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EXAMINING THE EFFECTIVENESS OF ARTIFICIAL INTELLIGENCE IN PROJECT MANAGEMENT: A CASE STUDY OF ZESCO CONSIDERING RENEWABLE ENERGY PROJECTS

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ABSTRACT

Zambia's heavy reliance on hydropower was exposed by the 2023–2024 drought, prompting ZESCO Limited, the national electricity utility, to accelerate renewable energy projects such as Kafue Gorge Lower and the Chisamba solar plants. At the same time, Artificial Intelligence (AI) tools are increasingly promoted as a means of improving project planning, monitoring and control. This study examined the effectiveness of AI in project management with reference to ZESCO's renewable energy projects, focusing on the types of AI tools used, their effectiveness, their relationship with project completion and the limitations of their use. Guided by a case study design and a mixed-methods approach, data were collected from 100 purposively selected respondents, including project managers, engineers, project team members, ICT officers and contractors, through questionnaires, interviews and document review, and were analyzed using descriptive statistics in STATA and thematic analysis. The findings revealed that AI-assisted scheduling and forecasting (34%) and predictive analytics (27%) were the most used tools, applied mainly in planning and monitoring, and introduced largely through existing software (48%) and contractors (26%). AI was viewed as effective, with 78% reporting improved planning accuracy, 72% rating it effective in monitoring and reporting and 58% reporting faster decision-making. A majority (54%) considered AI-supported projects to progress faster than similar projects without AI, and 85% rated the quality of works as high or very high. However, delays and budget overruns persisted, driven mainly by funding and foreign exchange issues, procurement procedures and exchange rate changes. Limited staff skills (33%), high costs (22%), poor data quality (19%) and the absence of an AI policy (36%) were the main constraints. The study concluded that AI is an effective but conditional enabler of project completion whose benefits depend on skills, data, infrastructure and governance, and recommended an organizational AI policy, staff training, stronger data management, wider use of AI in procurement and financial risk management, and resilient ICT infrastructure.

Keywords: Artificial Intelligence, Project Management, Renewable Energy, Project Completion, ZESCO, Zambia

1 INTRODUCTION

Artificial Intelligence (AI) has moved from a specialized field of computer science to a set of practical tools used across almost every sector of the economy. In project management, AI refers to computer systems that learn from data, recognize patterns, make predictions and support decisions in the planning, execution, monitoring and closing of projects (Taboada et al., 2023). Organizations now apply machine learning to forecast schedules and costs, natural

language processing to analyze contracts and reports, computer vision to inspect sites from drone images and generative AI assistants to draft plans, minutes and risk registers. Gartner (2019) predicted that by 2030 around 80% of routine project management tasks, such as data collection, tracking and reporting, would be performed by AI, while the Project Management Institute (PMI, 2023) reported that project professionals increasingly expect AI to change how projects are planned and controlled, but that many organizations lack the skills and governance to use it responsibly.

The energy sector has been among the earliest adopters of AI. In renewable energy, AI is used to forecast solar radiation and wind speed, predict power output, schedule maintenance before equipment fails and optimize dispatch on the grid (Jha et al., 2017; Ahmad et al., 2021). The International Renewable Energy Agency (IRENA, 2019) identified AI and big data as key innovations for integrating variable renewable energy, and the International Energy Agency (IEA, 2025) notes that AI is increasingly applied to grid planning, asset management and the construction of new generation capacity. Because large energy projects have a long history of delays and cost overruns (Flyvbjerg, 2014; Sovacool et al., 2014), tools that improve forecasting and early warning are of particular interest to utilities.

In Zambia, ZESCO Limited is the state-owned, vertically integrated utility responsible for generation, transmission, distribution and supply of electricity. More than 80% of the country's electricity has historically come from hydropower. The 2023–2024 El Niño drought, declared a national disaster on 29 February 2024, reduced available generation to about 1,680 MW against demand of about 2,400 MW and forced load-shedding that rose from 8 hours a day in March 2024 to 12 hours in May and longer in some areas (Mail & Guardian, 2026; African Arguments, 2024). In response, the Government and ZESCO accelerated a renewable energy program. Key projects include the 750 MW Kafue Gorge Lower Hydropower Station, fully commissioned in 2023 after construction began in 2015 and was halted by financial difficulties in 2019; the 100 MW Chisamba Solar Power Plant, built between July 2024 and mid-2025 at a cost of about US$100 million; and Chisamba Phase II, a further 100 MW commissioned in July 2026 at a reported cost of about US$70 million (pv magazine, 2025; pv magazine, 2026).

The speed and scale of this program place considerable demands on ZESCO's project management capacity. At the same time, ZESCO has begun to modernize its systems, including a 2024 initiative to digitalize transmission operations with an Internet of Things (IoT) enabled SCADA system, advanced analytics and dashboards (ZESCO, 2024), while the Ministry of Technology and Science has developed a National Artificial Intelligence Strategy (Ministry of Technology and Science, 2024). AI tools are therefore beginning to enter ZESCO's project environment through scheduling software with embedded AI features, analytics supplied by Engineering, Procurement and Construction (EPC) contractors, drone-based inspection and generative AI assistants. However, the presence of AI tools does not guarantee better outcomes; the benefits depend on data quality, staff skills, ICT infrastructure and governance (Fridgeirsson et al., 2021; Taboada et al., 2023). This study therefore examined how AI is used in managing ZESCO's renewable energy projects, how effective it is, how it relates to project completion and what limits its use.

1.1 Statement of the Problem

Zambia is implementing an ambitious renewable energy program to overcome the power deficit exposed by the 2024 drought, and ZESCO carries a large share of this responsibility through projects such as Kafue Gorge Lower, Chisamba Solar Phases I and II and a growing pipeline of solar and mini-grid projects. Large energy projects, however, are frequently affected by delays, cost overruns, quality problems and weak monitoring (Flyvbjerg, 2014). Kafue Gorge Lower, for example, was expected to be completed in 2020 but was only fully commissioned in 2023. AI is widely promoted as a way of improving forecasting, risk management, monitoring and decision-making (PMI, 2023), yet there is limited empirical evidence on whether AI tools are actually used in managing renewable energy projects in Zambia, which tools are used, how effective they are and whether their use is associated with better completion performance in terms of time, cost and quality. There is also little evidence on the skills, data, infrastructure and policy constraints that may limit the benefits of AI in a state-owned utility. Without such evidence, ZESCO and policy makers risk either investing in AI tools that do not deliver value or failing to adopt tools that could help deliver urgently needed generation capacity.

1.1.1 General Objective

The general objective of the study was to examine the effectiveness of Artificial Intelligence in project management with focus on ZESCO Limited's renewable energy projects.

1.1.2 Specific Objectives

- To establish the types of AI tools and applications used in the management of ZESCO's renewable energy projects.
- To analyze the effectiveness of AI in the project management of ZESCO's renewable energy projects.
- To ascertain the relationship between the use of AI and project completion performance.
- To identify the limitations and challenges of using AI in project management at ZESCO.

1.2 Research Questions

- What types of AI tools and applications are used in the management of ZESCO's renewable energy projects?
- How effective is AI in supporting planning, risk management, monitoring and decision-making in ZESCO's renewable energy projects?
- What is the relationship between the use of AI and the timely, cost-effective and quality completion of ZESCO's renewable energy projects?
- What are the main limitations and challenges associated with the use of AI in project management at ZESCO?

1.3 Theoretical Framework

The study was anchored on the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework, complemented by the Resource-Based View (RBV). TAM proposes that the use of a technology depends on its perceived usefulness and perceived ease of use, with facilitating conditions such as training and support shaping actual use (Davis, 1989; Venkatesh et al., 2003). The TOE framework explains organizational adoption through the technological context (the tools and their compatibility with existing systems), the organizational context (resources, management support and skills) and the environmental context (regulation, partners and government policy) (Tornatzky & Fleischer, 1990). The RBV holds that performance gains arise not from tools alone but from combining them with data, skills and processes into an organizational capability (Barney, 1991; Mikalef & Gupta, 2021).

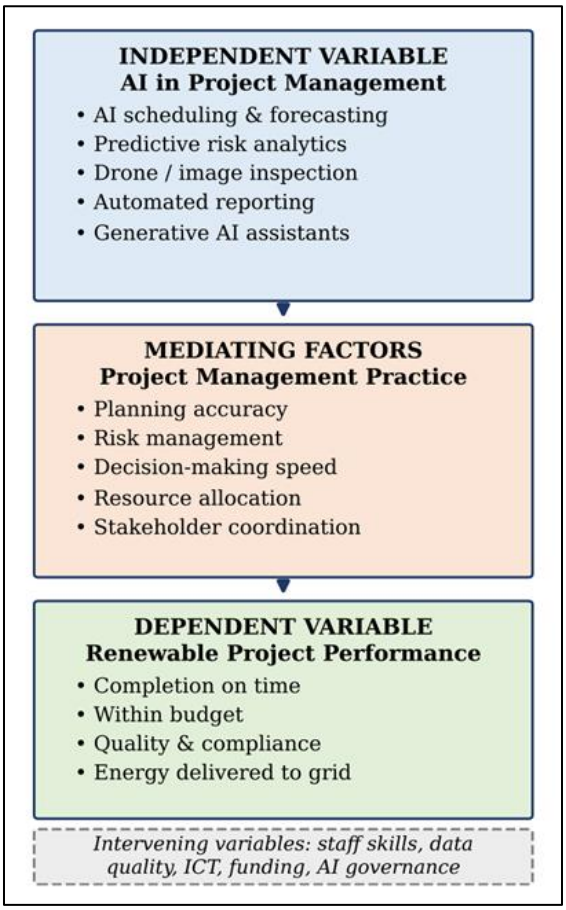


Figure 1: Conceptual framework

These theories informed a conceptual framework in which AI in project management (AI scheduling and forecasting, predictive analytics, drone and image inspection, automated reporting and generative AI) is the independent variable; project management practice (planning accuracy, risk management, decision-making speed, resource allocation and coordination) is the mediating factor; and renewable project performance (completion on time, within budget, quality and compliance, and energy delivered) is the dependent variable. Staff skills, data quality, ICT infrastructure, funding and AI governance act as intervening variables, as shown in Figure 1.

1.4 Significance of the Study

The study provides an evidence-based assessment of how AI is applied in the management of renewable energy projects at ZESCO. As Zambia moves rapidly to add solar and other renewable capacity, the findings can help ZESCO management

understand which AI tools add value, where they add value and what conditions they require, guiding investment in project management software, data systems and training. Project managers, engineers and contractors gain practical guidance on using AI for scheduling, risk management, monitoring and reporting. Policymakers in the Ministry of Energy, the Ministry of Technology and Science, the Energy Regulation Board and development partners can use the findings to align investment in generation with investment in the digital and human capacity needed to deliver it. Academically, the study adds rare Sub-Saharan African, energy-sector evidence to a literature dominated by studies from Europe, North America and Asia.

1.5 Scope of the Study

The study focused on renewable energy projects in which ZESCO is owner, implementing agency or principal off-taker, including solar photovoltaic projects such as Chisamba Phases I and II, hydropower projects such as Kafue Gorge Lower, and mini-grid and rooftop solar initiatives implemented through ZESCO and its subsidiaries. Thermal and coal projects and renewable projects with no ZESCO involvement were excluded. Respondents were ZESCO project managers, engineers, project team members, ICT and data officers, and representatives of contractors and consultants. The period of interest was 2019 to 2026, covering the period before the 2024 drought and the accelerated solar program that followed it.

2 LITERATURE REVIEW

2.1 Artificial Intelligence Tools and Applications in Project Management

AI in project management is not a single technology but a family of applications that differ in technique, purpose and the stage of the project life cycle at which they are applied. Reviews commonly group them into AI-assisted scheduling and forecasting, predictive analytics for cost and risk, computer vision and drone-based inspection, natural language processing and generative AI, resource optimization, and predictive maintenance (Pan & Zhang, 2021; Taboada et al., 2023). In a systematic review, Taboada et al. (2023) found that AI has been applied to almost all project management knowledge areas, but that research is concentrated in schedule, cost and risk management, mainly using machine learning and optimization. Darko et al. (2020) and Pan and Zhang (2021) likewise identify neural networks, genetic algorithms, fuzzy logic and, increasingly, deep learning as the dominant techniques in construction engineering and management.

Globally, much of this adoption happens through tools that project teams already use. Major scheduling and portfolio platforms have added AI features for schedule risk analysis, forecasting and automated status reporting, while general-purpose generative AI assistants are being used to draft charters, minutes and risk registers (Nenni et al., 2024). Gwagwa et al. (2020) observe that AI deployments in Africa remain concentrated in finance, agriculture, health and public services and are constrained by digital infrastructure, skills and regulation. In the energy sector, AI is widely used for resource assessment, design, output forecasting and maintenance (Jha et al., 2017; Voyant et al., 2017; Ahmad et al., 2021), and international contractors increasingly bring AI-enabled scheduling and inspection tools to utility projects. In Zambia, ZESCO's digital transformation initiative, which calls for advanced analytics and dashboards integrated with enterprise asset management (ZESCO, 2024), and the National AI Strategy (Ministry of Technology and Science, 2024) indicate that the data foundations and policy environment for AI-supported project management are beginning to emerge.

2.2 Effectiveness of AI in Project Management

The literature suggests that AI can improve project management across several dimensions, although the evidence is stronger for analytical tasks than for overall outcomes. For schedules, Gondia et al. (2020) showed that machine learning models can identify projects at high risk of delay before construction begins. For costs, Elmousalami (2020) found that AI-based estimation models such as neural networks and ensemble methods generally outperform traditional parametric regression, while Afzal et al. (2021) concluded that AI-based risk assessment better captures the interdependencies between complexity and risk that drive cost overruns. For quality, image-based deep learning is increasingly used for defect detection, progress measurement and safety monitoring (Akinosho et al., 2020), and aerial thermographic inspection allows faulty photovoltaic modules to be identified far more quickly than manual inspection (Gallardo-Saavedra et al., 2018).

Survey evidence points in the same direction but with caveats. Fridgeirsson et al. (2021) found that experts expect AI to have the greatest effect on cost, schedule and risk management and the least on knowledge areas that depend on human relationships. Holzmann et al. (2022) reported that project managers expect AI to automate reporting and scheduling but want to retain control over important decisions. Brynjolfsson et al. (2019) caution that the productivity benefits of AI are often delayed until organizations invest in complementary skills, data and processes, and Davenport

and Ronanki (2018) note that many corporate AI initiatives fail because they are poorly integrated or lack good data. Effectiveness is therefore conditional on organizational capability (Mikalef & Gupta, 2021).

2.3 AI and Project Completion in Renewable Energy Projects

Project completion is commonly measured by delivery on schedule, within budget, to the required quality and with the intended scope (PMI, 2021); for energy projects it also includes successful commissioning and delivery of contracted capacity. A major cause of late and over-budget projects is optimism bias at the planning stage (Flyvbjerg, 2014; Flyvbjerg, 2021), and AI-based forecasting extends data-driven approaches such as reference class forecasting by learning from large datasets of past projects. During execution, automated progress measurement, integrated schedule and cost data and near real-time dashboards can reveal deviations earlier than periodic reports (Akinosho et al., 2020).

Energy infrastructure shows why these matters. Sovacool et al. (2014), analyzing 401 electricity projects in 57 countries, found that hydroelectric dams and nuclear reactors had the largest cost overruns, while solar and wind had much smaller ones; Ansar et al. (2014) found an average cost overrun of 96% and schedule overrun of 44% across 245 large dams. In Zambia, Kafue Gorge Lower, built by Sinohydro at a contract price of about US$2 billion, slipped from an expected 2020 completion to 2023 after a funding halt (Renewable Energy World, 2023), while Chisamba Solar Phase II was reportedly built in seven months below its initial estimate (pv magazine, 2026). These cases suggest that completion depends on funding, procurement and technology type as well as on information, so that AI is best seen as one enabler among several. Taboada et al. (2023) note that few studies have measured the effect of AI on actual completion outcomes in live projects.

2.4 Limitations and Challenges of AI Adoption

The literature identifies several limitations that are especially relevant in developing countries. AI models require large volumes of accurate, consistent data, and trustworthy AI depends on sound data governance (Janssen et al., 2020). AI tools and the expertise to implement them can be costly, and Regona et al. (2022) found high initial costs and uncertain returns among the main reasons construction organizations are slow to adopt AI. Shang et al. (2023) identified lack of skilled personnel, implementation cost and organizational resistance as the key barriers in project management, with management support and demonstrated benefits as the key drivers. Infrastructure is a further constraint: AI tools depend on reliable connectivity and electricity, and the load-shedding of 2024 disrupted digital systems across Zambia (African Arguments, 2024). Finally, many AI models operate as black boxes, raising concerns about explainability and accountability in public organizations (Arrieta et al., 2020; Wirtz et al., 2019), while generative AI can produce plausible but incorrect content that must be verified (Dwivedi et al., 2021).

2.5 Personal Critique of Literature Review

The literature provides a broad account of AI applications in project management and in the energy sector and consistently shows that AI can improve forecasting, risk assessment and reporting. However, much of it is based on systematic reviews, expert opinion or models tested on historical or simulated data rather than on live projects, so it says more about the potential of AI than about its realized effects. Energy-sector studies focus mainly on operational uses such as forecasting and maintenance rather than on the planning and construction phases that determine whether new capacity is delivered on time and within budget. The literature also draws heavily on developed economies, with limited attention to how skills, data, infrastructure and governance shape AI use in state-owned utilities in Sub-Saharan Africa.

2.6 Establishment of Research Gaps

Despite growing interest in AI in Zambia, evidenced by the National AI Strategy and ZESCO's digital transformation initiatives, several gaps remain. First, there is limited empirical evidence on AI in project management in Sub-Saharan Africa. Second, research on AI in energy has concentrated on operations rather than on the management of renewable energy projects during planning and construction. Third, few studies examine the effectiveness of AI as experienced by project teams in live projects and how it relates to completion performance. Finally, no published study has examined the use of AI in managing renewable energy projects at ZESCO. This study addresses these gaps.

3 RESEARCH METHODOLOGY

3.1 Research Design

The study adopted a case study research design, appropriate for in-depth understanding of a contemporary phenomenon in its real-life context (Yin, 2018). ZESCO Limited was selected as Zambia's national utility and main implementing agency for the renewable energy program. A mixed-methods approach was used, in which quantitative questionnaire data were complemented by qualitative interview and document data (Creswell & Creswell, 2018).

3.2 Target Population

The target population comprised ZESCO staff and stakeholders directly involved in planning, implementing and supervising renewable energy projects, including project managers, engineers, project team members, ICT and data officers, and representatives of contractors and consultants, together with officials of ZESCO subsidiaries such as Kariba North Bank Extension Power Corporation and Kiyona Energy. The population was estimated at 300.

3.3 Sampling Design

Purposive sampling was used to select respondents with direct knowledge of, or experience in, managing ZESCO renewable energy projects and the digital tools used in them (Etikan et al., 2016). Within project teams, respondents were selected to represent the different roles involved in project delivery.

3.4 Sample Size Determination

Using Yamane's (1967) formula, $n = N / (1 + N(e)^2)$, with N = 300 and e = 0.05, the computed sample size was 171. A total of 100 respondents were considered adequate because they were deliberately selected for their direct involvement in the projects and because of time and financial constraints. They comprised 8 project managers, 24 engineers and technical staff, 12 ICT and data officers, 10 contractor and consultant representatives and 46 project team members.

3.5 Data Collection Methods

Structured questionnaires covering background characteristics, types and use of AI tools, perceived effectiveness, completion performance and challenges were administered to all respondents. Semi-structured interviews were held with selected project managers, senior engineers and ICT officers. Secondary data were drawn from project reports, ZESCO procurement and digital transformation documents, national policies and reports from IRENA and the IEA.

3.6 Data Analysis

Questionnaire data were coded and analyzed in STATA to produce frequencies, percentages, means and standard deviations, presented in figures and tables. Categorical responses were coded in the order of the questionnaire options. Interview data were transcribed and analyzed thematically (Braun & Clarke, 2006).

3.7 Triangulation

Data triangulation was applied by cross-checking questionnaire, interview and document evidence. Reliability was enhanced by pre-testing the questionnaire, using a standard interview guide and keeping detailed field notes.

3.8 Limitations of the Study

The single case limits generalizability, the findings rely mainly on respondents' perceptions, and some projects were still ongoing. Access to some confidential documents and senior officials was limited. These limitations were mitigated by using multiple data sources and comparing views with publicly available project information.

3.9 Ethical Considerations

Informed consent was obtained from all participants, who were assured of voluntary participation and confidentiality. Names were not recorded and data were stored securely in line with the Data Protection Act No. 3 of 2021. Clearance was obtained from the university's research ethics committee and from ZESCO management.

4 RESEARCH FINDINGS

4.1 Background Characteristics of the Respondents

The age distribution shows that most respondents were in the 31–35 age group (36%), followed by 25–30 years (27%) and 36–40 years (17%), with smaller proportions in older groups. The mean age was 35.42 years (SD = 7.18), ranging from 25 to 58 years. The sample was therefore dominated by younger to middle-aged professionals with several years of project experience who are likely to be familiar with digital tools.

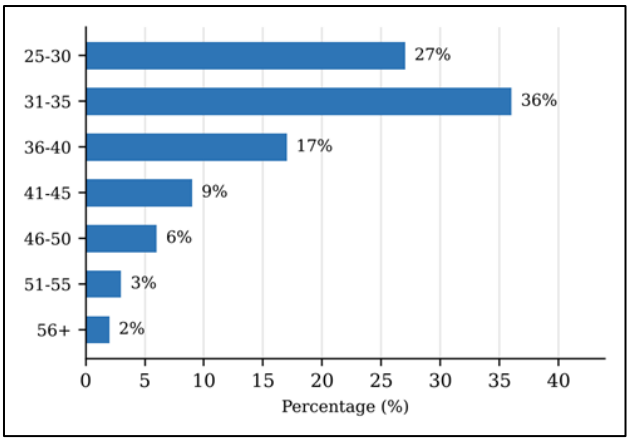


Figure 2: Age distribution of respondents

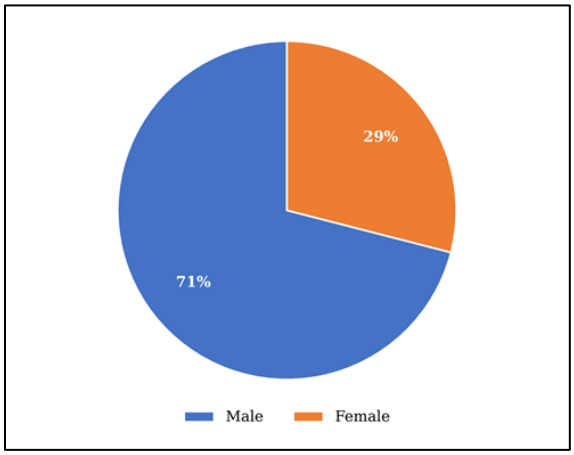


Figure 3: Gender of respondents

Males accounted for 71% of respondents and females for 29%, reflecting the gender composition of engineering and technical roles in the energy sector.

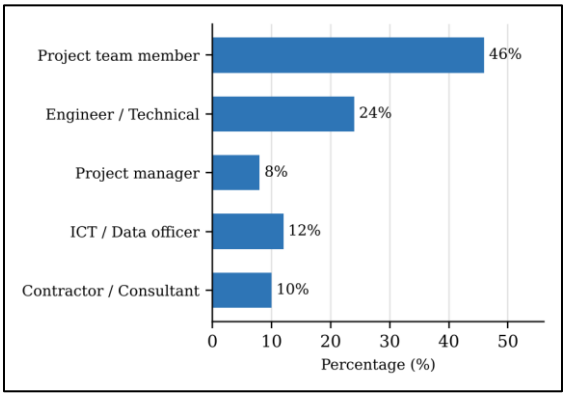


Figure 4: Role of respondents in the project

Project team members formed the largest group (46%), followed by engineers and technical staff (24%), ICT and data officers (12%), contractors and consultants (10%) and project managers (8%). The findings therefore largely reflect the views of personnel directly involved in day-to-day implementation, while also capturing the perspectives of managers and ICT specialists responsible for project systems.

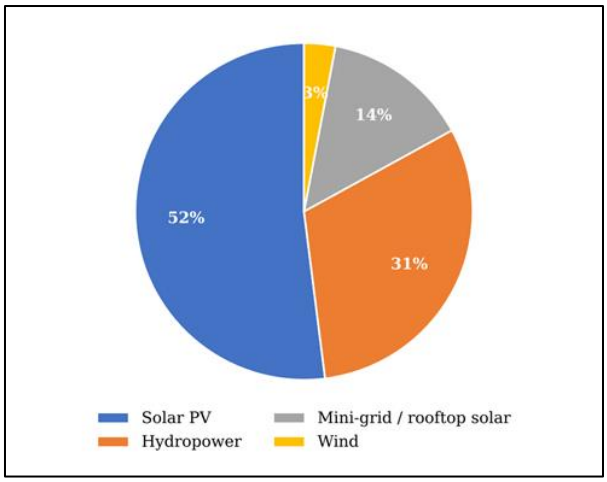


Figure 5: Type of renewable energy project

Most respondents had worked mainly on solar photovoltaic projects (52%), followed by hydropower (31%), mini-grid and rooftop solar (14%) and wind studies (3%), reflecting ZESCO's shift towards solar generation after the 2024 drought.

4.2 Types of AI Tools and Applications Used in ZESCO's Renewable Energy Projects

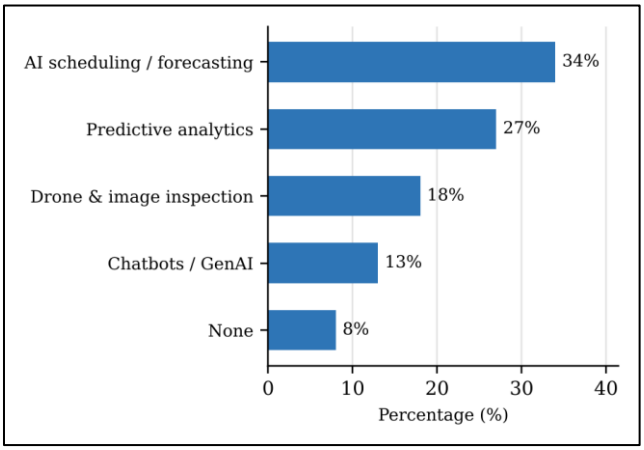


Figure 6: Type of AI tools used in the projects

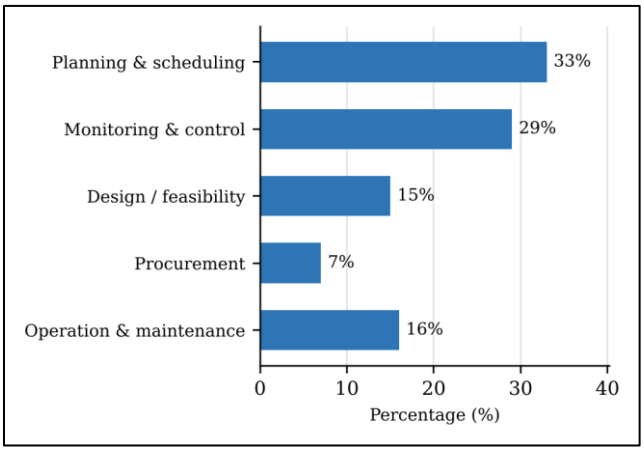


Figure 7: Project phase in which AI is mostly used

AI-assisted scheduling and forecasting tools were the most commonly used (34%), followed by predictive analytics (27%), drone and image-based inspection (18%) and chatbots or generative AI assistants (13%). Only 8% reported that

no AI tools were used. AI use is therefore concentrated in planning, forecasting and analytical applications. The mean of 2.34 (SD = 1.289) on the 1–5 coding range confirms the concentration of responses in the first two categories.

AI was mostly used in planning and scheduling (33%) and monitoring and control (29%), followed by operation and maintenance (16%), design and feasibility (15%) and procurement (7%). AI is thus applied mainly where scheduling, forecasting and progress monitoring matter most, while its use in procurement remains limited.

Table 1: Source of AI tools used in the projects

Source	Freq	Percent
Embedded in existing software	48	48.0
Provided by EPC contractor	26	26.0
Standalone commercial tool	19	19.0
Developed in-house	7	7.0
Total	100	100.0

Nearly half of respondents (48%) reported that AI tools came embedded in existing software such as scheduling, enterprise and asset management systems, and 26% that they were provided by EPC contractors. Standalone commercial tools (19%) and in-house development (7%) were less common, showing that AI enters ZESCO's projects mainly through existing platforms and contractors rather than deliberate internal development.

Table 2: Duration and frequency of AI use

Category	Freq	Percent
Used for less than 1 year	21	21.0
Used for 1–2 years	47	47.0
Used for 3–5 years	25	25.0
Used for above 5 years	7	7.0
Use daily	22	22.0
Use weekly	41	41.0
Use monthly	19	19.0
Use rarely	18	18.0

Most respondents (68%) had used AI for two years or less, indicating that adoption is recent and coincides with the accelerated solar program and the wider availability of generative AI. A majority (63%) used AI tools at least weekly, although 18% used them only rarely.

4.3 Effectiveness of AI in the Project Management of ZESCO's Renewable Energy Projects

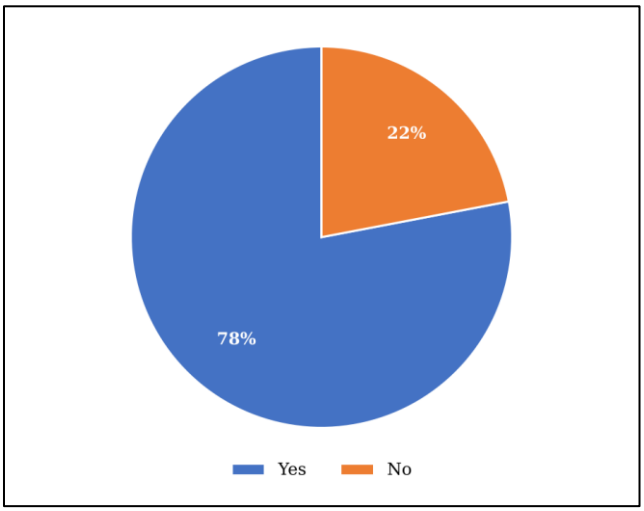


Figure 8: AI improved planning and scheduling accuracy

A large majority (78%) reported that AI had improved the accuracy of planning and scheduling, while 22% disagreed (mean = 1.22, SD = 0.416 on a 1–2 scale where 1 = yes).

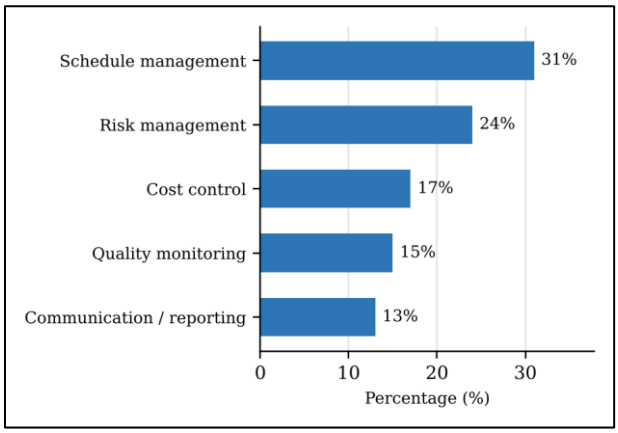


Figure 9: Project management area that benefited most from AI

Schedule management was identified as the area that benefited most (31%), followed by risk management (24%), cost control (17%), quality monitoring (15%) and communication and reporting (13%).

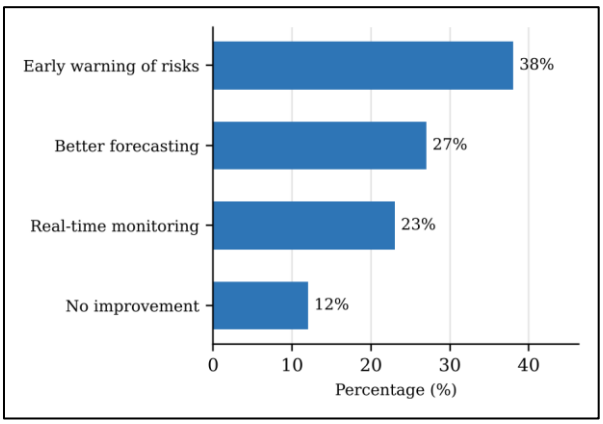


Figure 10: How AI improved risk management

Respondents associated AI mainly with early warning of risks (38%), better forecasting (27%) and real-time monitoring (23%), while 12% reported no improvement (mean = 2.09, SD = 1.045). The most frequent contribution of AI to risk management was therefore the earlier identification of risks.

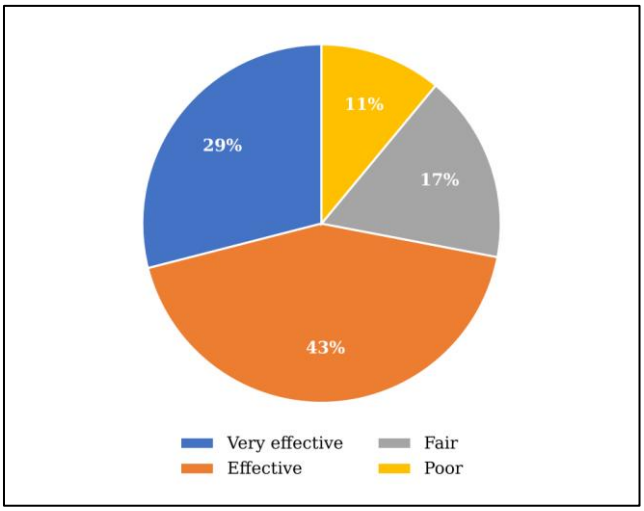


Figure 11: Effectiveness of AI in monitoring and reporting

In total, 72% of respondents rated AI as effective (43%) or very effective (29%) in monitoring and reporting, while 17% rated it fair and 11% poor.

Table 3: How AI improved project management efficiency

Response	Freq	Percent
Timely completion of tasks	35	35.0
Better resource allocation	30	30.0
Improved coordination	21	21.0
No improvement	14	14.0
Total	100	100.0

AI was perceived to improve efficiency mainly through timely completion of tasks (35%) and better resource allocation (30%), with 21% citing improved coordination and 14% no improvement (mean = 2.14, SD = 1.054).

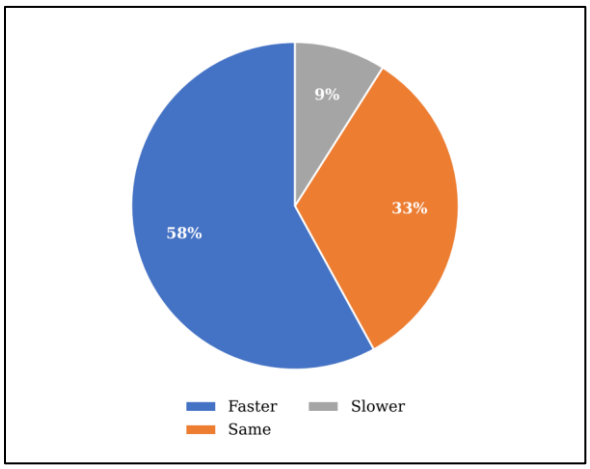


Figure 12: Decision-making speed with AI compared to traditional methods

More than half (58%) considered decision-making faster with AI, 33% saw no difference and 9% considered it slower (mean = 1.51, SD = 0.659 on a 1–3 scale where 1 = faster).

4.4 Relationship Between the Use of AI and Project Completion

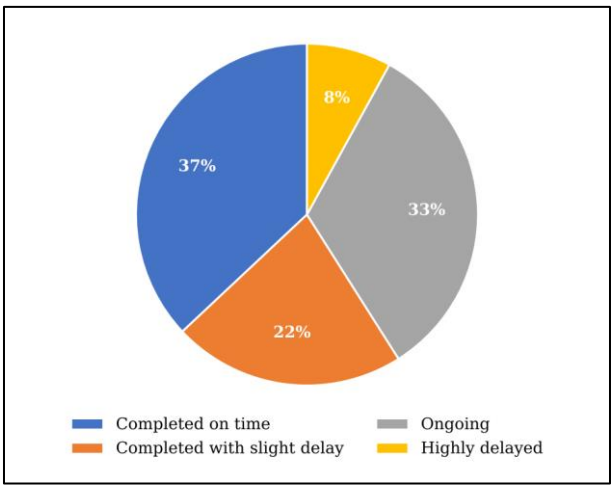


Figure 13: Completion status of renewable energy projects

Of the projects reported, 37% were completed on time and 22% with a slight delay, while 33% were still ongoing and 8% were highly delayed.

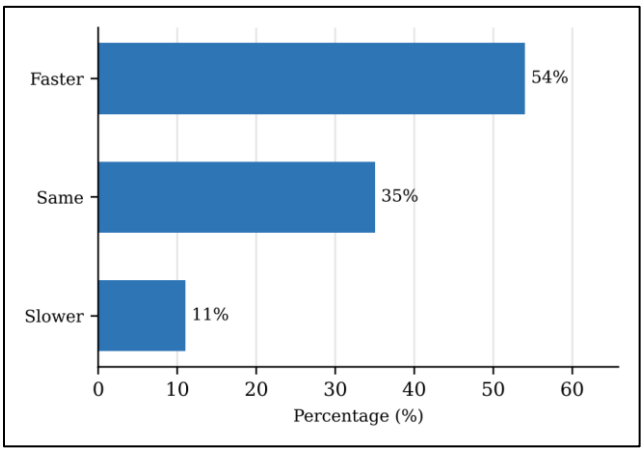


Figure 14: Project progress compared with similar projects without AI

A majority (54%) considered AI-supported projects to have progressed faster than similar projects without AI, 35% saw no difference and 11% considered them slower.

Table 4: Main causes of delays in project activities

Cause	Freq	Percent
Funding / foreign exchange issues	34	34.0
Procurement procedures	27	27.0
Weather / drought	14	14.0
Contractor performance	13	13.0
No delays	12	12.0
Total	100	100.0

Funding and foreign exchange issues (34%) and procurement procedures (27%) were the leading causes of delay, followed by weather and drought (14%) and contractor performance (13%); 12% reported no delays (mean = 2.42, SD = 1.387).

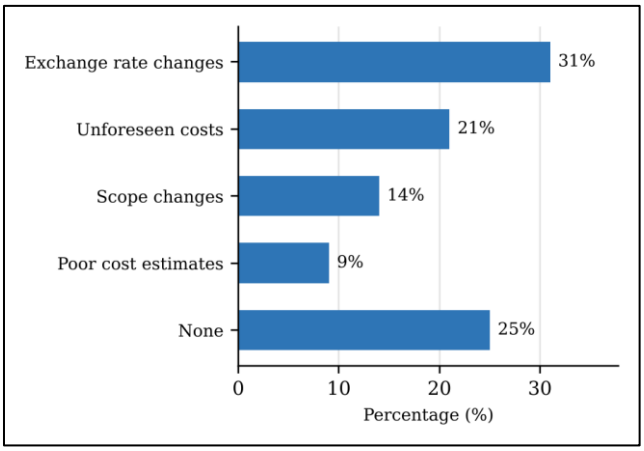


Figure 15: Causes of budget overruns

Budget overruns were reported by 44% of respondents. Exchange rate changes were the most common cause (31%), followed by unforeseen costs (21%), scope changes (14%) and poor cost estimates (9%), while 25% reported no overruns, reflecting the dependence of renewable projects on imported equipment priced in foreign currency.

Table 5: Quality of completed works and compliance with specifications

Category	Freq	Percent
Quality very high	36	36.0
Quality high	49	49.0
Quality moderate	12	12.0
Quality low	3	3.0
Fully compliant	64	64.0
Mostly compliant	31	31.0
Partly compliant	5	5.0

Quality outcomes were rated highly: 85% rated completed works as high or very high quality (mean = 1.82, SD = 0.757) and 95% reported full or mostly full compliance with technical specifications. In addition, 69% of respondents measured project success using a combination of time, cost and quality.

4.5 Limitations and Challenges of Using AI in Project Management

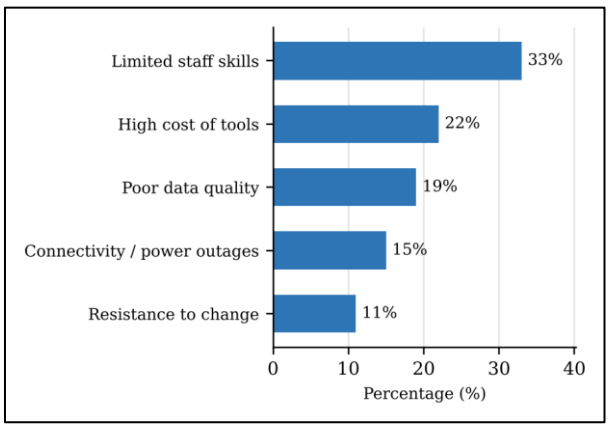


Figure 16: Main challenge in adopting AI in project management

Limited staff skills were the most frequently reported challenge (33%), followed by the high cost of AI tools (22%), poor data quality (19%), connectivity and power outages (15%) and resistance to change (11%) (mean = 2.49, SD = 1.374).

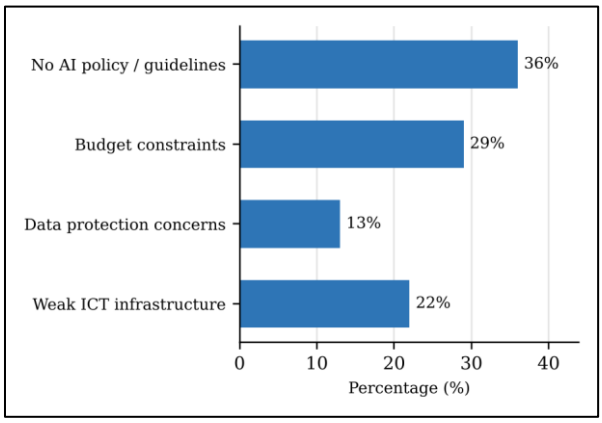


Figure 17: Institutional challenges affecting AI adoption

The absence of an AI policy or guidelines was the leading institutional challenge (36%), followed by budget constraints (29%), weak ICT infrastructure (22%) and data protection concerns (13%).

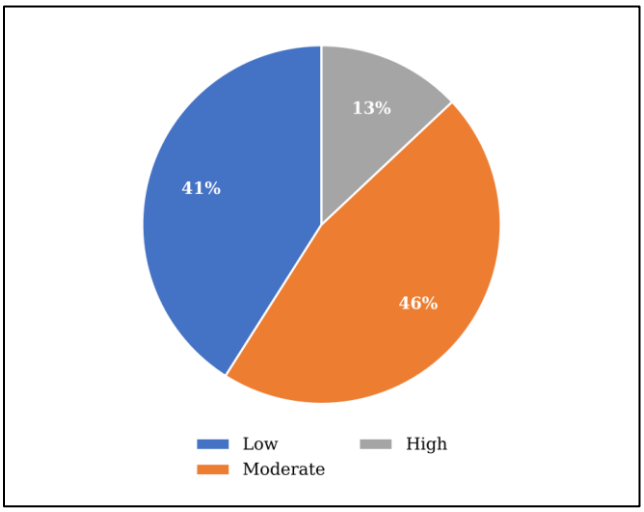


Figure 18: Level of AI skills among project staff

Most respondents rated AI skills among project staff as moderate (46%) or low (41%), with only 13% rating them high (mean = 1.72, SD = 0.683 on a 1–3 scale where 1 = low), confirming a significant skills gap.

Table 6: Critical improvements for future use of AI

Improvement	Freq	Percent
Staff training / capacity building	42	42.0
Better data systems	23	23.0
AI policy and governance	21	21.0
Investment in ICT infrastructure	14	14.0
Total	100	100.0

Staff training and capacity building was identified as the most critical improvement (42%), followed by better data systems (23%), AI policy and governance (21%) and investment in ICT infrastructure (14%).

5 DISCUSSION OF RESEARCH FINDINGS

5.1 Types of AI tools and applications used

The results show that AI is already part of ZESCO's renewable energy project environment, with only 8% of respondents reporting no use. The dominance of scheduling, forecasting and predictive analytics, applied mainly in planning and monitoring, mirrors the concentration of AI research and practice in schedule, cost and risk management reported by Taboada et al. (2023) and supports the expectation of Fridgeirsson et al. (2021) that data-intensive, repetitive tasks would be affected first. The predominance of solar projects in respondents' experience also helps explain the use of drone and image-based inspection, since solar plants involve large numbers of standardized components that can be tracked and inspected automatically (Gallardo-Saavedra et al., 2018).

The finding that AI enters projects mainly through existing software (48%) and EPC contractors (26%) indicates, in TOE terms, that adoption is driven as much by the technological and environmental context as by deliberate organizational strategy (Tornatzky & Fleischer, 1990). This lowers upfront cost but may limit ZESCO's control of data and its ability to build internal capability, which the RBV identifies as the basis of sustained performance (Barney, 1991; Mikalef & Gupta, 2021). The recency of use, with most respondents adopting AI within two years and 18% using it rarely, suggests that ZESCO is moving from early adoption to wider use, consistent with Rogers' (2003) diffusion process. The low use of AI in procurement (7%) is notable because procurement was a leading cause of delay.

5.2 Effectiveness of AI in project management

AI was generally perceived as effective, particularly in planning accuracy (78%), schedule and risk management, and monitoring and reporting (72% effective or very effective). These results are consistent with the predictive capability demonstrated by Gondia et al. (2020), the risk-assessment advantages reported by Afzal et al. (2021) and the expectations of project managers regarding reporting found by Holzmann et al. (2022). In TAM terms, AI tools are clearly perceived as useful (Davis, 1989).

The benefits, however, are uneven. Twelve per cent saw no improvement in risk management, 14% no efficiency gain and a third no change in decision speed. This suggests that AI accelerates the analysis that precedes decisions, but that approval layers in a state-owned enterprise absorb part of the gain, consistent with Brynjolfsson et al. (2019), who argue that AI benefits materialize only when processes and management practices adapt. AI therefore influences performance through project management practice rather than directly, as the conceptual framework proposes.

5.3 Relationship between AI use and project completion

The use of AI was associated with positive perceptions of completion performance: 54% judged AI-supported projects to progress faster than comparable non-AI projects, and quality and compliance ratings were high. These results align with arguments that data-driven forecasting reduces the optimism bias that leads to delays and overruns (Flyvbjerg, 2014; Flyvbjerg, 2021) and with the use of automated inspection to correct defects before handover (Akinosho et al., 2020).

At the same time, delays and overruns were driven mainly by funding, foreign exchange and procurement, factors that AI can help forecast but cannot remove. The experience of Kafue Gorge Lower, delayed by a funding halt rather than a lack of information, illustrates this (Renewable Energy World, 2023), while the fast delivery of Chisamba Phase II shows what is possible when funding, procurement and execution are aligned (pv magazine, 2026). The higher share of delays among hydropower projects is also consistent with international evidence that hydropower overruns far exceed those of solar (Sovacool et al., 2014; Ansar et al., 2014). The relationship between AI and completion is therefore positive but conditional: AI acts as an enabler, while funding, procurement, currency stability and contractor performance remain decisive. Because some projects were ongoing and findings rest on perceptions, a causal relationship cannot be confirmed.

5.4 Limitations and challenges of using AI

Limited skills, cost, data quality and connectivity were the main barriers, consistent with Regona et al. (2022), Shang et al. (2023) and Gwagwa et al. (2020). The finding that 87% rated staff AI skills as low or moderate implies low perceived ease of use, which TAM predicts will restrain actual use (Venkatesh et al., 2003). Poor data quality limits the reliability of AI outputs (Janssen et al., 2020), and power and connectivity problems are especially relevant after the 2024 load-shedding. The absence of an AI policy (36%) shows that the National AI Strategy and ZESCO's digital initiatives have not yet been translated into organizational guidelines, which Wirtz et al. (2019) regard as essential for accountable public-sector AI. The strong demand for training (42%) indicates that the effectiveness of AI at ZESCO depends less on the availability of tools than on the people, data and governance needed to use them well.

Overview

This section presents the conclusion and recommendations of the study, drawing together the findings on the types, effectiveness, completion effects and limitations of AI in the management of ZESCO's renewable energy projects.

6 CONCLUSION

The study established that AI is already used in ZESCO's renewable energy projects, mainly through AI-assisted scheduling and forecasting, predictive analytics, drone and image-based inspection and generative AI assistants. These tools are applied chiefly in planning and monitoring and are introduced largely through existing software and EPC contractors, and their use is recent.

AI was perceived as effective in improving planning accuracy, schedule and risk management, monitoring and reporting, and the speed of decision-making, although its benefits are not yet evenly realized across projects and teams. The use of AI was positively associated with faster progress and high quality and compliance, but delays and budget overruns remained, driven mainly by funding and foreign exchange issues, procurement procedures and exchange rate changes.

The main limitations were limited staff skills, high costs, poor data quality, unreliable connectivity and power, and the absence of organizational AI policies. The study concludes that AI is an effective but conditional enabler of project completion at ZESCO whose benefits depend on skills, data, infrastructure and governance, and that it cannot substitute for adequate funding and efficient procurement. A full assessment of its effect will require comparison of planned and actual schedules, budgets and quality over a longer period.

Recommendations

- Develop a ZESCO Policy and Guidelines on AI in Project Management

Since 36% of respondents cited the absence of AI policy as the main institutional challenge, ZESCO should develop an organizational AI policy aligned with the National AI Strategy and the Data Protection Act, setting out approved uses, staff responsibilities, human review of AI outputs, data protection and procedures for acquiring and evaluating AI tools.

- Invest in Training and Capacity Building for Project Staff

With limited skills the top barrier (33%) and 87% rating staff skills as low or moderate, ZESCO should run a structured data-literacy and AI program for project managers, engineers and team members, and require EPC contractors to transfer digital skills to ZESCO staff.

- Strengthen Project Data Management and Integration

Poor data quality (19%) undermines AI outputs. ZESCO should set standards for capturing and sharing schedules, costs, risks and inspection records, integrate them with its enterprise and asset management systems, and require contractors to deliver project data in agreed digital formats owned by ZESCO.

- Extend AI to Procurement and Financial Risk Management

As funding, foreign exchange and procurement were the main causes of delays and overruns, yet AI is least used in procurement (7%), ZESCO should apply AI to tracking procurement timelines, analyzing contracts and forecasting currency and supply chain risks, alongside streamlined procedures and stronger contingency planning.

- Improve ICT Resilience and Monitor the Benefits of AI

ZESCO should provide reliable connectivity and solar-plus-battery backup power at project sites, and establish indicators such as forecast accuracy, reporting time and planned-versus-actual variance to evaluate which AI tools deliver value.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflict of interest regarding this manuscript

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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