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Integrating Artificial Intelligence with Earned Value Management for Enhanced Performance in Smart Renewable Energy Projects

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Abstract

Renewable energy projects in Jordan continue to face persistent cost overruns and schedule delays, largely due to the limitations of traditional project control systems that rely on manual progress reporting, subjective assessments, and delayed decision cycles. This study evaluates the integration of Artificial Intelligence (AI) with Earned Value Management (EVM) as a comprehensive approach to improving performance monitoring and forecasting in smart renewable energy initiatives. A mixed-methods framework was adopted, combining an industry survey of 394 practitioners with an instrumental case study of a solar photovoltaic system upgrade modeled in Autodesk Revit and scheduled in Primavera P6. The case study revealed early and significant deviations, with an SPI of 0.75 and a CPI of 0.56 at Week 4, followed by a sharp decline in cost performance to approximately CPI 0.31, ultimately indicating an unavoidable budget overrun and a negative TCPI. Survey findings strongly support the potential of AI–EVM integration: 61.7% of respondents reported substantial improvements in decision-making, 57.1% emphasized enhanced real-time tracking, and over 55% highlighted gains in forecasting accuracy through AI techniques such as machine learning, computer vision, and natural language processing. Despite these positive perceptions, key barriers—including poor data quality, regulatory limitations, high implementation costs, and organizational resistance—remain significant. Overall, the findings demonstrate that AI–EVM integration offers a potential shift from reactive project control to predictive, data-driven management. The study concludes that adopting such an integrated framework is essential for improving cost efficiency, schedule reliability, and overall project outcomes in Jordan's rapidly expanding renewable energy sector.

Keywords*: Artificial Intelligence, Earned Value Management, Jordan, Project Control, Project Performance, Renewable Energy.*

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1 Introduction

The global transition toward low-carbon energy systems has intensified the demand for efficient planning and execution of renewable energy projects. Solar and wind initiatives, in particular, have become central to national energy security strategies, especially in developing economies where renewable resources are abundant but project delivery environments remain complex. Jordan exemplifies this challenge. Despite major national investments in solar photovoltaics and wind farms, local projects frequently experience cost overruns, schedule slippage, and inconsistencies in quality performance, limiting their long-term economic viability and contribution to national energy resilience [1,2]. These recurring challenges underscore the need for more advanced, data-driven project control systems capable of providing timely, objective, and predictive insights [3].

Renewable energy systems have increasingly been adopted in Jordan to support critical infrastructure applications, including energy–water nexus projects such as desalination, further increasing project scale and delivery complexity [4]. Despite major national investments in solar photovoltaics and wind farms, local renewable energy projects continue to experience cost overruns, schedule delays, and performance inefficiencies, particularly during the construction and execution phases [1,2].

Earned Value Management (EVM) is one of the most widely adopted performance measurement frameworks for integrating project scope, schedule, and cost. By continuously monitoring Planned Value (PV), Earned Value (EV), and Actual Cost (AC), EVM offers standardized metrics such as the Schedule Performance Index (SPI), Cost Performance Index (CPI), and Estimate at Completion (EAC). These indicators enable structured performance diagnosis and early warning signals for deviation trends [5–9]. However, despite its strengths, traditional EVM remains limited in practice due to several systemic constraints. Most project environments—especially in developing countries—still rely heavily on manual data entry, subjective progress estimates, and periodic reporting cycles [10-12]. These practices introduce delays, inaccuracies, and reactive decision-making, preventing managers from leveraging EVM's full predictive potential [5]. As modern renewable energy projects grow in scale and technical complexity, the shortcomings of manually driven EVM approaches become more pronounced.

Parallel to these limitations, rapid advancements in Artificial Intelligence (AI) present transformative opportunities for project control. AI techniques—such as machine learning for forecasting, natural language processing for automated document interpretation, and computer vision for real-time site monitoring—have demonstrated strong potential to enhance objectivity, automation, and predictive accuracy in engineering and construction environments [6]. When aligned with EVM, AI can shift project management from a retrospective assessment tool to an intelligent, forward-looking control system. Instead of relying on static formulas and periodic measurements, an AI-enhanced EVM framework can ingest continuous data streams, detect early anomalies, generate probabilistic forecasts, and provide actionable recommendations for proactive intervention.

Despite growing interest in the synergy between AI and traditional project control methods, empirical evidence remains limited—particularly in the context of renewable energy projects in developing economies. Jordan's renewable energy sector provides an ideal context for examining this integration due to its rapid expansion, diverse technical challenges, and persistent project performance issues. Moreover, the scarcity of structured digital data, limited AI adoption, and constraints in technical capacity create a unique environment for testing the practicality and value of AI-driven control systems [11–14].

Accordingly, this study investigates how integrating AI technologies with Earned Value Management can enhance the performance, monitoring, and forecasting capabilities of renewable energy projects in Jordan. By combining a detailed case study of a solar energy system upgrade project with a large-scale survey of 394 industry professionals, the study provides a dual-perspective assessment: (1) an empirical evaluation of traditional EVM performance and its limitations, and (2) a sector-wide perception analysis of the readiness, challenges, and expected benefits of AI-EVM integration. This approach addresses the existing gap in the literature and provides a practical, evidence-based foundation for designing intelligent project control systems suited to emerging energy markets.

Despite the growing interest in Artificial Intelligence applications in project management, the integration of AI with Earned Value Management (EVM) remains limited, particularly in renewable energy projects within developing economies. This study contributes to the literature in three main ways. First, it examines the potential of AI-supported project control in renewable energy projects, a sector that has received limited attention in AI–EVM research. Second, the study focuses on Jordan as a developing economy, providing insights into the challenges of adopting advanced digital project management systems in emerging markets. Third, the research employs a mixed-method empirical approach, combining a case study analysis with a survey of 394 industry professionals. In addition, the study proposes a conceptual framework linking AI technologies with EVM performance metrics, offering a foundation for future AI-enabled project control systems.

It is important to note that this study does not implement a fully operational Artificial Intelligence system. Instead, the research proposes a conceptual AI–EVM integration framework, supported by empirical evidence from a case study analysis and an industry perception survey assessing the feasibility and potential benefits of AI adoption in project control.

2 Literature Review

2.1 Earned Value Management (EVM) in Project Control

Earned Value Management (EVM) remains one of the most robust and widely adopted frameworks for integrating cost, schedule, and scope to assess project performance. Its core metrics—Planned Value (PV), Earned Value (EV), Actual Cost (AC), and derived indices such as CPI and SPI—provide objective indicators for controlling deviations and forecasting final outcomes [7,8]. EVM has evolved significantly since its origins in the U.S. defense industry and is now embedded in international project management standards, including PMBOK and ISO project control guidelines [9].

Despite its widespread adoption, traditional EVM implementations continue to face systemic limitations that undermine their effectiveness in complex engineering projects. First, the reliance on manual data collection introduces delays and inaccuracies, especially when progress measurement depends on subjective “percentage complete” estimates [9,10]. Second, EVM forecasts typically rely on linear extrapolation of past performance trends, limiting predictive accuracy under non-linear risk conditions common in renewable energy projects. Third, EVM's effectiveness depends heavily on the maturity of organizational processes, data discipline, and timely reporting—factors often lacking in developing construction sectors.

Communication inefficiencies among project stakeholders have been identified as a major contributor to coordination problems, delays, and performance shortfalls in Jordanian construction projects [11].

Renewable energy projects present additional challenges for EVM. These projects involve multidisciplinary engineering tasks, fluctuating site conditions, variable weather-dependent productivity, and frequent design changes, all of which reduce the reliability of static baselines. Several authors emphasize that traditional EVM, while analytically strong, is insufficient when applied in data-poor environments or in projects where progress is difficult to quantify visually or physically, such as cable works, inverter installation, and commissioning activities [10,12]. This makes renewable energy projects a strong candidate for enhanced, data-rich EVM approaches.

The growing technical sophistication of solar energy systems, including tracking and automated control mechanisms, has further increased execution complexity and performance monitoring requirements [13].

2.2 Artificial Intelligence in Engineering and Construction Projects

Artificial Intelligence (AI) has gained significant traction across engineering disciplines, offering transformative capabilities in automation, prediction, and real-time analysis. Machine Learning (ML) techniques have demonstrated strong potential for forecasting construction productivity, estimating risks, identifying anomalies, and optimizing schedules and resources [7]. Deep Learning (DL) models, including neural networks and hybrid optimization algorithms, have achieved notable success in energy systems forecasting, operational control, and anomaly detection [14,15,16].

Early applications of smart sensing technologies demonstrated the feasibility of low-cost sensor systems for automated data collection and monitoring in engineering applications, laying the groundwork for contemporary AI-enabled project control solutions [17].

Computer Vision applications—particularly drone-based inspections—enable automated recognition of physical progress, object counting, and construction verification, eliminating much of the subjectivity associated with manual site reporting [7]. Similarly, Natural Language Processing (NLP) has been applied to extract actionable insights from progress reports, emails, contractual claims, and daily logs, improving the transparency and frequency of project communication analysis [18].

The adoption of AI in project management remains uneven. Studies highlight persistent barriers including data scarcity, integration challenges, limited AI expertise, and organizational resistance [11–14]. Yet, the trajectory of research in construction engineering indicates that AI is shifting from experimental applications to mainstream adoption, particularly in energy management, smart infrastructure, and predictive control systems [19,16].

2.3 Integrating AI with Earned Value Management

The convergence of AI and EVM has emerged as a promising direction for improving project performance measurement. Current literature positions AI-enhanced EVM as a next-generation project control paradigm that addresses EVM's core limitations.

(a) Enhancing data acquisition and accuracy

Computer Vision techniques allow real-time tracking of physical progress—such as counting installed solar modules or measuring trench excavation—thereby improving the accuracy of EV calculations and reducing human estimation errors [7].

(b) Improving forecasting capabilities

Machine Learning models can outperform classical EVM forecasting equations by identifying nonlinear patterns, learning from historical data, and generating probabilistic EAC (Estimate at Completion) and ETC (Estimate to Complete) ranges [10,7].

(c) Automating reporting workflows

NLP applications automate extraction of schedule-related content from reports and communications, enabling more frequent and objective updates to EVM datasets. This addresses the traditional lag in reporting that restricts EVM to reactive decision-making.

(d) Supporting proactive and predictive control

Hybrid AI–EVM models provide early warnings for likely cost overruns, schedule slippage, or productivity drops. Instead of highlighting deviations after they occur, AI-EVM systems predict them in advance, shifting project control from diagnostic to preventive.

While the literature acknowledges the potential of integrating AI with EVM, empirical studies remain sparse. Existing research often focuses on conceptual models or simulations rather than real-world applications. A notable gap persists regarding practical, sector-specific implementations—particularly in developing economies where digital maturity varies and renewable energy projects face unique constraints [22–26].

To clarify the complementarities between AI capabilities and EVM performance metrics, Table 1 summarizes the core constructs underpinning the proposed integration framework and outlines how each technology aligns with project control functions.

Table 1: Definition of Core Constructs: Artificial Intelligence (AI) and Earned Value Management (EVM)

Construct	Definition & Purpose	Key Components / Techniques	Metrics / Outputs	Relevance to AI–EVM Integration
Artificial Intelligence (AI)	Computational systems designed to emulate human cognitive functions such learning, reasoning, perception, and decision-making. Enables automation, pattern detection, and predictive analytics in	• Machine Learning (ML): regression, random forest, neural networks (forecasting, anomaly detection) • Deep Learning (DL): multi-layer neural models for high-dimensional data	• Forecasting accuracy. •Anomaly detection rate. •Automated progress recognition. •Data	• Automates EV measurement via CV • Enhances EAC forecasting accuracy via ML • Enables

	complex project environments.	• Computer Vision (CV): image/video analysis for automated progress detection • Natural Language Processing (NLP): automated extraction of insights from text (reports, emails, logs) • Optimization & Reinforcement Learning: dynamic planning and adaptive control	processing efficiency.	continuous reporting through NLP • Provides early-warning signals for cost/schedule risks
Earned Value Management (EVM)	A standardized project control methodology integrating scope, cost, and schedule to provide objective performance measurements and forecasts.	• Planned Value (PV) • Earned Value (EV) • Actual Cost (AC) • CPI, SPI (efficiency indicators) • SV, CV (variance indicators) • EAC, ETC, TCPI (forecasting metrics)	• Schedule efficiency (SPI • Cost efficiency (CPI) •Variance thresholds (SV, CV) • Final cost prediction (EAC)	• Provides the structured baseline for AI • inputs Standardizes performance data for ML • training Enables objective benchmarking of AI-generated forecast

Building on the conceptual relationships presented in Table 1, the following subsection examines the remaining gaps in research regarding the implementation of AI-enhanced EVM systems in renewable energy projects.

Recent research has increasingly highlighted the role of Artificial Intelligence in enhancing project monitoring and predictive control systems. For example, studies have explored the use of machine learning techniques to improve forecasting accuracy in project performance evaluation and earned value analysis [27,33]. Other studies have examined the integration of digital twins and AI technologies to support automated construction monitoring and data-driven project management [28]. Furthermore, recent research emphasizes the potential of integrating AI capabilities with traditional project control frameworks to enhance forecasting reliability and decision-making processes in complex infrastructure projects [26,29]. These recent developments demonstrate the growing interest in AI-supported project management systems and provide an important foundation for the AI–EVM integration framework proposed in this study.

Several recent studies have explored the application of Artificial Intelligence in project monitoring and control systems. These studies have investigated various approaches including machine learning–based predictive models, digital twin technologies, and integrated BIM–AI frameworks. However, the majority of existing research remains conceptual or focuses on infrastructure and general construction contexts rather than renewable energy projects in developing economies. Table 2 summarizes recent studies on AI applications in project control and highlights the methodological gaps addressed in this study.

Table 2: Recent studies on AI Applications in Project Control

Study	Research Focus	Methodology	Key Findings	Research Gap
[27]	Predictive EVM using machine learning	ML modelling	Machine learning improves EAC prediction accuracy	Limited real-world validation
[33]	AI-supported predictive project control	Analytical study	AI enables predictive project monitoring	No empirical application
[28]	Digital twin + AI monitoring	Framework development	AI improves automated construction monitoring	Focused on infrastructure, not renewable energy
[29]	BIM–AI–EVM integration	Conceptual framework	Integrated digital systems improve project control	Lack of industry perception analysis
[26]	AI-enabled project control systems	Systematic review	AI adoption increasing in construction management	Limited studies in developing economies

The comparison presented in Table 2 demonstrates that recent studies increasingly recognize the potential of Artificial Intelligence to enhance project monitoring, forecasting, and decision-support systems. Nevertheless, most existing research either focuses on conceptual frameworks or examines AI applications within general construction environments. Empirical investigations that combine project performance analysis with industry perception studies remain limited, particularly in the context of renewable energy projects in developing economies. Therefore, this study contributes to the literature by examining AI–EVM integration through both a case study analysis and a large-scale industry survey conducted within Jordan’s renewable energy sector.

2.4 EVM and AI in Renewable Energy Projects: Gaps and Limitations

Previous research on infrastructure delivery models in Jordan highlights that governance structure, stakeholder alignment, and institutional capacity are critical success factors influencing project performance, particularly in complex public-sector and partnership-based projects [20].

Renewable energy projects benefit greatly from structured performance measurement, yet they also confront conditions—weather dependency, rapid technological change, and multidisciplinary coordination—that challenge traditional control methods. Studies in solar photovoltaic and microgrid system management highlight the usefulness of intelligent control systems, automated sensing, and predictive analytics for improving reliability and reducing operational inefficiencies [21,10].

However, there remains almost no empirical research on:

- integrating AI with EVM in renewable energy construction projects,
- evaluating AI-driven EVM performance using real project data,
- assessing industry readiness for adopting predictive EVM technologies in the Middle East,
- understanding organizational, regulatory, and data-related barriers to AI-EVM implementation.

Thus, the intersection of AI, EVM, and renewable energy project control represents an emerging but insufficiently studied research domain.

2.5 Identified Research Gap

The reviewed literature demonstrates substantial advancements in both EVM and AI, yet their integration—especially within the context of renewable energy project delivery in developing economies—remains underexplored. Specifically:

1. Traditional EVM lacks real-time, objective data inputs, reducing its effectiveness in complex renewable energy environments.
2. AI offers strong predictive and automation capabilities, but empirical applications in construction project control are limited.
3. No comprehensive framework exists that operationalizes AI-enhanced EVM for renewable energy projects in Jordan or comparable regions.
4. Industry readiness, barriers, and practitioner perceptions remain largely undocumented.

These gaps underscore the need for a practical, evidence-based assessment of AI-EVM integration—precisely what the current study provides through a combined case study and industry-wide survey.

3 Research Methodology

It should be emphasized that the AI component in this research is conceptual in nature. The study evaluates the potential integration of Artificial Intelligence technologies with Earned Value Management through a mixed-method approach consisting of a case study analysis and a practitioner survey rather than through the development of a fully implemented AI system.

As shown in Figure 1, this study adopts a mixed-methods research design to investigate the practical feasibility, performance implications, and industry readiness for integrating Artificial Intelligence (AI) with Earned Value Management (EVM) in renewable energy projects in Jordan. A mixed-methods strategy is particularly appropriate for bridging the gap between theoretical potential and real-world application, as it enables the triangulation of quantitative measurements, stakeholder perceptions, and project-level insights.

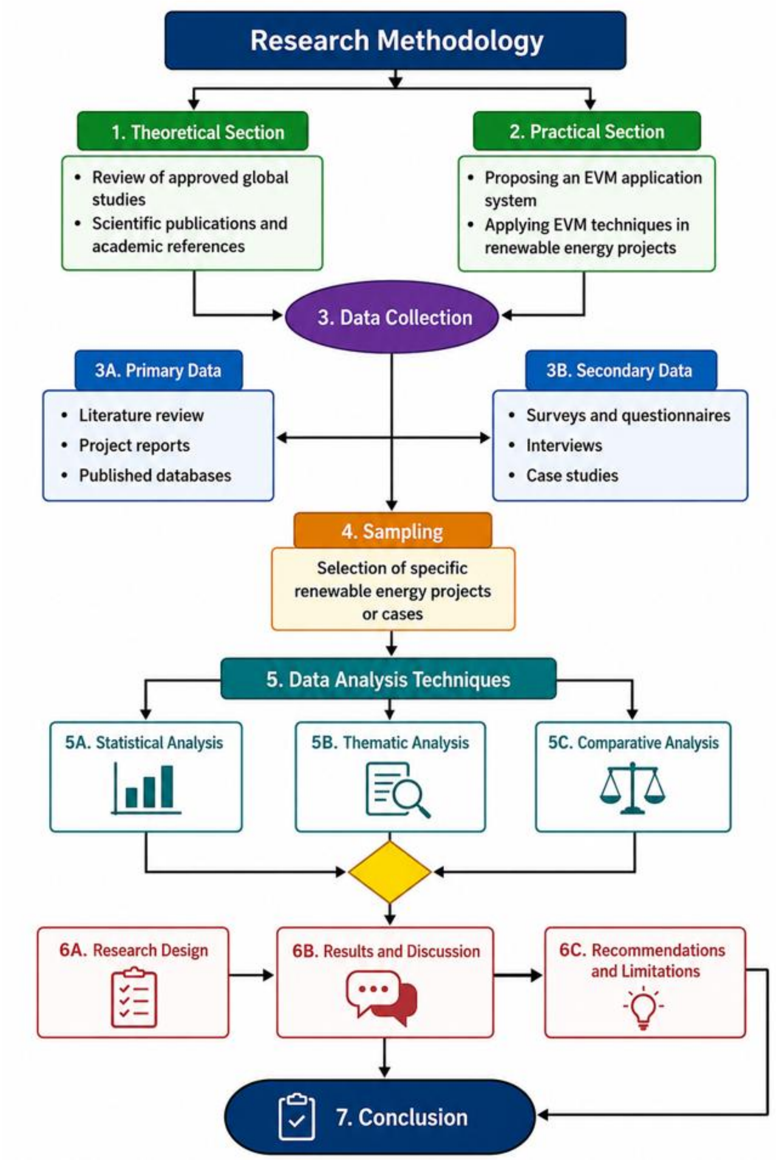

Fig. 1. Research Methodology Workflow

The flowchart illustrates the sequential stages of the research process, beginning with the literature review, followed by the case study simulation using Autodesk Revit and Primavera P6, the Earned Value Management (EVM) performance analysis, the conceptual modeling of AI integration, the survey administered to industry professionals, and the final integrated data analysis.

The integration of AI and EVM represents both a technical and behavioral transformation. Therefore, relying on a single method would be insufficient for capturing the multidimensional nature of the phenomenon. The case study provides empirical evidence of actual project performance under traditional EVM conditions and highlights systemic gaps that AI could mitigate. The survey captures industry-wide perspectives regarding challenges, opportunities, and readiness for adopting AI-driven project control systems. Combined, these methods enhance the validity, reliability, and generalizability of the findings.

The quantitative aspect consisted of a structured questionnaire administered to a purposive sample of professionals engaged in Jordan's energy and project management sectors. The target population comprised project managers, project engineers, planning and scheduling engineers, cost control engineers, renewable energy experts, and AI specialists. A total of 394 valid responses were obtained for statistical analysis. The survey instrument was carefully crafted, utilizing a five-point Likert scale to gauge respondents' perceptions, familiarity, and attitudes. It was divided into thematic sections that looked at demographics, knowledge and use of Earned Value Management, use of AI apps, and the perceived effects and problems of adding AI to EVM processes. The gathered data were methodically coded and examined utilizing the Statistical Package for the Social Sciences (SPSS) software, emphasizing the production of descriptive statistics such as frequencies, means, and standard deviations to discern dominant trends and patterns.

Along with the survey, a detailed case study of a solar energy project was conducted to provide a practical performance assessment. The chosen project entailed the augmentation of an existing solar system via DC-side oversizing, exemplifying a key initiative in Jordan's renewable energy strategy. The research simulation for this case study was carried out in an organized, multi-step way. To get an accurate digital picture of the project's scope, it started with the creation of a detailed 3D model using Building Information Modelling software, Autodesk Revit 2020. This model made it possible to get exact quantity take-offs, which helped with the next step of detailed project planning.

Oracle Primavera P6, a widely used project management software, was used to make the project schedule, resource allocation, and cost baseline. This established a robust Performance Measurement Baseline (PMB) against which project performance could be objectively measured. Then, the principles of Earned Value Management were strictly followed. At different points in the project, data on actual progress and costs were entered into the system to calculate key EVM metrics like Planned Value (PV), Earned Value (EV), Actual Cost (AC), Schedule and Cost Variances (SV, CV), and Performance Indices (SPI, CPI). This analysis gave a detailed account of how the project was doing over time.

The methodology also included a conceptual model of how AI could be integrated. The project's control processes were used to figure out how certain AI technologies could be used. This included using drone-based images to simulate computer vision for automatic verification of progress on site and the percentage of work that was done. It also included modelling the use of Natural Language Processing to automatically look at project reports and communications to find out how things are going and what people think, as well as Machine Learning algorithms to make predictions about the final cost and schedule based on past and current performance data. This comprehensive methodology, integrating empirical survey data with in-depth case study analysis, established a nuanced and evidence-based framework for assessing the feasibility, advantages, and obstacles of an AI-enhanced EVM system. Was theoretically structured within the case study framework.

The research design adopted in this study combines three complementary analytical components. First, a case study analysis was conducted using traditional Earned Value Management metrics to evaluate project performance deviations in a real renewable energy project. Second, an industry-wide survey involving 394 professionals was performed to examine practitioner awareness, readiness, and perceived value of AI adoption in project control. Third, the study develops a conceptual framework illustrating how Artificial Intelligence technologies could enhance traditional EVM processes. This triangulated research design strengthens the empirical grounding of the study while providing strategic insights into future AI-enabled project management systems.

3.1 Conceptual Framework for AI–EVM Integration

The integration of Artificial Intelligence (AI) with Earned Value Management (EVM) in this study is presented as a conceptual framework rather than a fully operational system. The objective is to illustrate how AI technologies could potentially enhance traditional EVM practices by improving data acquisition, forecasting capabilities, and decision-support mechanisms in renewable energy project management. Traditional EVM relies on periodic manual reporting to calculate key performance indicators such as Planned Value (PV), Earned Value (EV), and Actual Cost (AC). Although these metrics provide useful diagnostic insights, they are inherently reactive and depend heavily on subjective progress estimation. Consequently, project managers often identify performance deviations only after significant schedule delays or cost overruns have already occurred. Previous studies have highlighted these limitations, particularly in complex infrastructure and construction projects where performance conditions change dynamically [7,17].

Within the proposed conceptual framework, Artificial Intelligence technologies can enhance EVM through three primary mechanisms. First, Computer Vision (CV) systems can be used to automatically capture and analyze visual site data obtained from drones or surveillance cameras. These systems can detect installed components, measure construction progress, and provide objective updates to Earned Value (EV) calculations. Automated progress monitoring has been increasingly explored in construction research and has demonstrated significant potential to reduce reporting bias and improve project transparency [32].

Second, Machine Learning (ML) algorithms can analyze historical and real-time project performance data to improve forecasting accuracy. By identifying nonlinear relationships between cost, productivity, and schedule variables, ML models can estimate the likely range of final project costs (Estimate at Completion – EAC) and schedule outcomes. Several studies have shown that ML-based predictive models outperform traditional EVM forecasting equations in dynamic project environments [27,33]. Third, Natural Language Processing (NLP) techniques can extract relevant information from project documentation such as progress reports, meeting minutes, contractual correspondence, and daily site logs. These tools enable automated detection of project risks, delays, and change orders that may influence cost and schedule performance. NLP-based information extraction has been identified as a promising tool for improving communication analysis and project reporting efficiency [18]. It is important to emphasize that the present study does not implement a fully automated AI–EVM system. Instead, the research evaluates the potential value of such integration by combining two complementary empirical approaches. The first approach involves an EVM-based case study analysis of a solar photovoltaic project in Jordan to identify the limitations of traditional performance monitoring. The second approach consists of an industry-wide survey examining practitioner perceptions regarding the feasibility, benefits, and challenges associated with adopting AI-enhanced project control systems.

The conceptual framework developed in this study therefore provides a strategic blueprint for future AI-enabled EVM systems, particularly in the context of renewable energy projects within developing economies where digital maturity and data infrastructure are still evolving [26,29].

4 Results and Discussion

This section presents the empirical findings derived from the instrumental case study and the large-scale industry survey. Together, these results provide a comprehensive evaluation of the performance limitations of traditional Earned Value Management (EVM) practices and the perceived potential of integrating Artificial Intelligence (AI) into project control systems within Jordan's renewable energy sector.

4.1 Findings from the Case Study: Diagnostic Performance Assessment Using EVM

The EVM analysis conducted for the solar photovoltaic system upgrade project revealed significant deviations between planned and actual performance. Table 3 shows the results at Week 4, a critical early-stage milestone where performance inefficiencies became clearly visible.

Table 3: Earned Value Analysis at Week 4

Parameter	Value (JD)	Interpretation
BAC	54,700	Total project budget
PV	9,500	Planned progress
EV	7,125	Actual earned progress
AC	12,700	Actual cost incurred
SV	–2,375	Behind schedule
CV	–5,575	Over budget
SPI	0.75	Inefficient schedule performance
CPI	0.56	Severe cost inefficiency

The large negative schedule variance (SV) and cost variance (CV) indicate that the project, although only in its fourth week, was already experiencing productivity delays and budget overruns. The Integrated Performance Index (SPI) of 0.75 reflects a 25% delay compared to the planned pace, while the Cost Performance Index (CPI) of 0.56 suggests the project achieved a value of only 56 cents for every Jordanian dinar spent. These performance indicators reveal systemic deficiencies that require early corrective action.

As illustrated in Figure 2, schedule performance gradually recovered in subsequent weeks, while cost performance steadily deteriorated, with the cost performance index stabilizing at around 0.31 by the project's midpoint. This critical level of cost inefficiency ultimately led to a negative completion performance index (TCPI) by week 11, mathematically confirming the impossibility of completing the project within the original budget**.**

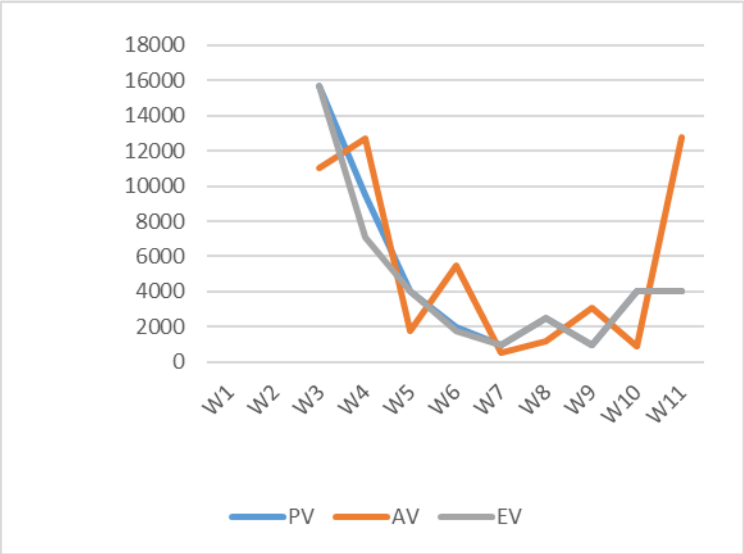

Fig. 2. EVM performance curves (PV, EV, and AC) over time.

As illustrated in Fig. 2, the EVM performance curves (PV, EV, and AC) show persistent cost overruns, with AC consistently exceeding both PV and EV throughout the reporting periods.

A root cause analysis indicated that the poor performance stemmed from:

a) inaccurate early cost and productivity estimates,

b) delays in subcontracted mechanical and electrical works,

c) unrecorded field changes and undocumented rework, and

d) inconsistent progress reporting due to manual measurement practices.

These findings demonstrate the inherent limitations of traditional manual EVM, which relies on subjective progress estimates, periodic reporting cycles, and static forecasting formulas. Had AI-based methods—such as computer vision for objective progress tracking or machine learning for predictive forecasting—been implemented, several deviations could have been identified earlier.

4.2 Reliability Analysis

To ensure the reliability of the survey instrument, Cronbach’s alpha coefficient was calculated using SPSS software to assess the internal consistency of the questionnaire constructs. Cronbach’s alpha is widely used in social science research to evaluate the reliability of multi-item measurement scales and is generally considered acceptable when the coefficient exceeds the recommended threshold of 0.70. The reliability analysis results indicate a high level of internal consistency across all constructs included in the questionnaire. The overall Cronbach's alpha coefficient for the instrument was 0.87, which indicates strong reliability. In addition, the individual constructs measuring perceptions of AI usefulness, AI–EVM integration benefits, and implementation barriers also demonstrated satisfactory reliability, with alpha values ranging from 0.82 to 0.89. The results summarized in Table 4 confirm that the survey instrument provides reliable measurements for evaluating practitioner perceptions regarding the integration of Artificial Intelligence technologies into Earned Value Management practices.

Table 4: Reliability Analysis of Survey Constructs

Construct	Number of Items	Cronbach's Alpha
AI Usefulness	6	0.89
AI–EVM Integration Benefits	5	0.86
Implementation Barriers	5	0.82
Overall Instrument	16	**0.87**

4.3 Correlation Analysis

To further explore the relationships between key variables in the survey data, a Pearson correlation analysis as shown in Table 5 was conducted using SPSS. The analysis examined the relationships between respondents' familiarity with Artificial Intelligence technologies, their knowledge of Earned Value Management (EVM), and their perceptions of the effectiveness of integrating AI with project control systems. The results indicate a statistically significant positive correlation between AI familiarity and perceived effectiveness of AI–EVM integration ($r = 0.61$, $p < 0.01$). This suggests that respondents who possess greater awareness of AI technologies are more likely to recognize their potential benefits for improving project monitoring and forecasting.

Table 5: Pearson Correlation Matrix for AI–EVM Survey Variables

Variables	AI Familiarity	EVM Knowledge
AI Familiarity	1	0.48
EVM Knowledge	0.48	1
AI–EVM Effectiveness	0.61**	0.54**

Note: **Correlation is significant at $p < 0.01$

4.4 Survey Results: Industry Awareness, Readiness, and Perceived Value

The analysis of 394 valid responses provided critical insights into the industry's perspective on AI and EVM.

4.4.1 Awareness and Current Application

Only 24.8% of respondents indicated familiarity with Earned Value Management, revealing a limited penetration of formal performance measurement frameworks in Jordan’s renewable energy projects. In contrast, 63.2% reported involvement in projects that utilized AI tools—mainly in solar energy design optimization, load prediction, or automated monitoring—suggesting that AI adoption is outpacing EVM adoption.

This mismatch underscores the potential of AI-driven performance frameworks to bridge existing knowledge gaps and modernize project control practices.

4.4.2 Perceived Effectiveness of AI-EVM Integration

Respondents expressed strong belief in the synergistic potential of AI and EVM. As shown in Table 6, a majority believed AI could "extremely" enhance key aspects of EVM, particularly in decision-making and forecasting.

Table 6: Perceived Impact of AI on EVM Aspects

EVM Function Enhanced by AI	% Rating “Extremely Useful”
Decision-making via predictive insights	61.7%
Real-time performance tracking	57.1%
Cost and schedule forecasting	55.3%
Automating data collection/reporting	53.6%

This perceived value translates directly to project outcomes. When asked about the effectiveness of the combined AI-EVM approach, an overwhelming majority found it "Very Effective" for improving core project constraints: Cost Performance (76.4%), Time Performance (72.6%), and Risk Forecasting (72.8%) as shown in figure3.

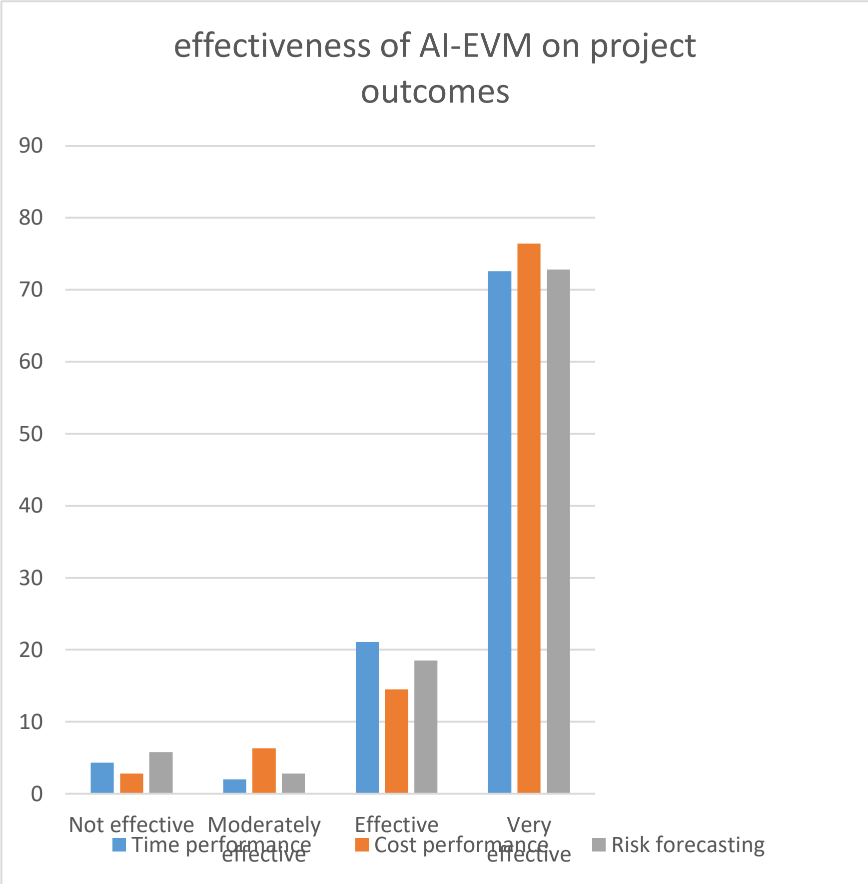

Fig. 3. Effectiveness of AI-EVM on Project Outcomes

(A bar chart illustrating the high percentage of respondents rating the integration as "Very Effective" for cost, time, and risk management.)

These results indicate strong industry confidence in the practical value of adopting AI-enhanced project control systems, particularly for predictive functions that traditional EVM struggles to perform.

4.4.3 Key Barriers to Adoption AI and EVM

Despite the recognized potential, significant barriers to adoption persist. The survey identified a complex set of interconnected challenges, ranked by the percentage of respondents who found them "extremely significant". Figure 4: Key Challenges in Implementing AI.

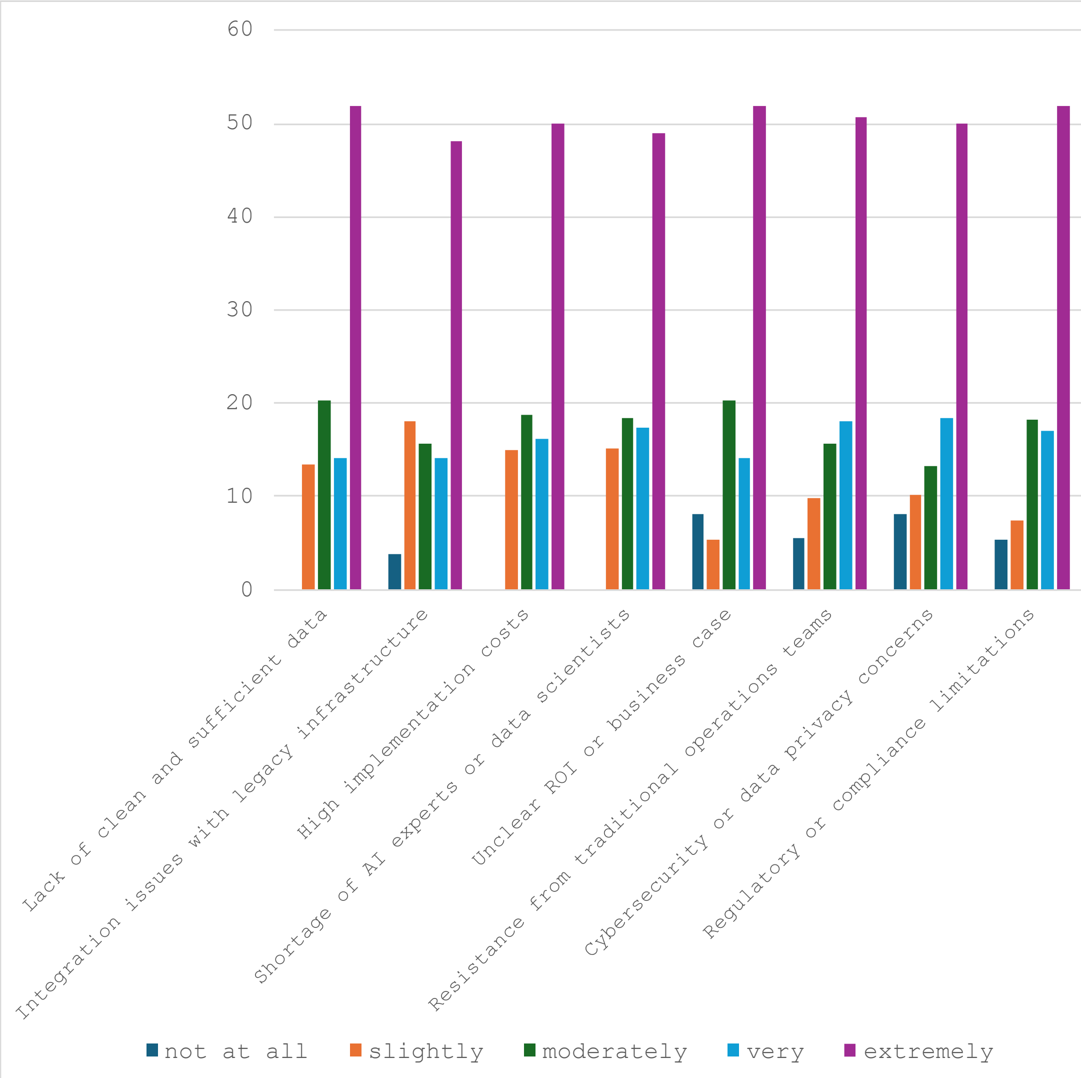

Fig. 4.

Key Challenges in Implementing AI

(A horizontal bar chart ranking obstacles: Lack of clean data (52%), Regulatory limitations (52%), Unclear ROI (52%), High implementation cost (50%), Cybersecurity concerns (50%), Resistance from teams (50.8%), Shortage of AI experts (49%), Integration with legacy systems (48.2%).)

These obstacles form a vicious cycle. The high cost and unclear ROI discourage investment, which perpetuates data quality issues and the shortage of skilled workforce, thereby preventing organizations from realizing the very benefits that would justify the investment. Synthesis of Applied AI–EVM Integration.

4.5 Synthesis of Applied AI-EVM Integration

The combined findings from the case study and the industry survey present a unified narrative regarding both the limitations of traditional Earned Value Management (EVM) and the transformative potential of integrating Artificial Intelligence (AI) into project control. The evidence clearly shows that conventional EVM, while effective in diagnosing performance deviations, is inherently reactive. Its dependence on manual data collection, subjective progress estimation, and periodic reporting restricts managers to identifying problems only after they have already occurred. This limitation was demonstrated in the case study, where significant cost overruns and schedule delays were detected by EVM, but only at a stage when corrective actions could no longer prevent budget escalation or declining productivity trends.

In contrast, integrating AI with EVM represents a paradigm shift from retrospective assessment to proactive, predictive control. The practical value of this integration is evident across several dimensions. Computer Vision (CV) technologies can autonomously assess physical progress—such as counting installed solar panels or detecting completed electrical work—thereby providing real-time, objective updates to Earned Value (EV) and eliminating the subjectivity that undermines traditional reporting practices. Natural Language Processing (NLP) can continuously analyze project communication channels, including reports, emails, and meeting minutes, to flag early signals of delays, scope changes, or emerging risks. This capability enables early warnings that directly support schedule and cost performance indicators (SPI and CPI).

Machine Learning (ML) models further enhance EVM's predictive capacity by analyzing historical and real-time performance data to produce probabilistic forecasts of the Estimate at Completion (EAC) and future schedule deviations. Instead of projecting future outcomes based solely on past performance trends, ML models can identify the underlying drivers of cost and schedule risks—such as poor subcontractor productivity or inaccurate early estimates—and quantify their likely impact. This transforms the EVM framework into an intelligent decision-support system capable of recommending timely corrective actions before deviations escalate.

The survey results reinforce these findings. Industry professionals demonstrated strong conceptual readiness for adopting AI-driven EVM enhancements, recognizing that AI directly addresses the core weaknesses of manual EVM processes. Respondents emphasized the potential of ML to improve forecasting accuracy, CV to enhance progress measurement, and NLP to automate reporting and risk detection. However, they also identified several organizational constraints—including limited data quality, skill shortages, and the absence of regulatory guidelines—that currently hinder widespread adoption.

Taken together, the case study and survey evidence highlight a compelling justification for implementing AI–EVM integration within renewable energy projects in Jordan. The sector's rapid expansion, complex technical requirements, and recurring performance inefficiencies make it an ideal environment for predictive, data-driven project control systems. By shifting from reactive monitoring to intelligent, real-time management, an AI-enhanced EVM framework offers the potential to significantly improve cost performance, schedule reliability, and overall project success.

5 Conclusion

This study examined the practical and strategic value of integrating Artificial Intelligence (AI) with Earned Value Management (EVM) to enhance project control in Jordan's renewable energy sector. By combining an instrumental case study of a solar photovoltaic system upgrade with a large-scale survey of industry professionals, the research provides robust empirical evidence highlighting the limitations of traditional EVM practices and the transformative potential of AI-enabled project monitoring and forecasting.

The case study demonstrated that conventional EVM, although effective in diagnosing early deviations, remains fundamentally reactive. Its reliance on manual progress measurement, subjective reporting, and static forecasting formulas constrained the project team's ability to intervene proactively. Persistent cost overruns, schedule delays, and inaccurate early estimates emphasized the need for more adaptive and data-driven performance measurement systems. AI technologies directly address these limitations. Machine Learning can enhance the accuracy of forecasting future cost and schedule outcomes, Computer Vision provides objective and continuous updates to Earned Value calculations, and Natural Language Processing enables automated risk detection from project communication channels. These capabilities collectively transform EVM from a historical reporting tool into an intelligent, predictive project control framework.

The survey findings reinforce this potential. Industry professionals expressed strong confidence in the ability of AI to improve project cost performance, schedule reliability, and risk forecasting. At the same time, respondents identified critical barriers—including inadequate data quality, shortage of skilled AI practitioners, regulatory gaps, and the high cost of digital transformation—that must be addressed to enable the successful adoption of AI-enhanced EVM systems. These challenges represent structural constraints that require coordinated action at organizational, sectoral, and national levels.

Overall, the study concludes that integrating AI with EVM is not merely an optional technological upgrade but a strategic necessity for improving the effectiveness of renewable energy projects in Jordan. To realize this potential, stakeholders should prioritize investment in digital infrastructure, workforce capacity-building, standardized data management practices, and supportive regulatory frameworks. Strengthening collaboration between industry, academia, and government agencies will also be essential to accelerate innovation and reduce barriers to implementation.

The proposed AI–EVM integration framework offers a pathway toward more efficient, reliable, and intelligent project control—one that aligns with global trends in digital transformation and supports Jordan's long-term renewable energy ambitions. Future research should focus on developing operational prototypes, testing AI–EVM systems across multiple project types, and evaluating their long-term impact on project delivery performance.

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