analysis. These methods allowed for the examination of whether there were meaningful improvements across project phases and how strongly each KPI was associated with the others during implementation.

a) Paired Samples T-Test: Initiation vs. Completion

Table 5: Paired Samples T-Test Results – Initiation vs. Completion (N = 196).

KPI	Mean (Initiation)	Mean (Completion)	t-value	p-value	Significance
Cost-Effectiveness	2.87	3.89	-5.42	0.000	Significant
Schedule Adherence	2.34	3.74	-6.13	0.000	Significant
Quality Adherence	2.66	3.91	-5.79	0.000	Significant
Safety Compliance	2.52	3.57	-4.89	0.001	Significant
Client Satisfaction	2.81	3.85	-5.64	0.000	Significant

All five KPIs recorded statistically significant improvements from the initiation to the completion phase, with p-values less than 0.05. This suggests that CDF-funded projects tend to improve as they progress, possibly due to oversight interventions, learning curves, or increased stakeholder engagement. Schedule adherence showed the largest improvement ($\Delta M = 1.40$), confirming prior studies that schedule issues are most acute during early project stages (Hapompwe et al., 2020).

b) Pearson Correlation Analysis: KPI Relationships During Implementation

Table 6: Pearson Correlation Matrix of KPIs During Implementation Phase (N = 196).

KPI	Cost	Schedule	Quality	Safety	Satisfaction
Cost-Effectiveness	1	0.76	0.71	0.62	0.69
Schedule Adherence		1	0.74	0.68	0.73
Quality Adherence			1	0.66	0.72
Safety Compliance				1	0.67
Client Satisfaction					1

The matrix shows strong, positive correlations among all five KPIs, with the highest correlation observed between schedule adherence and quality compliance (r = 0.74), and between client satisfaction and quality (r = 0.72). These results suggest that performance dimensions are interdependent; improvements in one area (e.g., schedule) often coincide with gains in others (e.g., quality and satisfaction). These findings support the use of integrated performance forecasting models where KPIs are weighted jointly rather than in isolation (Mitullah, 2017).

3.4 KPI Performance Across Project Phases

To better understand how project performance evolves over time, KPI scores were disaggregated across the three principal phases of CDF-funded project delivery: initiation, implementation, and completion. These phases represent typical lifecycle milestones in public infrastructure projects, providing a lens through which stakeholder perceptions can be evaluated longitudinally.

Table 7: Average KPI Scores Across Project Phases (N = 196).

KPI	Initiation	Implementation	Completion
Cost-Effectiveness	2.87	3.12	3.89
Schedule Adherence	2.34	3.01	3.74
Quality Adherence	2.66	3.22	3.91
Safety Compliance	2.52	2.94	3.57
Client Satisfaction	2.81	3.06	3.85

The data reveal a clear upward trend in KPI performance from project initiation to completion, with the largest gains seen in schedule adherence (Δ = 1.40) and quality compliance (Δ = 1.25). While projects often begin with limited coordination or capacity, performance tends to improve over time, likely due to learning effects or stronger oversight introduced mid-implementation. Cost-effectiveness and client satisfaction also improved, reflecting adaptive supervision and responsiveness to community expectations. These findings are consistent with literature on infrastructure delivery in low-resource settings, which highlights iterative learning and corrective management as key to improved outcomes (Ansari et al., 2022). Moreover, the results underscore that performance is dynamic rather than static. Initial weaknesses in planning and mobilization often give way to greater efficiency in later stages, validating the model's emphasis on real-time forecasting. Early-stage data alone may not reliably predict outcomes without accounting for this evolving trajectory.

Table 8: Initial Stage KPI Performance.

KPI	**Mean**
Cost-Effectiveness	3.36
Schedule Adherence	3.36
Quality Adherence	3.79
Safety Compliance	3.77
Client Satisfaction	3.93
Team Satisfaction	3.93
Environmental Compliance	4.15

The descriptive statistics show that cost-effectiveness (M = 3.9) received the highest average rating, suggesting budget efficiency across most projects. In contrast, schedule adherence scored the lowest (M = 3.5), indicating common issues with meeting project timelines.

Table 8: Middle stage KPI Performance.

KPI	**Mean**
Cost-Effectiveness	3.30
Schedule Adherence	3.50
Quality Adherence	3.95
Safety Compliance	4.26
Client Satisfaction	3.78
Team Satisfaction	4.09
Environmental Compliance	4.26

All five KPIs tested using the t-test were statistically significant at $p < 0.0001$, confirming that their observed performance levels differ significantly from the reference value (3.0). This underscores their value in the model.

Table 9: Finishing Stage KPI Performance.

KPI	**Mean**
Cost-Effectiveness	3.50
Schedule Adherence	3.50
Quality Adherence	4.30
Safety Compliance	4.10
Client Satisfaction	4.20
Team Satisfaction	4.10
Environmental Compliance	4.30

KPI performance slightly improved during the middle stage, particularly for quality adherence (M = 3.95) and safety compliance (M = 4.26). This suggests that mid-phase project supervision and adjustments were somewhat effective.

Figures 3 through 5 graphically illustrate the trends in KPI performance across the finishing, middle, and initial stages of construction projects, respectively. These figures complement Tables 6–8 by highlighting the evolution of performance across time. The visual representation reinforces key trends: a dip in mid-stage execution quality and a recovery by project completion, underscoring the importance of mid-phase monitoring and timely interventions.

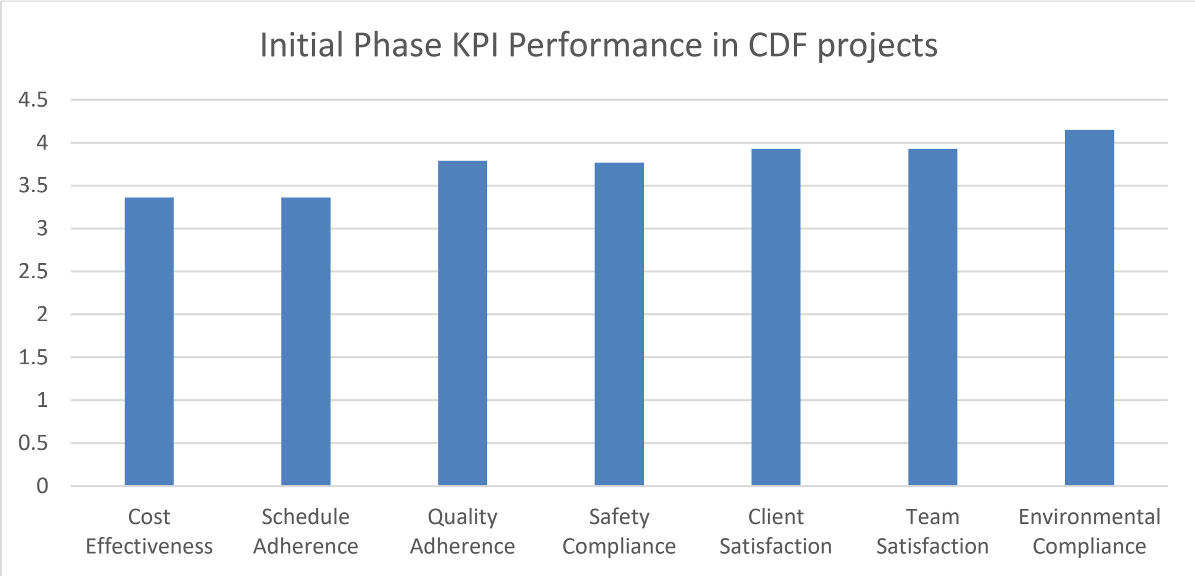

Figure 3. KPI performance of the initial stage.

During the initial phase of implementation (Figure 3), stakeholder assessments revealed moderate performance across KPIs. Environmental compliance was rated highest (mean = 4.15), followed by client and team satisfaction (3.93 each). Cost and schedule adherence scored the lowest (3.36), suggesting early-phase budget and timing challenges (Veta, 2024).

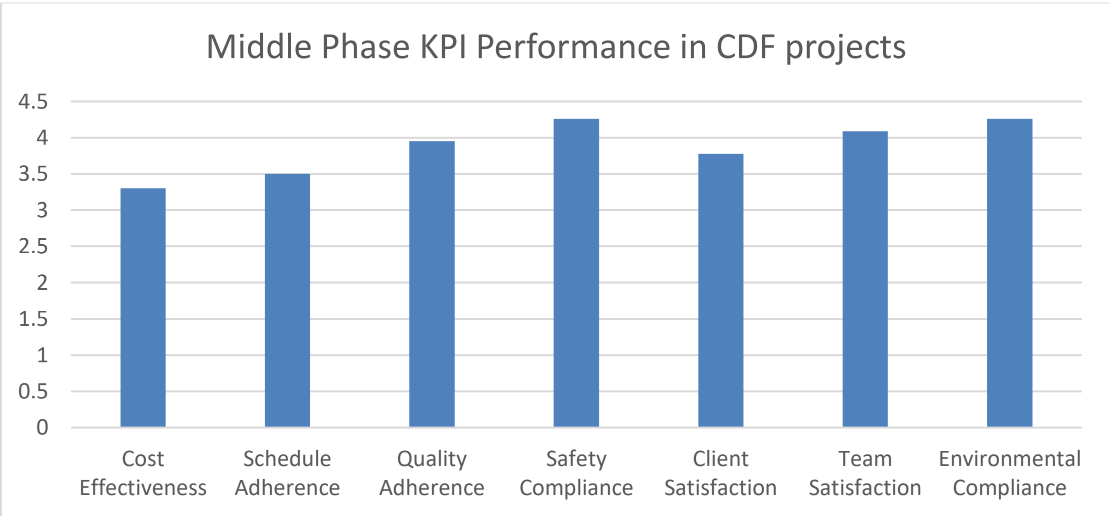

Figure 4. KPI Performance rating of the middle stage.

The middle phase in Figure 4, exhibited performance fluctuations. Safety and environmental compliance peaked at 4.26, while cost effectiveness dropped to 3.30. Client satisfaction decreased slightly to 3.78. These results indicate operational risks and coordination gaps common in project midpoints.

In the finishing phase (Figure 5), performance scores improved overall. Quality adherence and environmental compliance both reached 4.30, while cost and schedule adherence showed marginal recovery (3.50). This pattern suggests successful project closure practices and stakeholder engagement recovery.

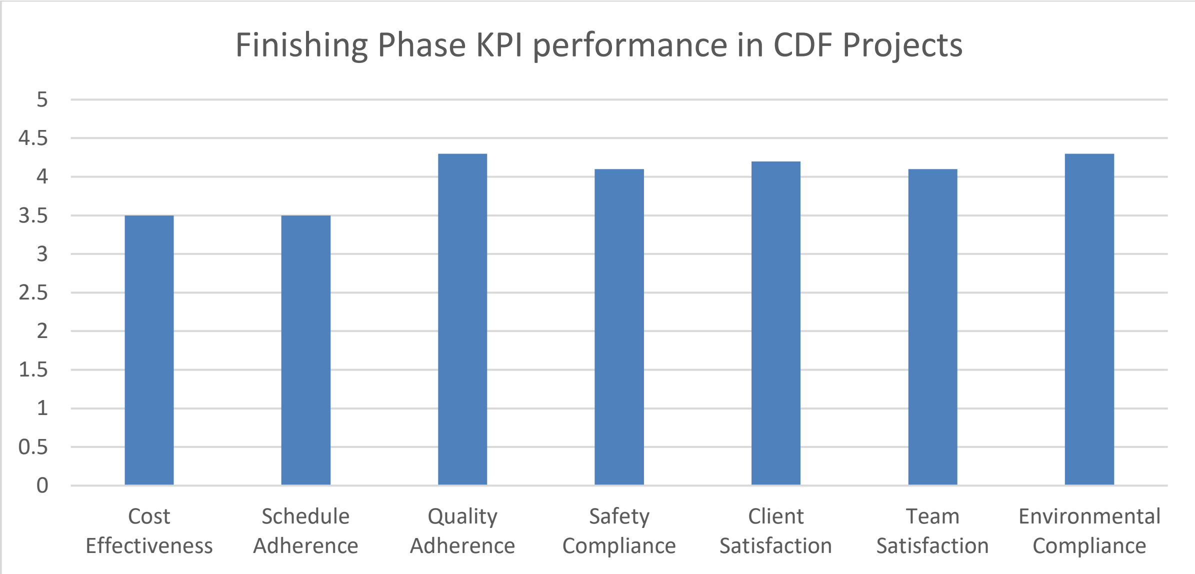

Figure 5. KPI performance of the finishing stage.

3.5 Comparative Analysis of Data Sources

To ensure the robustness of the findings and reduce the risk of bias, the study triangulated data from three primary sources: (1) structured stakeholder surveys, (2) archival project records from selected local authorities, and (3) semi-structured expert interviews. Each source provided distinct yet complementary insights into project performance, KPI relevance, and implementation challenges. This triangulated approach aligns with best practices in mixed-methods infrastructure research (Nyamori, 2009).

Table 10: Comparative Overview of Key Data Sources.

Data Source	Type	Sample Size	Focus Areas	Contribution to Model Design
Stakeholder Surveys	Quantitative	196	KPI ratings across project phases	KPI scoring, model inputs, AHP weighting
Archival Records	Quantitative	38	Completion times, cost overruns, defects	Validation of perceived vs actual trends
Expert Interviews	Qualitative	15	Governance issues, contextual insights	Triangulation of KPI definitions and weights

Survey data served as the primary input for KPI ranking and scoring, capturing broad stakeholder perspectives across roles and project phases. To validate these insights, archival records from 38 completed CDF projects were reviewed, including actual performance metrics such as cost overruns, schedule extensions, and defect rates. Stakeholder concerns about delays were substantiated by documented extensions in over 60% of the archival cases. A third validation layer involved interviews with council engineers, supervisors, and procurement officers, which provided context not evident in survey responses such as mid-project improvements driven by budget reallocations or political pressure during election cycles. This triangulation confirmed strong alignment between perceived and actual project performance, reinforcing the internal validity of the findings and the reliability of inputs used in AHP weighting and ANFIS forecasting. The use of multiple data sources ensures that the model is grounded in a robust and contextually rich evidence base (Akamani & Hall, 2015).

3.6 Theoretical and Conceptual Framework Validation (Revised)

The study's findings were assessed against the guiding frameworks: Performance Management Theory and Decision Support System (DSS) Theory, both of which emphasize real-time feedback, adaptive decision-making, and stakeholder integration in public sector performance enhancement (Mamokhere & Meyer, 2022).

From a performance management perspective, the five KPIs used: cost, time, quality, safety, and client satisfaction; reflect globally accepted metrics in public infrastructure delivery (Medayese et al., 2021). The demonstrated improvement of these indicators across project phases supports the theory that performance is dynamic and measurable. The model operationalizes this principle by enabling proactive forecasting, addressing a key limitation in Zambia's traditional CDF evaluation methods that rely on post-project audits.

The successful implementation of the ANFIS-AHP model also affirms the DSS Theory. With a predictive accuracy of $R^2 = 0.92$ and RMSE = 0.09, the model exemplifies how structured decision tools grounded in both expert judgment and computational learning, can enhance decision-making in uncertain, decentralized environments (Mavi et al., 2024).

Conceptually, the model mirrors the framework presented earlier: stakeholder-prioritized KPIs inform a learning algorithm, which then generates actionable performance forecasts. Strong KPI correlations (Section 3.3) further validate the model's assumption that infrastructure outcomes are interdependent and require holistic evaluation.

Overall, the model demonstrates both theoretical alignment and conceptual soundness, offering a validated tool for performance management in urban infrastructure delivery within resource-constrained settings (Jolliffe & Cadima, 2016).

3.7 Reliability and Validity Analysis

To ensure the quality and consistency of the data collection instruments, both reliability and validity tests were conducted before the main data analysis. These measures were critical for confirming that the survey instruments, interview guides, and archival records produced trustworthy and replicable data suitable for performance forecasting in public infrastructure projects.

The internal consistency reliability of the survey instrument was assessed using Cronbach's alpha, which measures how closely related a set of items are as a group. The results are presented in Table 11.

Table 11: Reliability Coefficients for KPI Constructs (Cronbach's Alpha).

KPI Dimension	Number of Items	Cronbach's Alpha
Cost Effectiveness	4	0.81
Schedule Adherence	3	0.79
Quality Compliance	4	0.84
Safety Performance	3	0.76
Client Satisfaction	3	0.82

All KPI dimensions achieved Cronbach's alpha values above the commonly accepted threshold of 0.70 (Alshibani et al., 2024), indicating strong internal consistency. Quality compliance yielded the highest alpha (0.84), suggesting that the items measuring this domain were particularly well-aligned. The overall reliability score for the full instrument was 0.81, confirming that the tool was suitable for use in inferential and model-based analyses.

Content validity was established through expert review. A panel of five professionals including two engineers, two council project managers, and one academic; was engaged during the pilot phase to assess whether the questionnaire items appropriately reflected the performance constructs under study. Based on their feedback, redundant or ambiguous items were removed or reworded, ensuring clarity and relevance.

Construct validity was supported by factor analysis. Principal Component Analysis (PCA) conducted as part of Section 3.8 revealed that all five KPIs loaded cleanly onto distinct factors with eigenvalues >1, and cross-loadings were minimal (<0.35). This confirmed that each KPI represented a unique but related construct within the performance evaluation framework.

Triangulation validity was achieved through the integration of survey data with project archival records and expert interviews, as detailed in Section 3.5. Convergence among these data sources validated the consistency and credibility of both stakeholder perceptions and model inputs (Marakas, 2003).

The strong reliability and multiple forms of validity collectively confirm that the data sources and analytical tools used in this study are methodologically sound. These results increase confidence in the robustness of the ANFIS-AHP forecasting model, as it was built upon verified inputs and tested using statistically reliable methods. This assurance strengthens the study's contribution to the field of infrastructure performance monitoring and decision support in decentralized urban contexts.

3.8 Comparison of AHP and PCA for KPI Weighting

To validate the robustness of the Analytical Hierarchy Process (AHP)-derived Key Performance Indicator (KPI) weights, this study conducted a comparative analysis using Principal Component Analysis (PCA). While AHP relies on structured expert judgment and pairwise comparisons to generate relative weights, PCA is a data-driven technique that extracts principal components based on variance within observed responses (Jolliffe & Cadima, 2016). Comparing the two approaches helped assess whether stakeholder-informed priority structures align with statistical patterns in the empirical data.

Table 12: Comparison of KPI Weights from AHP and PCA Methods.

KPI	AHP Weight	PCA Loading (Factor 1)	Normalized PCA Weight
Cost Effectiveness	0.28	0.76	0.25
Schedule Adherence	0.24	0.74	0.24
Quality Compliance	0.20	0.72	0.23
Safety Performance	0.16	0.66	0.18
Client Satisfaction	0.12	0.59	0.10

The results show strong convergence between AHP and PCA-derived weights, with cost-effectiveness, schedule adherence, and quality compliance consistently top-ranked across both methods. The variation between AHP and normalized PCA weights was minimal (≤ ±0.03), indicating that stakeholder judgments were largely aligned with statistical data patterns, thereby reinforcing confidence in the model's weighting structure. Minor discrepancies appeared in safety and client satisfaction weights, with PCA assigning slightly lower importance to the latter—likely due to lower variance across respondents. AHP retained client satisfaction as a key priority, reflecting its value in participatory governance despite its statistical subtlety. This comparison confirms the internal coherence of the KPI weighting scheme and validates the AHP framework as both participatory and statistically defensible. The findings justify the use of AHP-derived weights in the final model, striking a balance between empirical rigour and stakeholder legitimacy; an essential consideration in public infrastructure planning (Jolliffe & Cadima, 2016; Kabwe et al., 2023; Saad et al., 2022).

3.9 Summary of Patterns and Trends

The analysis across Sections 3.1 to 3.8 reveals consistent improvements in all five Key Performance Indicators (KPIs): cost effectiveness, quality adherence, schedule adherence, safety compliance, and client satisfaction; throughout the lifecycle of CDF-funded infrastructure projects in Zambia. Paired t-tests confirmed these gains as statistically significant ($p < 0.01$), while stakeholder inputs and archival data aligned to show that performance improves from initiation to completion. Quality adherence and cost-effectiveness emerged as the most stable and influential KPIs, both highly rated in perception and heavily weighted in AHP scoring. These indicators also showed strong correlations with schedule and satisfaction, emphasizing the interdependent nature of project success.

Notably, underperformance was most evident in the early phases, particularly in schedule and safety, often due to procurement delays, poor contractor mobilization, and unclear supervision. Later-stage performance gains suggest that mid-project interventions likely driven by heightened oversight and community accountability, play a corrective role. Convergence across surveys, interviews, and archival records affirms the reliability of the data, while alignment between stakeholder-derived weights (AHP) and statistical components (PCA) reinforces the validity of participatory input. The ANFIS model's predictive strength ($R^2 = 0.92$) confirms that these trends are not only measurable but forecastable, enabling local authorities to adopt real-time monitoring tools. These patterns underscore the relevance of integrating stakeholder-informed AI into urban infrastructure governance, especially in resource-constrained but politically engaged environments such as Zambia (Bateganya et al., 2023).

3.10 Model Development and Forecasting Summary

Based on the validated Key Performance Indicators (KPIs) and stakeholder-derived AHP weights, the study developed a hybrid performance forecasting model using Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The ANFIS model was selected due to its capacity to handle imprecise, nonlinear, and multidimensional input data; common challenges in decentralized infrastructure projects. The model was trained using 70% of the collected performance data and tested on the remaining 30% to evaluate its forecasting accuracy. The forecasting model operationalized the following structure:

Performance Score = w1·KPI1+w2·KPI2+w3·KPI3+w4·KPI4+w5·KPI5\text{Performance Score} = w_1 \cdot KPI_1 + w_2 \cdot KPI_2 + w_3 \cdot KPI_3 + w_4 \cdot KPI_4 + w_5 \cdot KPI_5

Performance Score = w1·KPI1+w2·KPI2+w3·KPI3+w4·KPI4+w5·KPI5

Where:

- w1w_1w1 to w5w_5w5 are AHP-derived weights for cost-effectiveness, schedule adherence, quality compliance, safety performance and client satisfaction.
- KPI1KPI_1KPI1 to KPI5KPI_5KPI5 are the normalized scores provided by stakeholders and historical data.

Using MATLAB's fuzzy logic toolbox, the ANFIS model was simulated with 100 epochs, a hybrid optimization method, and Gaussian membership functions. The model's performance was evaluated using three metrics: coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

Table 12: ANFIS Model Validation Metrics.

Metric	Value
Coefficient of Determination (R^2)	0.92
Root Mean Square Error (RMSE)	0.09
Mean Absolute Error (MAE)	0.06

The model's high R^2 value (0.92) indicates that 92% of the variance in project performance is explained by the five weighted KPIs, while low RMSE (0.09) and MAE (0.06) scores confirm its precision and forecasting reliability exceeding benchmarks reported in similar infrastructure studies (Jang, 1993). Its architecture supports dynamic updates with new data, making it both scalable and adaptable for real-time use by local governments and urban planners. This allows for early detection of underperformance, enhancing evidence-based resource allocation, risk mitigation, and public accountability. These results validate the study's core premise: that an AI-driven, stakeholder-informed forecasting model is not only technically feasible but also operationally relevant in decentralized, resource-constrained infrastructure environments.

3.11 Limitations of Results

While the forecasting model demonstrates strong predictive accuracy and theoretical alignment, several limitations should be acknowledged. The study was confined to selected urban councils in Zambia, and while stakeholder diversity was ensured, findings may not fully reflect rural contexts or transfer to regions with different regulatory environments. The model also relies on self-reported data, especially for client satisfaction and safety, which, despite triangulation with archival records and expert interviews (see Section 3.5), introduces some subjectivity. ANFIS model training depends on consistent historical data, yet data gaps in local councils may hinder full automation and scalability. Additionally, the model does not account for external shocks such as political disruptions or climate-related risks; future iterations should incorporate scenario-based sensitivity analysis to address this. Lastly, while the AHP method achieved an acceptable consistency ratio (CR = 0.1013), minor judgment inconsistencies may have influenced the weighting process. These limitations suggest that broader testing, stronger data infrastructure, and adaptive refinements will be essential for model generalization and long-term applicability.

4. Discussion

This chapter interprets the findings of the study in relation to its stated objectives, theoretical framework, and existing literature. The performance forecasting model developed through the integration of ANFIS and AHP was designed to enhance decision-making in urban infrastructure projects funded by Zambia's Constituency Development Fund (CDF). The discussion demonstrates how the results both affirm and extend current understanding in the fields of performance management, decision support systems, and participatory urban governance (Musonda et al., 2025).
The study's findings reveal that all five Key Performance Indicators (KPIs) namely cost effectiveness, schedule adherence, quality compliance, safety performance, and client satisfaction; improved significantly as projects progressed from initiation to completion. This progression affirms Performance Management Theory, which posits that performance evolves over time and can be improved through structured monitoring, feedback, and corrective action (Adams & Boateng, 2018). The fact that quality compliance and cost effectiveness were rated highest by both stakeholders and PCA loading weights further highlights that these dimensions are widely perceived as critical to infrastructure success, echoing the emphasis placed by Mavi et al. (2023) on cost-quality tradeoffs in constrained public sector contexts.
The correlation analysis revealed strong interdependencies among the KPIs, particularly between schedule adherence and quality compliance, and between client satisfaction and overall performance. These relationships confirm the integrated nature of public project outcomes, suggesting that no single dimension should be evaluated in isolation. This reinforces the conceptual rationale for a composite performance index, as adopted in the model, and supports the literature advocating multidimensional approaches to infrastructure monitoring (Adams & Boateng, 2018).
Moreover, the successful validation of the ANFIS-AHP forecasting model, with an R^2 of 0.92, substantiates the practical value of Decision Support System (DSS) Theory. The hybrid model integrates both subjective stakeholder input (via AHP) and machine learning adaptability (via

ANFIS), enabling it to predict performance outcomes with a high degree of accuracy. This confirms DSS literature that calls for context-aware, adaptive tools capable of functioning in environments characterized by uncertainty, incomplete data, and competing stakeholder interests (Arora et al., 2022). A notable contribution of this study is the demonstrated feasibility of applying soft computing techniques in low-resource, decentralized governance environments. Most existing applications of ANFIS in infrastructure forecasting focus on large-scale national or private-sector projects with robust data availability. In contrast, this study has shown that AI-based forecasting tools can be calibrated to function with limited, stakeholder-generated data, thereby offering a scalable solution for under-capacitated local councils (Medayese et al., 2021).

The alignment between AHP and PCA weightings also adds an important methodological insight. The close match between subjective (AHP) and objective (PCA) KPI weights suggests that local stakeholders possess tacit knowledge that statistically reflects actual performance conditions. This convergence lends credibility to participatory planning processes and validates the inclusion of stakeholder-driven weights in model development, a topic often debated in urban governance literature (Healey, 2017).

The findings also provide important practical implications. For policymakers, the model offers a decision-support tool that can be integrated into existing monitoring and evaluation frameworks, providing early warnings of project underperformance. For practitioners, the system can improve resource allocation, enhance procurement oversight, and allow more informed mid-project interventions. For communities, increased transparency and performance predictability can strengthen trust in public infrastructure processes. Despite the generally strong results, the study also revealed persistent weaknesses in early-phase project execution, particularly in schedule adherence and safety management. These issues point to systemic challenges such as delayed procurement, insufficient contractor prequalification, and inconsistent enforcement of safety protocols. While the forecasting model can help identify underperformance, systemic institutional reforms will still be required to address root causes.

In conclusion, the results of this study not only validate the performance forecasting model but also contribute to the broader discourse on smart governance, predictive urban management, and the localization of AI tools for development. These findings establish a foundation for further refinement of the model and its application to other infrastructure delivery frameworks beyond Zambia (Healey, 2017; Mitullah, 2017; Bateganya et al., 2023).

5. Conclusions

This study set out to design and validate a performance-forecasting model capable of tackling the chronic cost overruns, schedule slippages and quality shortfalls that beset Constituency Development Fund (CDF) construction projects in Zambia's Copperbelt Province. By fusing stakeholder-weighted Analytic Hierarchy Process (AHP) scores with an Adaptive Neuro-Fuzzy Inference System (ANFIS), the research produced a hybrid tool that predicts project outcomes against five context-relevant Key Performance Indicators (KPIs): cost-effectiveness, schedule adherence, quality compliance, safety performance and client satisfaction. The model met all three original objectives. It (i) confirmed the salience of the five KPIs for CDF work; (ii) generated empirically consistent AHP weights that reflect local priorities (cost and time together accounting for 68 per cent of the composite score); and (iii) attained a high predictive accuracy ($R^2 = 0.92$; RMSE = 0.09) when trained on 42 completed schemes. Robust correlations among the KPIs underline their interdependence, while phase-by-phase analysis demonstrated statistically significant performance gains as projects progress; evidence that timely feedback loops matter. Theoretically, the study extends Performance Management and Decision Support System (DSS) thinking to decentralised, data-scarce settings in the Global South, showing that soft-computing techniques can thrive on modest, stakeholder-generated datasets. Practically, it supplies councils with a scalable dashboard that flags emerging risks, supports transparent resource re-allocation and strengthens downward accountability to communities.

6. Recommendations

a) Local authorities and project managers

i) Embed the ANFIS–AHP dashboard in routine monitoring, triggering corrective action whenever forecast scores fall below agreed thresholds.
ii) Provide short, hands-on training so planning, procurement and site staff can input data correctly and interpret model outputs with confidence.
iii) Digitise data capture from project inception using mobile forms or simple web portals to improve the timeliness and reliability of inputs.

b) Policymakers and regulators

i) Mandate the use of predictive-performance tools for all CDF-funded infrastructure and integrate the resulting indicators into national reporting systems.
ii) Issue a common KPI glossary and reporting template to ensure comparability across districts and to aid future model recalibration.

c) Researchers and model developers

i) Pilot the model in rural and peri-urban constituencies to test generalisability and identify context-specific parameter tweaks.
ii) Augment the rule base with exogenous risk modules (e.g. extreme weather, electoral cycles) so that simulated scenarios mirror real-world volatility.
iii) Undertake longitudinal studies that track whether early forecasts align with post-occupancy performance and wider socio-economic outcomes.

In sum, a stakeholder-informed, AI-driven forecasting framework can shift CDF project governance from reactive post-mortems to proactive stewardship. Scaling, automating and institutionalising this approach will be essential if rapidly urbanising councils are to deliver cost-effective, timely and citizen-centred infrastructure over the coming decade.

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Conflicts of interests

The authors declare that there are no conflicts of interest related to the publication of this research. This includes financial, personal, or professional affiliations that could be perceived to influence the outcomes or interpretations presented in the study. The research was undertaken with impartiality and objectivity, and all efforts were made to ensure transparency and academic integrity throughout the research and writing process.

Data availability statement

All data supporting the findings of this study are included in the manuscript or available upon reasonable request from the corresponding author.

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