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Examining the Effectiveness of Artificial Intelligence (AI) Tools in Project Performance: A Case Study of Mongu Municipal Council, Western Province, Zambia

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Abstract: Public infrastructure projects in Zambia continue to face schedule delays, cost pressures and quality challenges. This study examined the effectiveness of artificial intelligence (AI) tools in project performance at Mongu Municipal Council, Western Province. A mixed-methods case-study design was used, drawing on 100 structured questionnaires and key-informant interviews, alongside document review. Descriptive statistics, Pearson correlation and multiple regression were used to examine AI utilisation and project performance. Findings show that 72% of respondents reported using no AI tools. Automated reporting was the most frequently identified application (18%), while routine use remained limited. AI use had weak positive correlations with schedule performance (r = 0.278) and cost performance (r = 0.241), both reported as statistically significant.

Keywords*: Artificial Intelligence, Project Performance, Local Government, Mongu Municipal Council, Technology Adoption, Public Infrastructure, Zambia, Digital Transformation.*

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I. INTRODUCTION

➢ *Background of the Study*

Organizations increasingly use digital tools to track delays, monitor progress and forecast project costs.

Globally, the adoption of AI in project management has accelerated. The [1] reports that organizations using AI-enabled tools for scheduling and risk management see timeline variances drop by an average of 25% compared to those using traditional methods. [1] found that among firms that had integrated generative AI into their workflows, project delivery efficiency improved by nearly 30% within the first year.

Public sector infrastructure projects face a different set of pressures than private ones. Budgets are tighter, political oversight is heavier, and the consequences of failure go beyond lost profits to eroded public trust.

The researchers documented cases where delay reports took three weeks to travel from remote construction sites to district offices, by which time contractors had already moved on to other work.

Sub-Saharan Africa presents a more complicated picture. The [3] tracks digital transformation across the region and finds that while every government has some kind of e-strategy on paper, actual implementation lags far behind.

Zambia's story fits this regional pattern. [18] has been pushing a national digital transformation agenda since 2021, with particular emphasis on improving public financial management and service delivery.

So the question becomes: could AI tools change that? We don't really know for sure, because nobody's studied it in this specific context. That's where this research comes in.

Mongu Municipal Council sits right in the middle of this gap. As the administrative hub for Western Province, it manages a portfolio of infrastructure projects funded by both government allocations and donor partners.

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➢ *Statement of the Problem*

Despite the documented potential of Artificial Intelligence (AI) to improve project management through reduced schedule delays and cost overruns, existing empirical evidence has largely focused on developed countries and private-sector organisations [1]. Meanwhile, Mongu Municipal Council experienced significant project performance challenges between 2022 and 2024, with seven of twelve major capital projects exceeding their approved budgets and nine recording delays of more than six months [5]. However, limited empirical evidence exists on the effectiveness of AI tools in addressing such project management challenges within local government institutions, particularly in the Zambian context. This knowledge gap limits evidence-based decision-making by municipal administrators and policymakers regarding AI adoption. Therefore, the study examined the potential effectiveness of AI applications in improving project performance at Mongu Municipal Council.

➢ *Objectives and Research Questions*

The primary objective of this study is to examine the effectiveness of Artificial Intelligence (AI) tools on public infrastructure project performance at Mongu Municipal Council in the Western Province of Zambia by addressing four core areas: (i) to determine the extent of AI tool utilization within municipal project management cycles, (ii) to assess the statistical effect of AI tools on specific public infrastructure project performance domains, (iii) to identify systemic and institutional challenges hindering AI tool adoption and continuous utilization in local authority project environments, and (iv) to examine strategic deployment frameworks for enhancing effective AI tool adoption and integration to optimize project performance parameters at Mongu Municipal Council.

➢ *Study Area and Policy Context*

Mongu Municipal Council is the local authority examined in this study and is located in Western Province, Zambia. The council manages public infrastructure and service-delivery projects within its jurisdiction.

II. LITERATURE REVIEW

➢ *Utilization of Artificial Intelligence Tools in Project Management*

Global project management research increasingly examines data-driven decision-making and AI-supported workflows. Recent literature identifies AI as a developing area in project management, while adoption varies by organizational context [32], [34].

➢ *Effect of Artificial Intelligence Tools on Project Performance*

AI-supported scheduling can adjust timelines and resource assignments as project conditions change. The benefits depend on reliable data, appropriate system configuration and staff capacity.

The global body of research examining the relationship between artificial intelligence tools and project performance reveals a complex and nuanced picture, characterized by both significant opportunities and notable limitations. Comprehensive studies conducted across developed economies have demonstrated that AI technologies substantially enhance operational efficiency through the automation of routine tasks, optimization of resource distribution, and real-time performance tracking capabilities [11].

➢ *Challenges Hindering AI Adoption in Project Management*

Adoption is also constrained by limited training data, inconsistent team processes and uneven staff capability. These conditions can reduce the reliability and reuse of AI-assisted workflows.

Furthermore, the complexity of AI systems and the need for specialized skills to implement and manage these technologies create substantial barriers, as many organizations lack the internal expertise required to effectively deploy and maintain AI solutions [9].

AI adoption also raises concerns about output reliability, data quality and the need for human oversight. Organizations should validate AI-generated outputs before using them in project decisions [9], [27].

➢ *Strategic Deployment Frameworks for AI Integration*

AI deployment frameworks emphasize iterative implementation, stakeholder alignment, risk management and continuous learning. These principles support piloting and refining AI applications as organizational readiness develops [27], [37].

➢ *Personal Critique of Literature Review*

Looking across this literature, several patterns emerge. First, the global literature is extensive and detailed, but it is overwhelmingly from developed country contexts and private sector organizations.

➢ *Establishment of Research Gaps*

The literature review identified the need for further investigation into the effectiveness of Artificial Intelligence (AI) tools in improving project performance within municipal institutions. The study focused on predictive analytics and other AI applications as decision-support tools for project planning, resource scheduling, risk identification, and performance reporting [9]. Project performance was examined through budget adherence, schedule compliance, structural quality, and stakeholder value creation [6], within the broader context of project management practices [10]. The investigation specifically considered municipal councils and local authorities as public institutions responsible for infrastructure development, financial management, and local service delivery [4, 5]. Effectiveness was assessed based on the extent to which AI applications minimized project performance variances and improved institutional outcomes [1].

Artificial Intelligence (AI) refers to machine-based systems capable of processing large datasets, identifying patterns, and performing cognitive tasks such as learning, reasoning, and autonomous problem-solving [8].

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Geographically and institutionally, the study is confined to Mongu Municipal Council, Western Province, Zambia, targeting professional staff involved in project management, including management, engineering, planning, auditing, ICT, and finance personnel. Private contractors, beneficiary communities, and external ministries are excluded. The study provides practical insights for municipal management and development partners while addressing the limited research on AI integration in project management within rural municipal institutions in Sub-Saharan Africa.

The integrated Technology Acceptance Model–Task-Technology Fit (TAM–TTF) framework examines the relationship between AI applications (independent variables) and project performance (dependent variables), with institutional readiness acting as an intervening factor. Institutional readiness encompasses digital infrastructure, staff technical competence, and organisational resistance to technological change.

➢ *Conceptual Framework*

Fig. 1. Integrated TAM–TTF conceptual framework linking AI tools, institutional readiness and project performance.

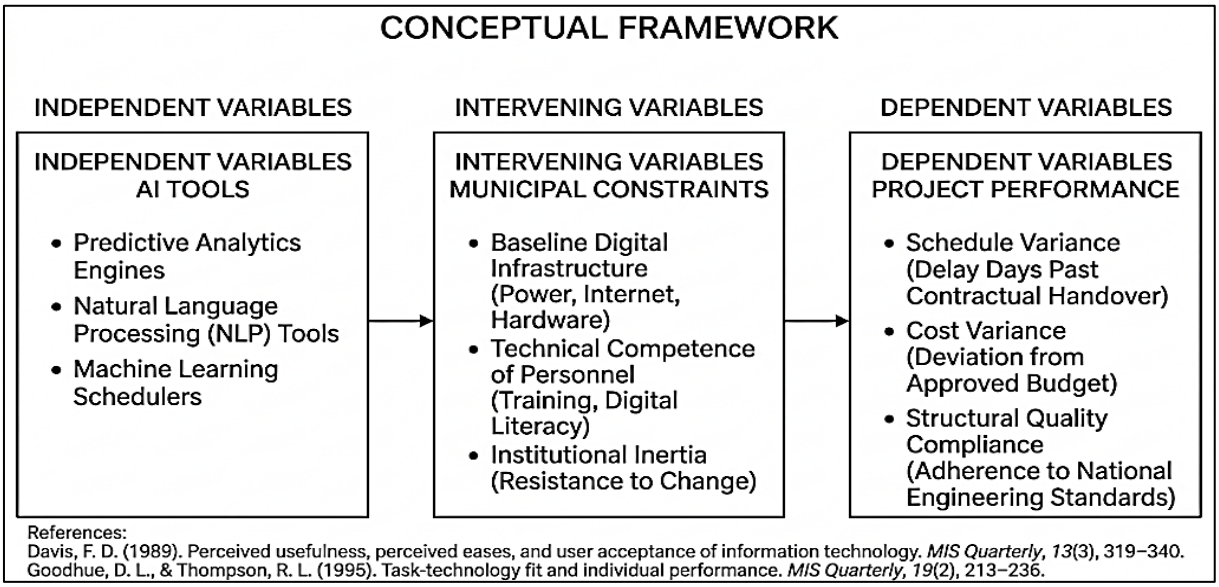


Fig 1 Conceptual Framework

III. METHODOLOGY

➢ *Research Design*

The study employed a convergent parallel mixed-methods design, in which quantitative and qualitative data were collected simultaneously, analysed independently, and integrated during interpretation. This approach enabled statistical examination of relationships while providing contextual insights into the factors influencing project performance, thereby offering a comprehensive and cross-validated assessment [12].

➢ *Target Population*

The target population comprised professional staff at Mongu Municipal Council directly involved in infrastructure project planning, financing, implementation, monitoring, and evaluation. These included senior management, engineering, planning, finance, internal audit, and information technology personnel. The population consisted of 120 staff members distributed across Engineering and Infrastructure (34), Planning and Development (28), Finance (22), Internal Audit (16), and Information Technology (20).

➢ *Sampling Design*

The study employed stratified random sampling for the quantitative component to ensure adequate representation of staff across the council's administrative departments and minimize selection bias. Purposive sampling was used for the qualitative component to select key informants with relevant professional experience and knowledge of municipal project management for semi-structured interviews.

➢ *Sample Size Determination*

The quantitative sample size was determined using: Yamane's formula:

$$n = \frac{N}{1+N(e^2)} \quad (1)$$

Based on a target population of 120 and a 5% margin of error, yielding 100 respondents. Proportional allocation across the five departments resulted in Engineering and Infrastructure (28), Planning and Development (23), Finance (19), Internal Audit (14), and Information Technology (16). Additionally, five key informants were purposively selected, giving a combined sample of 105 participants and providing both statistical representation and qualitative depth.

➢ *Data Collection and Analysis*

Data were collected using a convergent parallel mixed-methods approach involving structured questionnaires, semi-structured interviews, and document reviews. Quantitative

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data from closed-ended questionnaires and five-point Likert scales were analyzed using SPSS version 26 to generate descriptive and inferential statistics. Qualitative data obtained through audio-recorded, semi-structured interviews were transcribed verbatim and analyzed thematically to identify key patterns relating to digital tracking benefits, institutional challenges, organizational readiness, and project delivery improvements. Municipal project records and audit reports were also reviewed to support data triangulation. Finally, quantitative and qualitative findings were integrated during interpretation to provide a comprehensive assessment of project performance factors.

➢ *Triangulation*

Triangulation was applied to strengthen the validity and credibility of the findings through multiple strategies. Data triangulation involved collecting data from multiple sources: structured surveys from 100 respondents, semi-structured interviews from 5 key informants, and document reviews from council records.

➢ *Limitations and Ethical Considerations*

The study acknowledged potential limitations, including respondent bias arising from organizational confidentiality concerns, possible misunderstandings of technical terms, and recall bias when reporting historical project performance. These limitations were mitigated through pre-survey briefings, clarification of technical definitions, and triangulation of self-reported information with project completion reports and audit records.

Ethical principles were observed throughout the study by maintaining participant anonymity through alphanumeric codes, ensuring confidentiality, and presenting findings in aggregate form to prevent individual identification. Furthermore, the researcher commits to sharing the findings with Mongu Municipal Council and providing participants with a debriefing session to promote transparency and ensure the study benefits the host institution and community.

IV. RESULTS

➢ *Results*

Table 1 Study Objectives, Research Hypotheses and Empirical Outcomes

Objective	Research hypothesis (if stated)	Empirical outcome
AI tool utilization	No formal hypothesis stated; utilisation was assessed descriptively.	72% reported no AI tool use; automated reporting was reported by 18%.
Project performance	No formal hypothesis stated; association was tested statistically.	Schedule r=0.278; cost r=0.241; both reported significant at p<0.05.
Adoption barriers	No formal hypothesis stated; barriers were assessed through responses.	Infrastructure, skills, cost and policy deficits were reported.
Deployment framework	No formal hypothesis stated; staff priorities informed the framework.	Training, infrastructure, policy and partnerships were prioritised.

Table 2 Effect of AI on Project Performance

Performance domain	No change	Improvement / reduction reported	Not applicable / other
Completion time	30%	Slight 24%; moderate 16%; significant 8%	Not applicable 20%; delay increase 2%
Budget adherence	32%	Slight 22%; moderate 18%; significant 6%	Not applicable 20%; worsened 2%
Quality	34%	Slight 26%; moderate 14%; significant 4%	Worsened 2%; not applicable 20%.

Table 3 Multiple Regression Analysis Results

Predictor Variable	Unstandardized Coefficient (B)	Standardized Coefficient (Beta)	t-value	p-value
(Constant)	2.842		5.124	0
AI Usage	0.185	0.256	2.641	0.01
Staff Experience	0.124	0.302	3.124	0.002
Funding Adequacy	0.092	0.218	2.214	0.029

Table 4 Challenges Hindering AI Adoption

Challenge	Reported response pattern	Percentage
ICT infrastructure	Inadequate / very inadequate / unavailable	38% / 30% / 16%
AI skills	Low / very low	40% / 26%
Implementation cost	Very expensive / expensive / prohibitively expensive	40% / 28% / 26%
Resistance to change	Moderate / high	38% / 24%
Internet and power	Unreliable / very unreliable	38% / 26%
Data quality	Poor / very poor	36% / 14%

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Table 5 Priority Level for ICT Infrastructure Investment

Priority	Percentage
Very high	48%
High	32%
Medium	16%
Low	6%

- Note: Percentages are reproduced as reported in the source results and total 102%; the original dataset should be checked before publication.

Table 6 Management Support and Employee Involvement

Indicator	Response category	Percentage
Management support	Very supportive / supportive / neutral / unsupportive / very unsupportive	4% / 16% / 28% / 32% / 20%
Employee involvement	Always / often / sometimes / rarely / never	6% / 14% / 26% / 30% / 24%

Table 7 Summary of Objectives and Key Findings

Objective	Research hypothesis (if stated)	Implication
AI utilisation	No formal hypothesis stated; utilisation was assessed descriptively.	Adoption remains at an early stage.
Project performance	No formal hypothesis stated; association was tested statistically.	AI contributes, but experience and funding also matter.
Adoption barriers	No formal hypothesis stated; barriers were assessed through responses.	Readiness must precede scale-up.
Deployment strategy	No formal hypothesis stated; staff priorities informed the framework.	Use phased, institution-led implementation.

Table 8 Proposed Strategic AI Deployment Framework

Phase	Priority actions	Expected institutional output
Phase 1: Readiness	Audit ICT, power, connectivity and data; develop governance and AI-use policy.	Baseline readiness and accountability arrangements.
Phase 2: Capacity and pilot	Train staff; engage employees; partner with universities/providers; pilot reporting and scheduling tools.	Staff capability and tested low-risk applications.
Phase 3: Integration and review	Scale proven tools; monitor time, budget and quality indicators; review risks and performance.	Evidence-led integration and continuous improvement.

➢ *Presentation of Results on the Background Characteristics of the Respondents*

- *Gender Distribution*

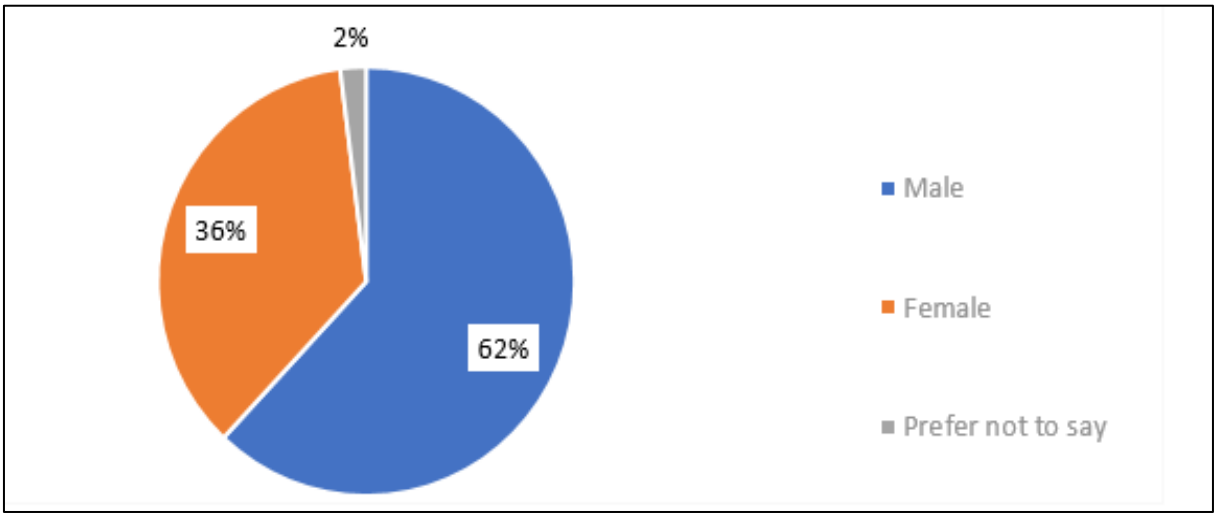


Fig 2 Gender Distribution

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Fig. 2., Male respondents constituted the majority (62%), while females accounted for 36% of the sample. The remaining 2% preferred not to disclose their gender. This distribution reflected the council's staffing pattern, particularly the male-dominated engineering and infrastructure departments.

- *Educational Levels of Respondents*

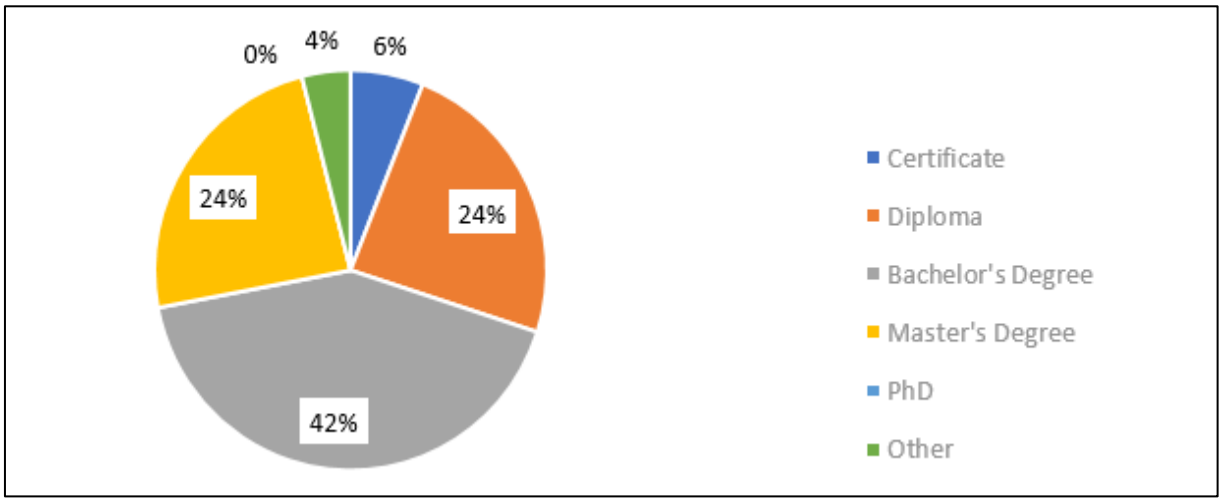


Fig 3 Educational Qualification

Fig. 3., According to the results, a Bachelor's degree was the most common qualification, held by 42% of respondents. Diploma holders and Master's degree holders each accounted for 24%. Certificate holders made up 6%, and 4% had other qualifications.

- *Departmental Distribution*

Fig. 4, Engineering and Infrastructure had the highest representation (28%), followed by Planning and Development (23%), Finance (19%), IT (16%) and Internal Audit (14%). This distribution reflected the council's staffing structure and ensured representation of all departments involved in project management.

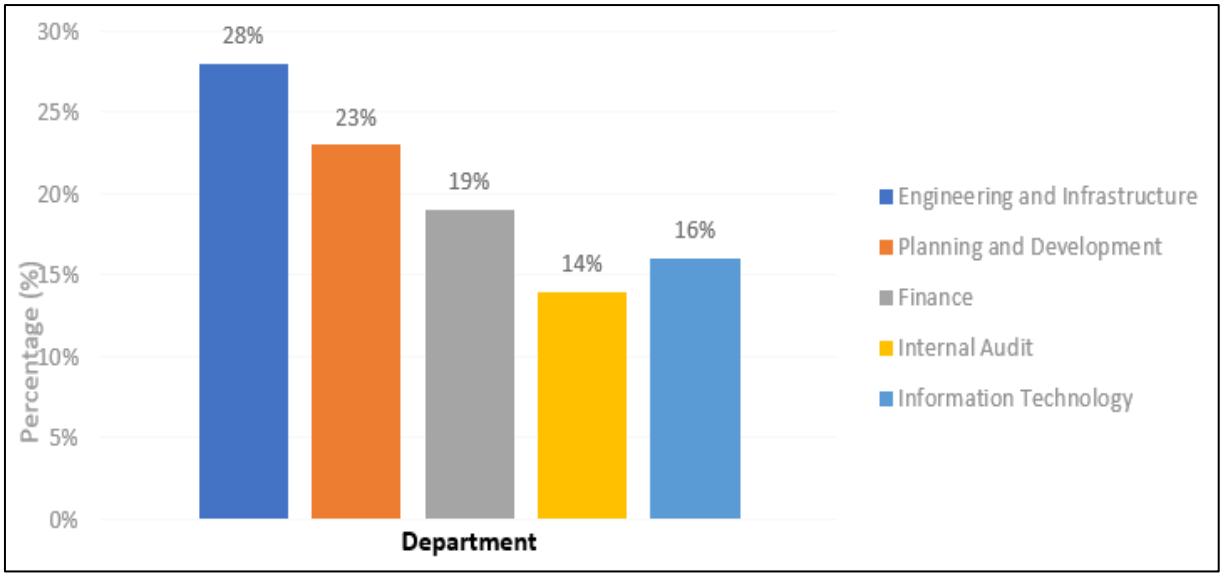


Fig 4 Departmental Distribution

➢ *Presentation of Results Based on Objectives*

- *Objective One:*

To determine the extent to which Artificial Intelligence tools are currently utilized within the project management cycles at Mongu Municipal Council.

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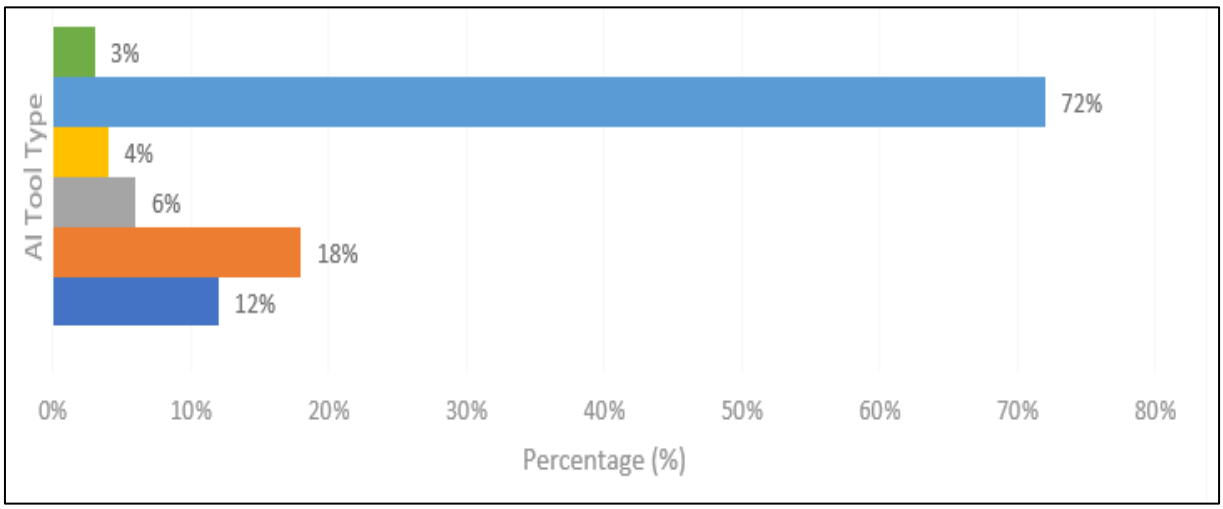


Fig 5 Types of AI Tools Used.

The findings (Fig.5) showed that 72% of respondents did not use AI tools in project management. Automated reporting (18%) was the most commonly used tool, followed by predictive analytics (12%) and other AI applications. Overall, AI adoption at Mongu Municipal Council remained low, with most project management activities relying on traditional methods.

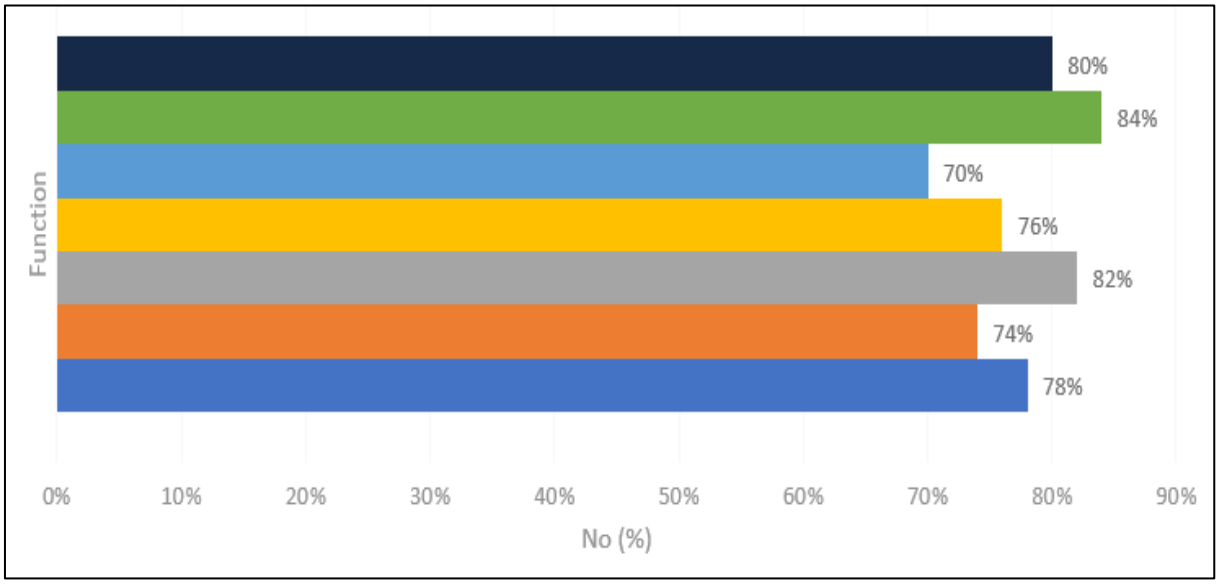


Fig 6 AI Usage by Function (Bar Chart)

Fig. 6, Automated reporting was the most common AI application (30%), followed by scheduling (26%) and monitoring (24%), while risk management had the lowest usage (16%). This suggested that AI was mainly applied to routine administrative tasks rather than complex risk management activities.

- *Objective Two:*

To assess the statistical effect of Artificial Intelligence tools on specific public infrastructure project performance domains at Mongu Municipal Council.

✓ *Effect on Project Completion Time*

Fig.7, 30% reported no change in completion time due to AI, 24% reported a slight reduction, 16% reported a moderate reduction, and 8% reported a significant reduction, while 2% reported increased delays; 20% said it was not applicable because they do not use AI.

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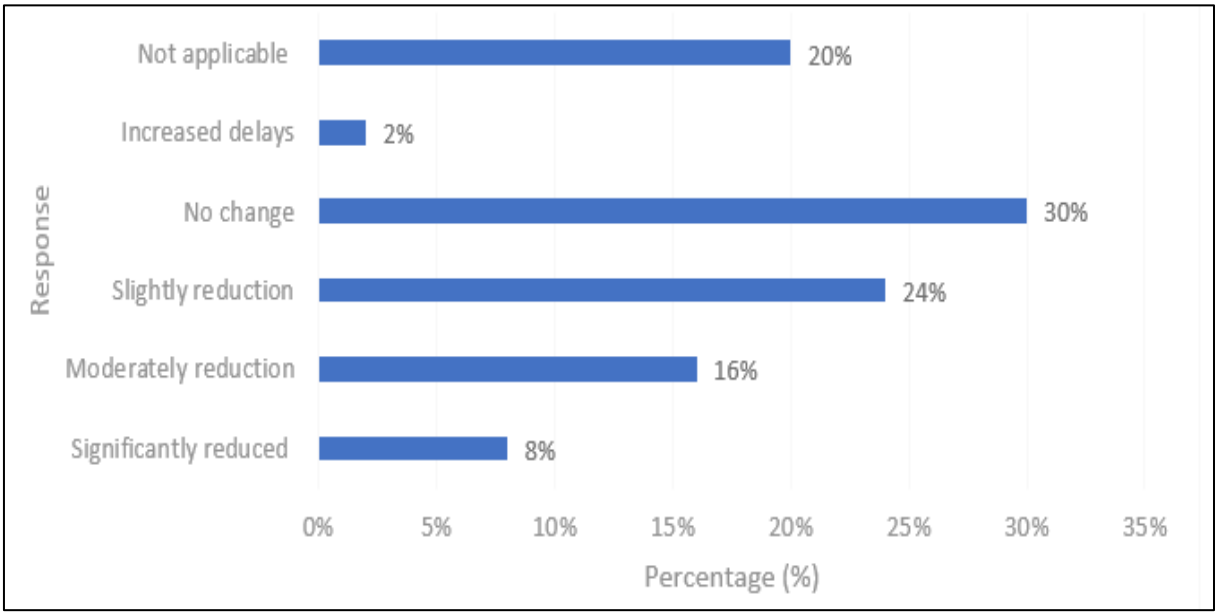


Fig 7 Effect on Project Completion Time (Bar Chart)

✓ *Effect on Budget Adherence.*

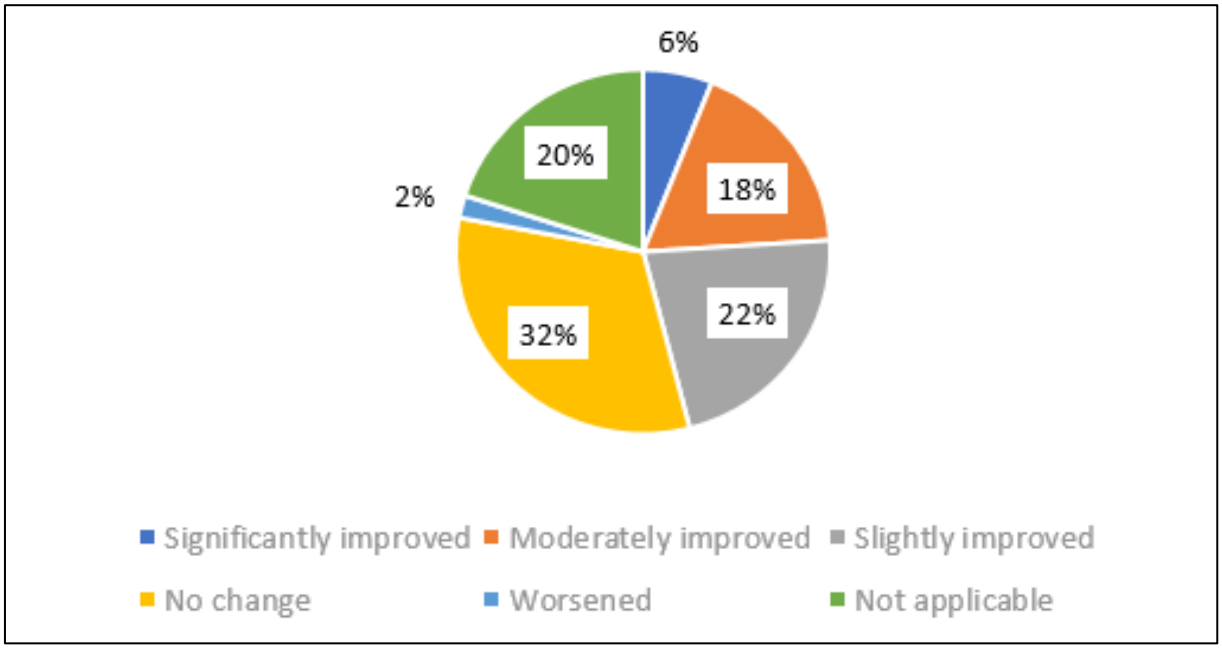


Fig 8 Effect on Budget Adherence (Pie Chart)

According to the results (Fig. 8), 32% of respondents reported no change in budget adherence, while 22% reported slight improvement and 18% reported moderate improvement. Only 6% reported significant improvement, and 2% reported that budget adherence had worsened. The remaining 20% said the question wasn't applicable.

✓ *Effect on Quality of Project Deliverables*

According to the results (Fig. 9), 34% of respondents saw no change in quality, while 26% saw slight improvement and 14% saw moderate improvement. Only 4% saw significant improvement. Similar to the other performance metrics, quality effects were modest at best.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26nov455

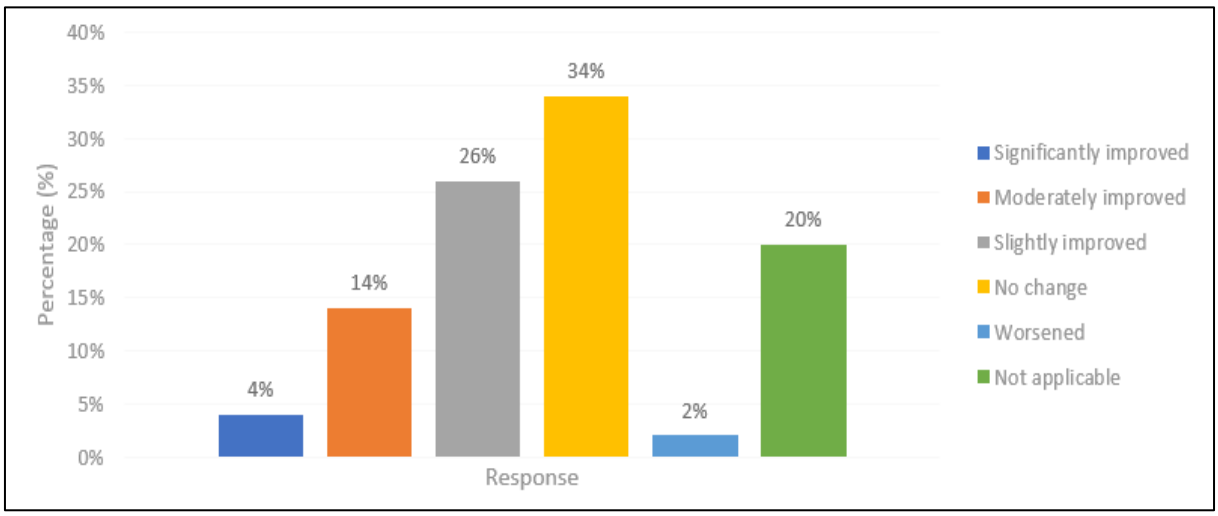


Fig 9 Effect on Quality of Deliverables (Bar Chart)

✓ *Average Percentage Reduction in Schedule Delays and Cost Overruns*

Table 10 below, indicates that among respondents who reported using AI tools and saw some improvement, the average reduction in schedule delays was 10.8%, while the average reduction in cost overruns was 8.2%. These figures are modest compared to the 20-30% reductions reported in global literature from developed countries.

Table 9 Average Percentage Reduction Attributed to AI Tools

Performance Indicator	Mean (%)	Standard Deviation
Schedule delay reduction	10.8	8.4
Cost overrun reduction	8.2	7.1

✓ *Correlation Between AI Usage and Project Performance*

Table 10 Pearson Correlation Between AI Usage and Project Performance

Variable	AI Usage	Schedule Performance	Cost Performance
AI Usage	1		
Schedule Performance	0.278*	1	
Cost Performance	0.241*	0.612*	1
• Correlation sig. at 0.05% level (2-tailed)			

Table 10 above, indicates weak but significant positive correlations were found between AI usage and schedule performance ($r = 0.278$, $p < 0.05$) and cost performance ($r = 0.241$, $p < 0.05$), with AI explaining only ~7–8% of performance variation, suggesting staff experience, contractor performance, and funding availability remain more important determinants.

- *Objective Three:*

Systemic and institutional challenges hindering AI tool adoption and continuous utilization identified at Mongu Municipal Council.

✓ *Cost of Implementation*

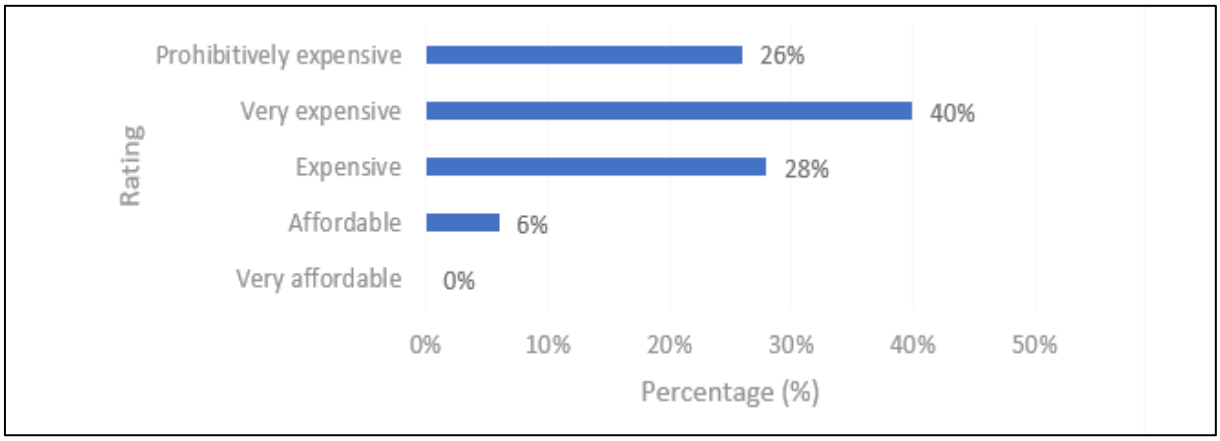


Fig 10 AI Implementation Costs (Bar Chart)

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Fig.10, 40% of respondents rated AI implementation as very expensive, 28% as expensive, and 26% as prohibitively expensive. Only 6% considered it affordable. Cost is clearly a major barrier to adoption.

✓ *Internet and Power Reliability*

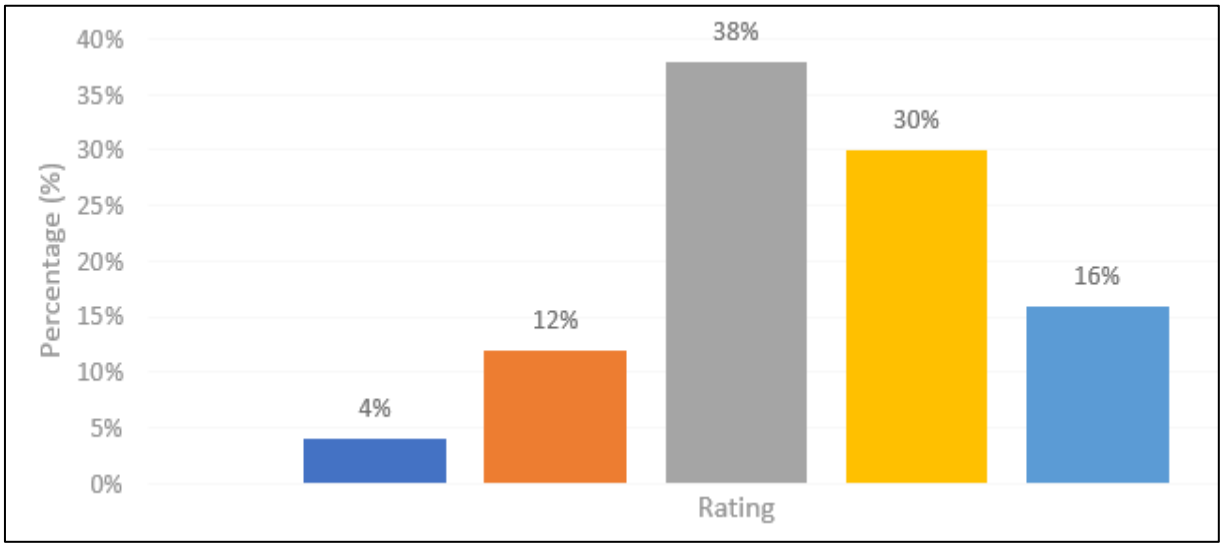


Fig 11 Internet and Power Reliability

Fig. 12, According to the results, 38% of respondents rated internet and power reliability as unreliable, and 26% as very unreliable. Only 2% rated it as very reliable. This is a critical finding because AI tools require consistent connectivity and power to function.

✓ *ICT Infrastructure Adequacy*

Figure 12, 38% rated ICT infrastructure as inadequate, 30% as very inadequate, and 16% as unavailable, with only 12% rating it as adequate and 4% as very adequate, indicating that infrastructure deficits are a major barrier to AI adoption.

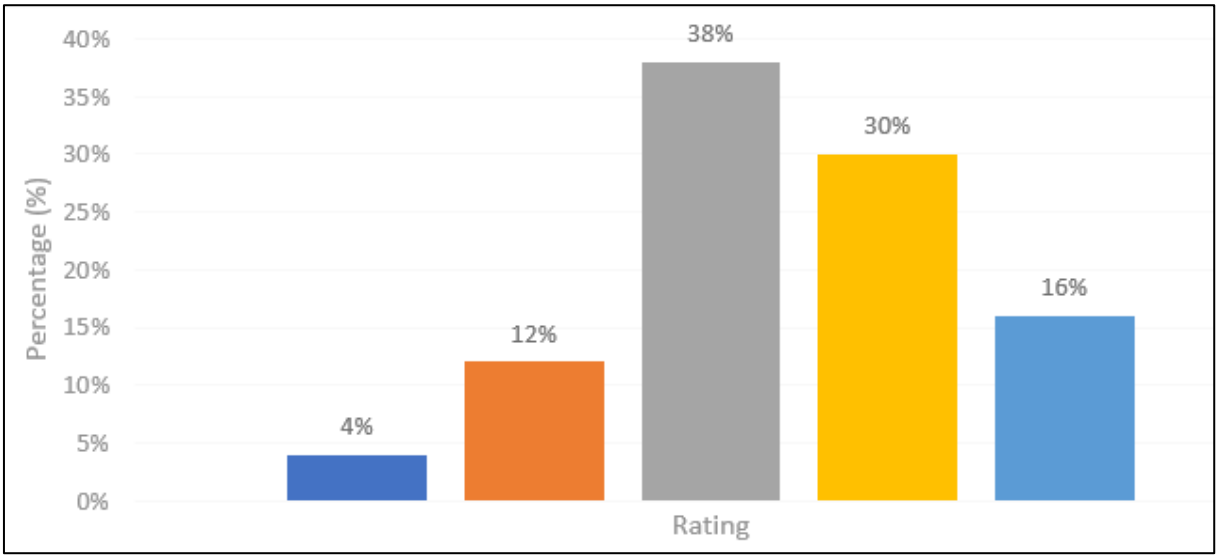


Fig 12 ICT Infrastructure Adequacy (Bar Chart)

- *Objective Four:*

To examine strategic deployment frameworks that can enhance the effective adoption and integration of Artificial Intelligence tools to optimize project performance parameters at Mongu Municipal Council.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26nov455

✓ *Priority Level for AI Training*

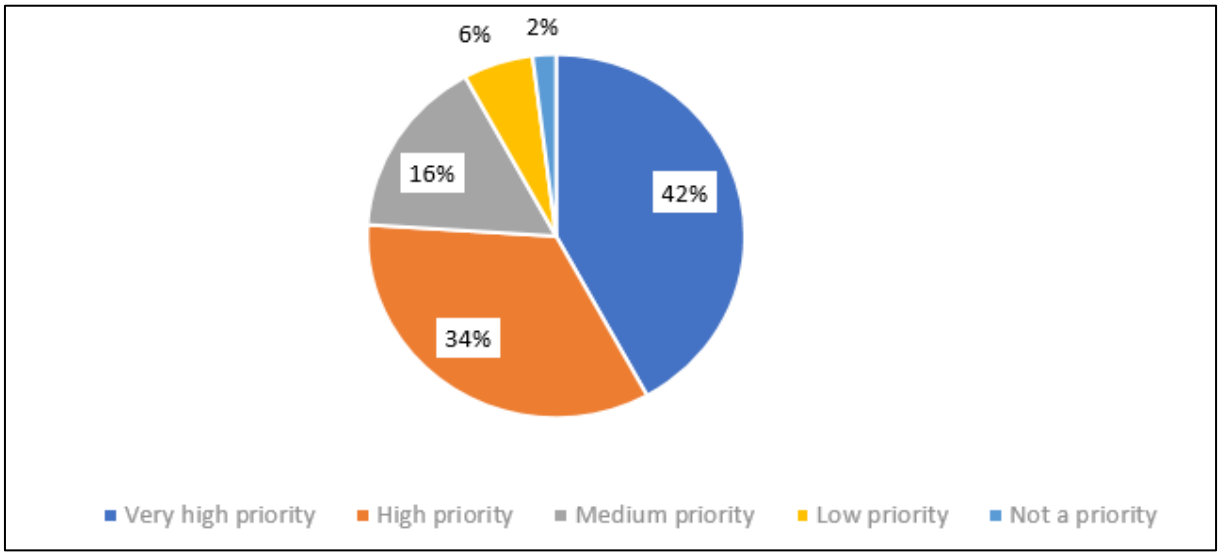


Fig 13 Training Needs and Priority for AI Training.

According to the results, 42% of respondents rated regular AI training as a very high priority, and 34% as a high priority. Only 2% considered it not a priority. This suggests strong demand for training among staff.

✓ *Employee Involvement in AI Selection*

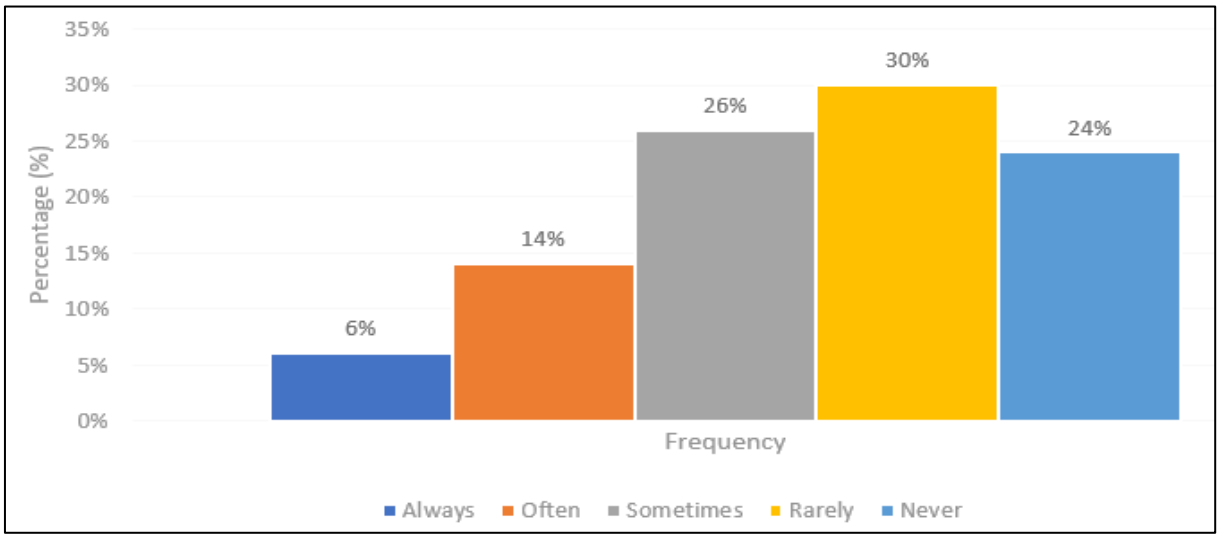


Fig 14 Management Willingness and Employee Involvement in AI Implementation.

According to the results, 30% of respondents said employees were rarely involved in AI selection and implementation, and 24% said never. Only 6% said always. This lack of involvement likely contributes to resistance and low adoption.

V. DISCUSSIONS

➢ *Discussion of Findings on Objective One: AI Utilization*

According to the results, AI adoption at Mongu Municipal Council is minimal. The finding that 72% of respondents reported using no AI tools at all aligns closely with what [14] found across Western Province councils, where technology adoption was limited to basic digital tools at best. This is also consistent with [15] study across five Sub-Saharan African countries, which found that 94% of project managers relied on manual tracking methods.

Automated reporting tools were the most frequently identified AI application (18%), followed by predictive analytics (12%). Other reported tools included machine-learning schedulers (6%), risk-prediction software (4%) and other applications (3%).

What's interesting is that even the tools staff considered "AI" often weren't actually AI. The key informant interviews revealed that staff often confused basic databases and Excel spreadsheets with AI tools.

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The finding that usage frequency was low even among those with access to tools 38% rarely used them, 22% never did aligns with what [6] found globally: having the software doesn't guarantee using it. But the PMI study found higher usage rates (38% overall adoption) than what we found in Mongu, suggesting that even when tools are available in this context, they're not being used effectively.

- *Discussion of Findings on Objective Two: Effect of AI Tools on Project Performance*

According to the results, the effect of AI tools on project performance at Mongu was modest. The finding that 30% of respondents saw no change in schedule delays and 32% saw no change in budget adherence suggests that AI tools aren't delivering the performance benefits that the global literature predicts [6].

The average reduction in schedule delays (10.8%) and cost overruns (8.2%) is considerably lower than the 22% and 19% reductions that [6] reported in their global study. This gap likely reflects the difference between developed country private sector contexts and a rural Zambian municipal council.

The regression analysis showed that staff experience was a stronger predictor of project performance than AI usage (Beta = 0.302 vs 0.256).

The weak correlation between AI usage and performance (r = 0.278 for schedule, r = 0.241 for cost) suggests that AI tools explain only about 7-8% of the variation in project outcomes. This is lower than the effect sizes reported in global meta-analyses. [9] found effect sizes of 0.42 and 0.38 for schedule and cost performance respectively, which are substantially larger.

- *Discussion of Findings on Objective Three: Challenges Hindering AI Adoption*

According to the results, infrastructure deficits are the primary barrier to AI adoption at the council. The finding that 68% of respondents rated ICT infrastructure as inadequate, very inadequate, or not available is consistent with what [14] found in their study of Western Province councils: only 44% had reliable electricity and 31% had consistent internet.

The finding that 66% of respondents rated implementation costs as expensive, very expensive, or prohibitively expensive is significant. [41] estimates that AI implementation for a mid-sized organization in Sub-Saharan Africa costs between $50,000 and $150,000, which exceeds the annual operating budgets of many councils.

The finding that 52% of respondents rated management support as unsupportive or very unsupportive is particularly problematic because, as [16] noted, organizations where senior leaders actively use AI tools have adoption rates four times higher than those where leadership delegates AI matters to technical staff. Without management support, AI adoption is unlikely to succeed.

- *Discussion of Findings on Objective Four: Strategic Deployment Frameworks*

According to the results, staff recognize what needs to be done. The finding that 80% of respondents rated ICT infrastructure investment as a very high or high priority, and 84% rated improving internet and power as a very high priority, suggests staff understand that infrastructure is the foundation.

The finding that 76% of respondents rated AI training as a very high or high priority reflects recognition of the skills gap. As [7] emphasized, organizations need to invest in data quality improvement and staff training before, not after, deploying AI tools. The fact that staff recognize this is encouraging.

The demand for AI policies (82% rated this as very urgent or urgent) reflects recognition that policy frameworks are needed. [18] has developed a national framework that includes a phased approach to digital transformation, but the council hasn't implemented it locally. Developing local policies would provide guidance and legitimacy to AI adoption efforts.

The finding that only 20% of respondents said employees were always or often involved in AI selection and implementation suggests a governance gap. [1] recommended that organizations treat AI adoption as organizational transformation rather than technical implementation, which means engaging staff early. The lack of employee involvement at Mongu likely contributes to resistance.

The finding that 70% of respondents rated partnerships as very important or important is notable. Staff recognize that the council lacks internal capacity and needs external help.

The priorities reported by respondents indicate that adoption requires coordinated institutional action. Eighty per cent prioritized ICT infrastructure investment, 76% prioritized AI training, and 82% considered AI policy development urgent or very urgent. At the same time, only 20% reported that employees were often or always involved in AI selection and implementation. This contrast suggests that implementation planning should combine technical investment with staff participation, clear accountability and regular evaluation of project outcomes.

VI. CONCLUSION AND RECOMMENDATIONS

- *Conclusion*

- *Conclusion on Objective One: Extent of AI Utilization*

The study found that AI utilization at Mongu Municipal Council is extremely limited. Seventy-two percent of respondents reported using no AI tools whatsoever in their project management work. Where tools did exist, they were primarily basic reporting systems rather than true AI applications like predictive analytics or machine learning schedulers.

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- *Conclusion on Objective Two: Effect of AI Tools on Project Performance*

The study found that AI tools have a modest but statistically significant effect on project performance at Mongu Municipal Council. Among respondents who reported using AI tools, the average reduction in schedule delays was 10.8%, and the average reduction in cost overruns was 8.2%.

- *Conclusion on Objective Three: Challenges Hindering AI Adoption*

The study identified multiple challenges hindering AI adoption, with infrastructure deficits, skills gaps, lack of training, high costs, institutional resistance, and management indifference being the most significant.

- *Conclusion on Objective Four: Strategic Deployment Frameworks*

The study found that respondents have clear views on what needs to be done. The top strategic priorities identified were improving internet and power reliability (84% rated as very high or high priority), developing AI policies (82%), investing in ICT infrastructure (80%), providing regular AI training (76%), increasing funding allocation (72%), and strengthening partnerships (70%).

- *Overall Conclusion*

The overarching conclusion is that AI tools have a statistically significant but modest positive effect on project performance at Mongu Municipal Council, but their potential is severely limited by infrastructure deficits, skills gaps, lack of training, high costs, institutional resistance, and weak management support. The council is not ready for advanced AI adoption and should focus on foundational investments in infrastructure, training, and capacity building before pursuing sophisticated AI tools.

➢ *Recommendations*

- *Recommendations for Policy and Institutional Framework*

The council should develop a formal AI policy that provides guidance on technology adoption, data governance, and implementation standards. This policy should align with the Smart Zambia Institute's (2024) national digital transformation framework but be tailored to the council's specific context.

- *Recommendations for Implementation*

The council should implement a phased rollout that starts with foundational work before attempting advanced AI deployment. Phase 1 (12 months) should focus on infrastructure assessment, basic IT training, data quality improvement, and policy development. Phase 2 (12 months) should implement basic digital tools like reporting systems and databases.

- *Recommendations for Sustainability*

The council should establish a monitoring and evaluation framework for AI initiatives to track progress, identify problems early, and make data-driven adjustments. This should include regular reviews of infrastructure performance, training effectiveness, tool utilization rates, and project performance metrics.

- *Recommendations for Future Research*

A comparative study should examine AI adoption across multiple Zambian councils, comparing urban and rural contexts. This would help determine whether the findings from Mongu are generalizable and whether different types of councils face different challenges. It would also allow for benchmarking and identification of best practices.

➢ *Contributions to Knowledge*

- *Theoretical Contributions*

This study makes several theoretical contributions. First, it applies the integrated TAM-TTF framework to AI adoption in Zambian local government, which hasn't been done before. The study demonstrates that both individual perceptions and task-technology fit matter, but that structural constraints like infrastructure deficits and management support are equally important.

- *Methodological Contributions*

The convergent parallel mixed-methods design used in this study is a methodological contribution. It demonstrates the value of combining quantitative surveys with qualitative interviews in a single study, as the interviews provided critical context for interpreting the survey data. For example, the interviews revealed the conceptual confusion around AI that the survey alone couldn't capture.

- *Practical Contributions*

The study provides practical guidance for local authorities in Zambia and similar contexts. The recommendations are grounded in specific findings from the study, making them more actionable than generic advice. The phased implementation framework is particularly practical, providing a step-by-step approach that acknowledges the constraints faced by rural councils.

Table 11 Proposed Phased AI Deployment Framework for Mongu Municipal Council.

PHASE 1: READINESS	**PHASE 2: CAPACITY AND PILOT**	**PHASE 3: INTEGRATION AND REVIEW**
Audit ICT, power and connectivity; assess data quality; develop governance and AI-use policy.	Train staff; engage employees; partner with universities/providers; pilot reporting and scheduling tools.	Scale proven tools; monitor time, budget and quality indicators; review risks and performance.

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