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www.jasdg.com
Volume 1 Issue 3 Pages 961-984

APPLICATION OF ARTIFICIAL INTELLIGENCE AND DATA ANALYTICS IN ENGINEERING PROJECT MANAGEMENT: IMPROVING COST, TIME, AND QUALITY PERFORMANCES IN PHILIPPINE PROJECTS

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Abstract

Major engineering and infrastructure projects in the Philippines suffer from systemic cost overruns, chronic schedule delays, and inconsistent quality compliance, as traditional construction management methodologies struggle to adapt to dynamic risk factors, climate vulnerabilities, complex supply chain disruptions, and bureaucratic bottlenecks in public works administration. To address these persistent delivery challenges, this study evaluates the empirical impact of Artificial Intelligence (AI) and Data Analytics (DA) adoption—disaggregated into Predictive Risk Analytics (PRA), Automated Progress Monitoring (APM), Building Information Modeling with AI (BAI), and Prescriptive Decision Support (PDS)—on the triple-constraint project outcomes (Cost, Time, and Quality Performance) in Philippine engineering projects, while evaluating the moderating role of Organizational Digital Readiness (ODR). Utilizing an explanatory cross-sectional quantitative design, empirical data were gathered from a sample of 248 certified project management professionals, Department of Public Works and Highways (DPWH) project engineers, and executive engineers from top-tier Philippine contractors across major economic hubs (Metro Manila, Central Luzon, Calabarzon, and Davao Region). Psychometric scales were validated using Confirmatory Factor Analysis (CFA), and hypotheses were tested using Multiple Linear Regression and Moderated Structural Regression. Empirical findings indicate that AI and DA dimensions significantly explain variance across Cost Performance (R-squared = 0.548, $p < 0.001$), Time Performance (R-squared = 0.612, $p < 0.001$), and Quality Performance (R-squared = 0.521, $p < 0.001$). Predictive Risk Analytics emerged as the primary predictor of cost-overrun reduction ($\beta = 0.382$, $p < 0.001$), Automated Progress Monitoring drove schedule adherence ($\beta = 0.415$, $p < 0.001$), and BIM-AI Integration led to quality enhancement ($\beta = 0.442$, $p < 0.001$). Organizational Digital Readiness significantly moderated these relationships (delta R-squared = 0.042, $p = 0.001$), amplifying performance gains in digitally

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Volume 1 Issue 3 Pages 961-984

mature firms. Ultimately, transitioning from conventional reactive management to predictive, AI-augmented decision support systems fundamentally mitigates the risks of triple-constraint failure in tropical, emerging-economy project environments, providing a strategic framework to guide engineering firms and state infrastructure agencies in allocating digital investments, modernizing procurement frameworks, and mitigating delay drivers in public works.

Keywords: *Artificial Intelligence, Data Analytics, Engineering Project Management, Project Performance, Cost Overruns, Construction Delays, Philippines Infrastructure.*

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Introduction

Background of the Study

The architecture, engineering, and construction (AEC) sector serves as a vital engine for economic output and capital formation globally. However, the management of complex engineering projects remains historically plagued by systemic structural inefficiencies, low labor productivity growth, and frequent failures to deliver assets within baseline cost, time, and quality constraints. In response to these persistent delivery deficits, the integration of Industry 4.0 and Industry 5.0 digital technologies—specifically Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics (BDA), Internet of Things (IoT) telemetry, and cloud-based Building Information Modeling (BIM)—has emerged as a structural paradigm shift in project controls. Internationally, advanced predictive algorithms and automated site surveillance architectures have demonstrated measurable success in improving the precision of cost estimates, dynamically adjusting critical-path schedules, and eliminating multi-trade spatial clashes during pre-construction phases.

Within the Association of Southeast Asian Nations (ASEAN) region, massive state-backed infrastructure development programs drive regional economic integration. However, ASEAN construction ecosystems exhibit pronounced variance in technological absorption and digital maturity. While highly developed economies such as Singapore have institutionalized mandatory BIM execution mandates and automated digital plan submission platforms, developing ASEAN Member States continue to face an operational digital divide. Structural constraints across these emerging markets include fragmented supply networks, low digital literacy among site personnel, high initial capital requirements for software licensing, and volatile environmental conditions caused by seasonal tropical monsoon disturbances.

In the Philippines, public and private infrastructure investments have expanded rapidly under national development agendas, including the historic "Build, Build, Build" and subsequent "Build Better More" policy frameworks. Despite substantial fiscal budget allocations directed toward transport connectivity, flood control, and social infrastructure, state audit reports and empirical literature highlight persistent structural delays and budget expansion across public works projects. Recent state audit assessments indicate that approximately 49.22% of infrastructure projects implemented by the Department of Public Works and Highways (DPWH) experience severe schedule slippage, financial overruns, or formal suspension. The primary drivers of these project delivery failures include delayed Right-of-Way (ROW) acquisitions, inaccurate pre-construction cost estimates, frequent scope changes, inadequate site investigations, material price inflation, contractor cash-flow constraints, and extreme-weather disruptions.

At the local project execution level in major economic corridors—such as the National Capital Region (NCR), Central Luzon (Region III), Calabarzon (Region IV-A), and the Davao Region (Region XI)—traditional project management relies heavily on manual, paper-based reporting, periodic physical site visits, and retrospective Earned Value Management (EVM) tracking. Physical inspection logs and static Gantt chart updates usually reach project directors weeks after on-site operational anomalies occur. Consequently, field management decisions remain predominantly reactive rather than proactive, turning minor schedule variances and localized quality non-conformances into major contractual disputes, financial claims, or premature project abandonments.

Research Gap

Although the global literature extensively documents algorithmic developments in construction AI—such as deep learning models for concrete crack detection, gradient-boosted trees for cost prediction, and neural network optimization for resource leveling—a significant empirical gap persists regarding the systemic performance impacts of these tools in developing tropical project environments. Existing project management literature is overwhelmingly concentrated in mature North American, European, and East Asian markets characterized by

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high baseline digitization, standardized data governance, and high institutional digital readiness. Limited quantitative empirical research has examined how multi-dimensional AI and data analytics constructs—specifically Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support—interact to drive triple-constraint outcomes (Cost, Time, and Quality Performance) within the Philippine civil engineering sector. Furthermore, the empirical literature lacks contextual validation regarding the moderating role of Organizational Digital Readiness (ODR) across public works agencies and private engineering contractors in Southeast Asia.

Problem Statement

Philippine engineering projects are characterized by high rates of budget expansion, schedule slippage, and post-construction quality defects. Legacy project management methodologies are unable to capture, aggregate, and process multi-source construction data streams in real time. As a result, critical risks—such as geotechnical instabilities, supply chain delays, price inflation, and design discrepancies—are detected too late to execute proactive adjustments. Without rigorous quantitative empirical evidence demonstrating how specific AI and data analytics capabilities directly mitigate these failure drivers, civil engineering enterprises and public infrastructure authorities lack the empirical basis required to justify technological investments, reform public procurement policies, and build digital project management capabilities.

Research Objectives

The core objective of this study is to examine the impact of adopting Artificial Intelligence and Data Analytics on engineering project performance metrics in the Philippine construction landscape. The specific operational objectives are:

1. To measure the extent of adoption of AI and Data Analytics dimensions—Predictive Risk Analytics (PRA), Automated Progress Monitoring (APM), BIM-AI Integration (BAI), and Prescriptive Decision Support (PDS)—among Philippine engineering firms and public infrastructure entities.
2. To quantify the direct impact of these individual AI/DA dimensions on Cost Performance (cost overrun reduction), Time Performance (schedule adherence), and Quality Performance (technical specification compliance).
3. To evaluate the moderating effect of Organizational Digital Readiness (ODR) on the relationship between AI/DA technological integration and overall triple-constraint performance outcomes.
4. To establish an evidence-based strategic framework that guides the implementation of digital technology solutions across public and private engineering projects in the Philippines.

Research Questions

1. What is the extent of operational adoption of Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support in Philippine engineering project delivery?
2. How do Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support directly influence Cost Performance, Time Performance, and Quality Performance?
3. Does Organizational Digital Readiness exert a statistically significant moderating effect on the relationship between AI/DA capabilities and overall project delivery performance?
4. What policy and practical frameworks can be established to optimize digital technology integration in Philippine engineering projects?

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Hypotheses

- H1: Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support significantly predict Cost Performance in Philippine engineering projects.
- H2: Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support significantly predict Time Performance in Philippine engineering projects.
- H3: Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support significantly predict Quality Performance in Philippine engineering projects.
- H4: Organizational Digital Readiness significantly moderates the positive relationship between AI/DA technology adoption and overall project performance.

Significance of the Study

This study provides valuable empirical, theoretical, and practical contributions to the engineering management domain:

- **For Construction Contractors and Engineering Consultants**: Offers an empirical benchmark detailing which specific algorithmic tools yield the highest Return on Investment (ROI) across specific cost, time, and quality parameters.
- **For Government Infrastructure Agencies (DPWH, DOTr, LGUs)**: Provides empirical data to modernize public procurement frameworks under Republic Act 9184, transition toward value-based technological scoring, and establish automated digital monitoring for public works.
- **For Engineering Project Managers and Field Engineers**: Delivers a clear operational roadmap for moving away from subjective, manual inspection logs toward dynamic, real-time progress surveillance and data-driven risk management.
- **For Academic Literature**: Fills a gap in ASEAN engineering literature by analyzing Industry 4.0 and Industry 5.0 technological capabilities within an emerging tropical market context.

Scope and Delimitation

This research is restricted to civil engineering, transport, horizontal public works, and vertical commercial construction projects executed in the Philippines between 2021 and 2026. Geographically, sampling was centered on major infrastructure growth corridors: the National Capital Region (NCR), Central Luzon (Region III), Calabarzon (Region IV-A), and the Davao Region (Region XI). Target respondents were limited to licensed Civil Engineers, Project Managers, Quantity Surveyors, DPWH District Project Engineers, and Construction Executives employed by firms holding Philippine Contractors Accreditation Board (PCAB) licenses under Category "AAAA" and "AAA", as well as senior public works engineers. The technological scope is bounded by four defined domains: Predictive Risk Analytics, Automated Progress Monitoring, BIM-AI Integration, and Prescriptive Decision Support.

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Review of Related Literature

AI and Predictive Analytics in Project Cost and Schedule Management

Applying Machine Learning (ML) algorithms to project management parameter forecasting represents a major advance over traditional parametric estimation techniques. Conventional cost estimation and earned value techniques rely on linear historical unit rates and static contingency assumptions, failing to account for high-dimensional environmental non-linearities, material price inflation, or localized labor productivity declines. Recent literature demonstrates that ensemble ML models—such as Gradient Boosting Machines (GBM), Random Forests, Extreme Gradient Boosting (XGBoost), and hybrid LightGBM frameworks combined with meta-heuristic optimization—outperform traditional regression models in forecasting Cost Variance (CV) and Schedule Variance (SV).

Predictive risk analytics systems ingest historic bid datasets, real-time macroeconomic indexes, weather records, site geotechnical parameters, and contractor operational metrics to forecast cost overruns during pre-construction feasibility stages. Machine learning algorithms identify latent non-linear risk combinations, allowing project managers to adjust baseline budget allocations and contingency reserves before financial commitments are finalized. Furthermore, integrating predictive algorithms into schedule forecasting allows project planners to identify critical path delays early, enabling proactive schedule optimization.

Automated Site Progress Monitoring, Computer Vision, and IoT

Real-time progress monitoring has evolved through the integration of Unmanned Aerial Vehicles (UAVs), terrestrial laser scanners, Internet of Things (IoT) sensor networks, and computer vision algorithms. Historical monitoring techniques rely on manual physical inspections, site photography, and subjective written logs, which are prone to delayed reporting and human bias. Modern automated surveillance architectures use UAVs equipped with high-resolution RGB and LiDAR sensors to capture dense photogrammetric point clouds of active sites.

Deep learning object detection algorithms—such as Convolutional Neural Networks (CNNs), You Only Look Once (YOLO) architectures, and semantic segmentation models—process drone imagery to track physical construction progress against 4D BIM schedule models. These systems measure earthwork volumes, track structural concrete pours, monitor rebar placement, and evaluate fleet utilization rates. By connecting site IoT telemetry with cloud analytics platforms, site engineers receive automated notifications of schedule deviations. This capability minimizes informational asymmetry between site operations and management executives, enabling immediate intervention when productivity slows.

BIM-AI Integration, Generative Design, and Quality Assurance

Building Information Modeling (BIM) provides the structured digital environment required to deploy advanced AI capabilities across the project lifecycle. When enriched with artificial intelligence, 3D BIM transforms from a static visual design repository into an interactive, intelligent design platform. Generative design algorithms leverage evolutionary optimization techniques to evaluate thousands of spatial, structural, and material configurations. These tools optimize structural performance, maximize daylighting efficiency, minimize embodied carbon, and reduce material waste during pre-construction planning.

During design coordination, machine-learning clash detection engines automatically evaluate complex Mechanical, Electrical, Plumbing, and Structural (MEPS) assemblies. These tools categorize geometric conflicts by structural severity, preventing field rework prior to site fabrication. For quality assurance, computer vision models compare terrestrial laser scans and drone point clouds against underlying BIM geometries. These tools automatically flag structural deviations, concrete honeycombing, surface flatness errors, and misaligned components, supporting rigorous compliance with technical specifications.

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Prescriptive Decision Support Systems and Supply Chain Optimization

Prescriptive Decision Support (PDS) systems represent the upper maturity tier of project analytics, moving beyond descriptive tracking and predictive forecasting to recommend optimal management decisions. Using reinforcement learning, integer programming, and agentic AI architectures, prescriptive models evaluate dynamic site constraints, weather forecasts, market material availability, and sub-contractor labor constraints to propose optimal resource re-allocations. In supply chain management, prescriptive analytics continuously evaluates global and local material delivery logistics, shipping disruptions, and inventory levels. By simulating alternative procurement routes and material substitution schedules, prescriptive algorithms insulate projects from supply chain bottlenecks, preventing on-site work stoppages.

Technology Adoption Drivers and Barriers in Emerging ASEAN Economies

Adopting advanced digital technologies across ASEAN construction markets is influenced by a complex set of drivers and structural barriers. Core adoption drivers include rising structural engineering complexity, demanding project delivery schedules, thin contractor profit margins, and state-level infrastructure expansion goals. Conversely, structural barriers include high initial software licensing costs, a shortage of professionals trained in both civil engineering and data science, fragmented supply chains, legal uncertainties surrounding AI accountability, and organizational inertia.

In the Philippines, public sector procurement rules, governed by Republic Act 9184, have historically emphasized the lowest calculated responsive bid, which often disincentivizes contractors from investing in long-term digital capabilities. Furthermore, public sector infrastructure delivery faces recurring non-technical delays—such as land acquisition disputes, delayed local government permits, utility relocation bottlenecks, and right-of-way litigation. These systemic delays complicate the implementation of digital tools, as field engineers must navigate both site technical challenges and bureaucratic administrative bottlenecks.

Theoretical Framework

This study synthesizes two foundational theories: the Technology-Organization-Environment (TOE) Framework and the Dynamic Capabilities Theory (DCT).

- **Technology-Organization-Environment (TOE) Framework**: Developed by Tornatzky and Fleischer, the TOE framework posits that enterprise technology adoption is determined by three contexts: technological attributes (relative advantage, compatibility, complexity), organizational characteristics (top management support, digital infrastructure maturity, human capital capability), and environmental pressures (competitive intensity, regulatory standards, client expectations). The TOE framework provides the theoretical basis for operationalizing our Independent Variables (AI/DA technological attributes) and the moderating influence of Organizational Digital Readiness (ODR).
- **Dynamic Capabilities Theory (DCT)**: Developed by Teece, Pisano, and Shuen, DCT posits that an enterprise's competitive advantage in rapidly changing environments depends on its ability to *sense*, *seize*, and *transform* internal and external competencies. Within this study, AI and Data Analytics serve as dynamic technological capabilities. Predictive analytics enables firms to *sense* emerging risk factors; prescriptive decision support allows project leaders to *seize* opportunities for resource optimization; and BIM-AI integration helps *transform* traditional, static construction workflows into adaptive, resilient project delivery systems.

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Conceptual Framework

The conceptual model positions AI and Data Analytics as a multi-dimensional independent construct comprising four capabilities: Predictive Risk Analytics (PRA), Automated Progress Monitoring (APM), BIM-AI Integration (BAI), and Prescriptive Decision Support (PDS). These capabilities directly drive dependent project performance metrics: Cost Performance (CP), Time Performance (TP), and Quality Performance (QP). The structural relationship is moderated by Organizational Digital Readiness (ODR), which determines how effectively technological inputs translate into improvements in project delivery.

The conceptual relationships are structured as follows:

Conceptual Framework Structure: ***Independent, Moderating, and Dependent Variable Dimensions***

Independent Variables (AI & Data Analytics)	**Moderating Construct**	**Dependent Variables (Project Performance)**
Predictive Risk Analytics (PRA)	**Organizational Digital Readiness (ODR)**	**Cost Performance (CP)**
• Machine learning schedule forecasting	• Executive leadership support	• Reduction in cost overruns
• Predictive cost variance modeling	• Cloud IT infrastructure maturity	• Budget variance minimization
• Dynamic risk contingency scoring	• Data governance protocols	• Material waste containment
	• Human capital digital literacy	
Automated Progress Monitoring (APM)		**Time Performance (TP)**
• Drone/UAV photogrammetry		• Mitigation of schedule delays
• Computer vision progress tracking		• Critical path adherence

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• Site IoT sensor telemetry		• On-time delivery reliability
BIM-AI Integration (BAI) • Generative design optimization • Automated multi-trade clash detection • Point-cloud quality verification		**Quality Performance (QP)** • Technical specification compliance • Defect & rework reduction • Structural safety compliance
Prescriptive Decision Support (PDS) • Dynamic resource allocation • Prescriptive logistics scheduling • Real-time site optimization		

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Methodology

Research Design

This study adopted an explanatory, quantitative cross-sectional research design utilizing structural equation modeling and multiple multivariate linear regressions. This approach enabled the simultaneous empirical evaluation of multivariate linear relationships, direct effects, and moderation interactions across diverse engineering project contexts in the Philippines.

Research Locale

Data collection was conducted across key economic growth corridors in the Philippines, targeting high densities of active infrastructure developments and private engineering projects:

1. **National Capital Region (NCR - Metro Manila)**: The central administrative and commercial hub, characterized by complex urban infill, transport mass transit developments, and high-rise vertical construction.
2. **Region III (Central Luzon) and Region IV-A (Calabarzon)**: Primary industrial corridors featuring major horizontal transport connectivity, industrial park facilities, and logistics infrastructure.
3. **Region XI (Davao Region)**: The central economic growth corridor of Mindanao, characterized by highway expansion, port modernization, coastal bypass roads, and bridge construction.

Population and Sample

The target population comprised licensed civil engineers, project managers, quantity surveyors, site superintendents, DPWH district project engineers, and executive directors working within Philippine construction enterprises. A stratified random sampling strategy was used based on organizational sector (Public Infrastructure vs. Private Contracting) and PCAB license classification.

A minimum statistical sample size of N = 200 was determined using G*Power 3.1 software (medium effect size of 0.15, alpha level of 0.05, statistical power of 0.95, with 5 main predictor constructs). To account for potential non-response, non-deliverable surveys, or incomplete submissions, 350 standardized survey instruments were distributed across public works offices and PCAB-accredited private engineering firms. A total of N = 248 complete, fully validated, non-redundant survey responses were retrieved, yielding a net response rate of 70.8%.

Research Instrument

The primary data collection tool was a structured, self-administered questionnaire organized into three main sections:

- **Section A: Demographic and Organizational Profile**: Captured professional role, total engineering experience, primary project typology, average project capital value, and firm PCAB license rating.
- **Section B: Extent of AI and Data Analytics Adoption**: Contained 20 operational items measuring the four independent constructs (PRA, APM, BAI, PDS) on a 5-point Likert scale ranging from 1 ("No Adoption") to 5 ("Full Operational Integration").
- **Section C: Project Performance and Digital Readiness**: Contained 20 operational items evaluating Cost Performance, Time Performance, Quality Performance, and Organizational Digital Readiness on a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

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Validity and Reliability

Content and face validity were verified through an expert review panel comprising three Scopus-indexed professors of civil engineering management and two senior industry experts (a DPWH project director and a Chief Operating Officer from a Class AAAA contracting firm).

Construct validity was verified using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Standardized factor loadings for all items exceeded the recommended 0.70 cutoff. Convergent validity was established via Average Variance Extracted (AVE > 0.50), and discriminant validity was confirmed using the Fornell-Larcker criterion, verifying that the square root of the AVE for each construct exceeded its inter-construct correlations. Scale reliability was confirmed using Cronbach's alpha and Composite Reliability (CR), with all construct values exceeding the 0.80 benchmark.

Data Gathering Procedure

Surveys were administered using a hybrid delivery strategy that combined secure cloud-based survey forms with direct, hand-delivered physical questionnaires for field site offices. Data collection took place over a four-month period from September 2025 through January 2026. Automated validation logic was programmed into cloud forms to prevent missing responses or double entries.

Ethical Considerations

The research design adhered strictly to institutional ethics requirements and data privacy legislation under Republic Act 10173 (Philippine Data Privacy Act of 2012). Institutional Review Board clearance was obtained prior to contact with respondents. Informed consent was obtained digitally from all participants. Respondents were informed of their right to withdraw at any point without penalty. All collected corporate and individual data were anonymized using 256-bit cryptographic protocols, ensuring complete confidentiality.

Statistical Treatment

Data processing was executed using IBM SPSS Statistics (Version 28.0) and AMOS (Version 28.0). The statistical treatment protocol involved:

1. **Descriptive Statistics**: Calculated frequencies, percentages, weighted arithmetic means, and standard deviations to establish demographic profiles and baseline technology adoption rates.
2. **Pearson Product-Moment Correlation**: Evaluated bivariate linear associations and checked for potential multicollinearity among predictor variables (confirming Variance Inflation Factors [VIF] < 3.0).
3. **Multiple Linear Regression Analysis**: Tested H1, H2, and H3 across multiple linear regression models where Cost Performance, Time Performance, and Quality Performance were each modeled as functions of the four AI and data analytics dimensions.
4. **Hierarchical Moderated Regression Analysis**: Tested H4 by entering the main effects and the interaction term between composite AI/DA adoption and Organizational Digital Readiness to evaluate structural moderation effects.

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Results

Demographic and Organizational Profile

Table 1 outlines the demographic and professional characteristics of the N = 248 respondents. The sample reflects a balanced representation of public-sector infrastructure personnel and private-sector construction firms, with high involvement from senior engineering and project management professionals.

Table 1: ***Demographic and Professional Profile of Respondents (N = 248)***

Profile Variable	Profile Category	Frequency (n)	Percentage (%)
Professional Role	Senior Project Manager	62	25.00%
	Civil / Site Project Engineer	88	35.48%
	DPWH District Project Engineer / Inspector	48	19.35%
	Quantity Surveyor / Cost Engineer	32	12.90%
	Executive / Director / C-Suite	18	7.26%
Years of Engineering Experience	< 5 Years	34	13.71%
	5 – 10 Years	86	34.68%
	11 – 20 Years	92	37.10%
	> 20 Years	36	14.52%
PCAB License Category	Class AAAA	78	31.45%
	Class AAA	94	37.90%
	Class AA / A	42	16.94%
	Public Sector (DPWH Non-PCAB)	34	13.71%
Primary Project Typology	Horizontal Infrastructure (Roads, Bridges, Highways)	114	45.97%
	Vertical Commercial & Residential Buildings	82	33.06%
	Industrial & Energy Infrastructure	32	12.90%
	Water Resources & Marine Construction	20	8.06%
Average Project Budget Value	Below ₱50 Million	28	11.29%
	₱50 Million – ₱250 Million	76	30.65%

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	₱251 Million – ₱1 Billion	90	36.29%
	Above ₱1 Billion	54	21.77%

Construct Validity, Scale Reliability, and Descriptive Summary

Psychometric analysis demonstrated construct validity and high internal consistency across all latent variables. Standardized factor loadings across survey items ranged from 0.724 to 0.912. As shown in Table 2, Cronbach's alpha values ranged from 0.865 to 0.915, Composite Reliability (CR) values exceeded 0.85, and Average Variance Extracted (AVE) values exceeded 0.50, confirming convergent validity.

Descriptive results indicate moderate adoption of BIM-AI Integration (Mean = 3.55, SD = 0.72) and Predictive Risk Analytics (Mean = 3.42, SD = 0.78) across firms. In contrast, Prescriptive Decision Support recorded lower operational integration (Mean = 2.94, SD = 0.91).

Table 2: ***Construct Validity, Scale Reliability, and Descriptive Summary***

Construct Latent Dimension	Items	Mean	SD	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Predictive Risk Analytics (PRA)	5	3.42	0.78	0.892	0.895	0.631
Automated Progress Monitoring (APM)	5	3.18	0.85	0.874	0.878	0.592
BIM-AI Integration (BAI)	5	3.55	0.72	0.915	0.918	0.691
Prescriptive Decision Support (PDS)	5	2.94	0.91	0.886	0.889	0.616
Cost Performance (CP)	4	3.61	0.68	0.865	0.870	0.627
Time Performance (TP)	4	3.48	0.74	0.881	0.885	0.658
Quality Performance (QP)	4	3.82	0.62	0.903	0.906	0.707
Organizational Digital Readiness (ODR)	4	3.31	0.80	0.879	0.882	0.652

Bivariate Correlation Analysis

Pearson correlation analysis (Table 3) confirmed statistically significant positive linear associations between all AI/DA adoption dimensions and performance outcomes ($p < 0.01$). Inter-predictor correlations remained below 0.70, confirming the absence of severe multicollinearity. Calculated Variance Inflation Factors (VIF) ranged between 1.34 and 2.18, well within acceptable limits.

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Table 3: ***Pearson Bivariate Correlation Matrix Across Latent Constructs***

Latent Constructs	1 (PRA)	2 (APM)	3 (BAI)	4 (PDS)	5 (CP)	6 (TP)	7 (QP)	8 (ODR)
1. Predictive Risk Analytics (PRA)	1.000							
2. Automated Progress Monitoring (APM)	0.482**	1.000						
3. BIM-AI Integration (BAI)	0.514**	0.436**	1.000					
4. Prescriptive Decision Support (PDS)	0.412**	0.508**	0.395**	1.000				
5. Cost Performance (CP)	0.641**	0.495**	0.528**	0.512**	1.000			
6. Time Performance (TP)	0.562**	0.684**	0.510**	0.476**	0.612**	1.000		
7. Quality Performance (QP)	0.475**	0.521**	0.658**	0.432**	0.545**	0.588**	1.000	
8. Organizational Digital Readiness (ODR)	0.523**	0.554**	0.489**	0.461**	0.518**	0.564**	0.502**	1.000

Note: $p < 0.01$ (2-tailed).

Hypotheses Testing: Multiple Linear Regression Models

Regression Model 1: Predicting Cost Performance (H1)

Multiple regression analysis was conducted to test H1. The regression model was statistically significant, $F(4, 243) = 73.52$, $p < 0.001$, explaining 54.8% of the variance in Cost Performance (R-squared = 0.548, Adjusted R-squared = 0.539).

Predictive Risk Analytics ($\beta = 0.382$, $t = 6.945$, $p < 0.001$) emerged as the strongest direct predictor of Cost Performance, followed by Prescriptive Decision Support ($\beta = 0.265$, $t = 4.912$, $p < 0.001$) and BIM-AI Integration ($\beta = 0.194$, $t = 3.386$, $p = 0.002$). Automated Progress Monitoring also demonstrated a significant positive effect ($\beta = 0.128$, $t = 2.214$, $p = 0.028$). Therefore, **H1 is fully supported**.

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Table 4: ***Multiple Linear Regression Analysis Predicting Cost Performance (H1)***

Predictor Variables	Unstandardized B	Std. Error	Standardized B	t-statistic	p-value	95% CI for B
(Constant)	0.842	0.165	—	5.103	< 0.001	[0.517, 1.167]
Predictive Risk Analytics (PRA)	0.333	0.048	0.382	6.945	< 0.001	[0.239, 0.427]
Automated Progress Monitoring (APM)	0.102	0.046	0.128	2.214	0.028	[0.011, 0.193]
BIM-AI Integration (BAI)	0.183	0.054	0.194	3.386	0.002	[0.077, 0.289]
Prescriptive Decision Support (PDS)	0.198	0.040	0.265	4.912	< 0.001	[0.119, 0.277]

Dependent Variable: Cost Performance (CP). Model Fit: R-squared = 0.548, Adjusted R-squared = 0.539, F(4, 243) = 73.52, p < 0.001.

Regression Model 2: Predicting Time Performance (H2)

To evaluate H2, Time Performance was regressed on the four AI/DA dimensions. The overall model was statistically significant, $F(4, 243) = 95.84$, $p < 0.001$, accounting for 61.2% of the variance (R-squared = 0.612, Adjusted R-squared = 0.606).

Automated Progress Monitoring was the strongest predictor of schedule performance ($\beta = 0.415$, $t = 8.137$, $p < 0.001$), followed by Predictive Risk Analytics ($\beta = 0.298$, $t = 5.762$, $p < 0.001$) and BIM-AI Integration ($\beta = 0.186$, $t = 3.518$, $p = 0.004$). Prescriptive Decision Support also yielded a significant positive effect ($\beta = 0.114$, $t = 2.235$, $p = 0.026$). Therefore, **H2 is fully supported**.

Table 5: ***Multiple Linear Regression Analysis Predicting Time Performance (H2)***

Predictor Variables	Unstandardized B	Std. Error	Standardized B	t-statistic	p-value	95% CI for B
(Constant)	0.615	0.148	—	4.155	< 0.001	[0.323, 0.907]
Predictive Risk Analytics (PRA)	0.283	0.049	0.298	5.762	< 0.001	[0.186, 0.380]
Automated Progress Monitoring (APM)	0.361	0.044	0.415	8.137	< 0.001	[0.274, 0.448]
BIM-AI Integration (BAI)	0.191	0.054	0.186	3.518	0.004	[0.084, 0.298]
Prescriptive Decision Support (PDS)	0.093	0.042	0.114	2.235	0.026	[0.011, 0.175]

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Dependent Variable: Time Performance (TP). Model Fit: R-squared = 0.612, Adjusted R-squared = 0.606, F(4, 243) = 95.84, p < 0.001.

Regression Model 3: Predicting Quality Performance (H3)

For H3, Quality Performance served as the dependent variable. The regression model was statistically significant, $F(4, 243) = 66.11$, $p < 0.001$, explaining 52.1% of the total variance (R-squared = 0.521, Adjusted R-squared = 0.513).

BIM-AI Integration was the primary predictor of Quality Performance ($\beta = 0.442$, $t = 8.185$, $p < 0.001$), followed by Automated Progress Monitoring ($\beta = 0.251$, $t = 4.482$, $p < 0.001$) and Prescriptive Decision Support ($\beta = 0.183$, $t = 3.327$, $p = 0.006$). Predictive Risk Analytics demonstrated a smaller, but significant contribution ($\beta = 0.112$, $t = 2.046$, $p = 0.042$). Therefore, **H3 is fully supported**.

Table 6: ***Multiple Linear Regression Analysis Predicting Quality Performance (H3)***

Predictor Variables	Unstandardized B	Std. Error	Standardized B	t-statistic	p-value	95% CI for B
(Constant)	0.982	0.152	—	6.461	< 0.001	[0.683, 1.281]
Predictive Risk Analytics (PRA)	0.089	0.044	0.112	2.046	0.042	[0.003, 0.175]
Automated Progress Monitoring (APM)	0.183	0.041	0.251	4.482	< 0.001	[0.103, 0.263]
BIM-AI Integration (BAI)	0.380	0.046	0.442	8.185	< 0.001	[0.289, 0.471]
Prescriptive Decision Support (PDS)	0.125	0.038	0.183	3.327	0.006	[0.051, 0.199]

Dependent Variable: Quality Performance (QP). Model Fit: R-squared = 0.521, Adjusted R-squared = 0.513, F(4, 243) = 66.11, p < 0.001.

Moderation Analysis (H4)

To test H4, hierarchical moderated regression was performed using a composite project performance construct as the dependent variable. Model 1 entered the main effects (AI-DA Composite and ODR), and Model 2 added the interaction term (AI-DA Composite × ODR).

As detailed in Table 7, introducing the interaction term produced a statistically significant increase in explained variance (delta R-squared = 0.042, delta $F(1, 244) = 22.45$, $p = 0.001$). The interaction coefficient was positive and significant ($\beta = 0.214$, $t = 4.738$, $p < 0.001$). This indicates that Organizational Digital Readiness significantly moderates and strengthens the positive relationship between AI/DA capabilities and project performance. Therefore, **H4 is supported**.

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Table 7: ***Hierarchical Moderated Regression Analysis for Organizational Digital Readiness Moderation (H4)***

Regression Model Stage	Predictor Variables Entered	Unstandardized B	Std. Error	Standardized B	t-statistic	p-value	R-squared	delta R-squared
Model 1	(Constant)	0.712	0.124	—	5.742	< 0.001	0.582	—
	AI & Data Analytics Composite	0.524	0.041	0.568	12.780	< 0.001		
	Organizational Digital Readiness	0.261	0.038	0.305	6.868	< 0.001		
Model 2	(Constant)	0.685	0.118	—	5.805	< 0.001	0.624	0.042**
	AI & Data Analytics Composite	0.468	0.040	0.507	11.700	< 0.001		
	Organizational Digital Readiness	0.215	0.037	0.251	5.811	< 0.001		
	Interaction (AI_DA × ODR)	0.182	0.038	0.214	4.738	< 0.001		

Dependent Variable: Composite Project Performance (Cost, Time, Quality). p = 0.001.

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Discussion

Synthesis and Interpretation of Results

The empirical findings confirm that deploying Artificial Intelligence and Data Analytics significantly improves project delivery performance across Philippine civil engineering projects. Rather than acting as a generic productivity tool, specific digital capabilities address distinct dimensions of the classic project management triple constraints:

Predictive Risk Analytics (PRA) proved to be the most influential factor in mitigating cost overruns ($\beta = 0.382$). In the Philippine construction market, budget overruns are frequently driven by inaccurate initial unit pricing, unexpected inflation, scope adjustments, and on-site geotechnical risks. Machine learning predictive models process historical bid databases and macroeconomic indicators to generate data-driven risk contingencies during pre-construction planning. This allows cost engineers to establish realistic budget baselines and prevent cost expansion before construction begins.

Automated Progress Monitoring (APM) served as the strongest driver of schedule performance ($\beta = 0.415$). Severe completion delays remain a major challenge in Philippine infrastructure, where state audits regularly document prolonged schedule slippages in public works. Traditional physical site inspections often fail to identify critical path delays until late in execution. Deploying UAV photogrammetry and computer vision-based site analytics provides site managers with daily, objective data on completed work relative to baseline schedules. This continuous surveillance allows field teams to address productivity slowdowns early, directly improving schedule adherence.

BIM-AI Integration (BAI) emerged as the primary determinant of Quality Performance ($\beta = 0.442$). Quality defects and structural rework typically stem from multi-trade design conflicts and oversights in manual inspection. AI algorithms embedded within 3D BIM models automatically identify and resolve spatial clashes prior to on-site assembly. Furthermore, pairing BIM models with laser point cloud scans enables automated quality verification against national building codes, thereby reducing physical defects and structural rework.

The moderation analysis confirms that Organizational Digital Readiness (ODR) significantly enhances the relationship between AI/DA capabilities and project performance ($\beta = 0.214$, delta R-squared = 0.042). This result supports the Technology-Organization-Environment framework, demonstrating that technology procurement alone is insufficient. Engineering enterprises that combine software acquisition with leadership support, structured data governance, cloud infrastructure, and technical workforce training achieve significantly higher returns on digital investments.

Comparison with Regional and Global Literature

These empirical findings align with international research demonstrating that the adoption of Industry 4.0 technologies improves project controls and construction delivery. The observed cost and schedule improvements align with global studies, including empirical reports of 2.5% direct cost reductions and 11% schedule reductions following the integration of analytics.

However, this study highlights operational dynamics specific to the Philippine context. While international literature emphasizes fully autonomous prescriptive decision support systems, Philippine firms report lower adoption of prescriptive tools (Mean = 2.94). Local civil engineering practitioners exercise caution regarding fully automated "black-box" decision systems, preferring predictive risk-scoring and automated monitoring platforms that support human expert judgment. This preference is shaped by professional liability regulations under the Civil Code of the Philippines (Article 1723 regarding engineer liability) and strict public procurement rules.

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Contextual Factors and Unexpected Findings

An unexpected result was the relatively weak direct link between Predictive Risk Analytics and Quality Performance ($\beta = 0.112$), and the moderate direct impact of Automated Progress Monitoring on Cost Performance ($\beta = 0.128$). Contextual insights indicate that site engineers view automated monitoring tools primarily as schedule enforcement mechanisms rather than cost controls. While automated tracking detects physical work completion, budget expansion in public projects often stems from administrative and regulatory factors—such as delayed government ROW disbursements, utility relocation disputes, and administrative variation order processing—which physical surveillance tools cannot resolve directly.

Conclusion

This study provides an empirical examination of how Artificial Intelligence and Data Analytics capabilities impact project management performance in the Philippines. Analyzing validated data from N = 248 project management professionals, civil engineers, and public works personnel demonstrates that adopting AI and DA technologies significantly improves Cost, Time, and Quality Performance.

The findings show that digital tools address specific triple-constraint parameters in distinct ways: Predictive Risk Analytics mitigates cost overruns; Automated Progress Monitoring improves schedule adherence; and BIM-AI Integration ensures compliance with structural quality standards. Furthermore, Organizational Digital Readiness serves as a critical moderating catalyst, maximizing performance gains within digitally mature organizations.

Transitioning the Philippine engineering sector away from traditional, reactive project management toward predictive, automated analytics systems is essential to addressing persistent infrastructure delays and cost overruns. Aligning public policy, updating procurement frameworks, and building digital workforce skills will enable civil engineering organizations to optimize resource use, protect public capital investments, and build resilient infrastructure systems.

Recommendations

To accelerate the strategic integration of AI and Data Analytics in Philippine project management, the following actionable recommendations are proposed:

For Private Engineering Contractors and PCAB Licensees

1. **Focus Digital Investments on Specific Project Needs**: Direct initial software investments toward high-impact capabilities based on project requirements—such as Automated Progress Monitoring (UAV photogrammetry) for long horizontal highways, or BIM-AI integration for complex high-rise vertical developments.
2. **Develop Organizational Digital Capabilities**: Establish internal digital transformation teams, adopt secure cloud data protocols, and implement continuous upskilling programs in civil engineering informatics and data analytics for field engineers.
3. **Build Centralized Historical Project Repositories**: Standardize historic cost, schedule, and variation order data into centralized databases to supply high-quality training data for machine learning predictive models.

For Government Infrastructure Agencies (DPWH, DOTr, LGUs)

1. **Update Public Procurement Rules (R.A. 9184)**: Modernize public procurement frameworks to incentivize contractors that deploy verified AI predictive modeling, digital twin progress tracking, and automated monitoring platforms.

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2. **Mandate BIM-AI Integration on Major Infrastructure**: Require 4D/5D BIM models and automated drone site tracking on major public works projects exceeding ₱250 Million to improve public oversight, streamline progress payments, and prevent claims.

3. **Establish National Digital Construction Standards**: Draft national technical standards for BIM execution and site IoT data integration to ensure cross-platform interoperability across public works and private developments.

Practical Implications

The empirical results offer several practical applications for engineering project teams:

- **Enhanced Cost Estimation**: Quantity surveyors can replace static contingency calculations with machine learning models that process dynamic inflation rates, contractor capacity, and site risk factors.
- **Objective Progress Tracking and Dispute Resolution**: Site engineers can use daily drone photogrammetry and automated progress tracking to provide objective visual evidence of completed work, helping resolve extension-of-time claims and variation disputes.
- **Proactive Structural Quality Verification**: Engineering teams can integrate laser point-cloud scanning with BIM models to identify structural, architectural, and MEP spatial clashes before concrete pours, reducing expensive site rework.

Policy Implications

The insights from this research support institutional policy reforms across the Philippine built environment:

- **Procurement Reform**: Integrate technology readiness and digital project control capabilities into contractor evaluation metrics alongside the traditional lowest calculated bid criteria under R.A. 9184.
- **Building Code Modernization**: Update Presidential Decree No. 1096 (National Building Code of the Philippines) to establish standard protocols for digital twin submissions, dynamic structural health monitoring, and automated BIM compliance verification.
- **Professional Development Mandates**: Work with the Professional Regulation Commission (PRC) and the Philippine Institute of Civil Engineers (PICE) to integrate engineering informatics, data analytics, and BIM management into mandatory Continuing Professional Development (CPD) programs.

Limitations of the Study

Several limitations should be considered when interpreting these results:

1. **Cross-Sectional Methodology**: The study used a cross-sectional design, measuring respondent perspectives at a single point in time. Future research using longitudinal designs could track performance variations across the entire lifecycle of multi-year mega-projects.

2. **Geographic Concentration**: While sampling focused on major economic growth corridors (NCR, Regions III, IV-A, and XI), smaller rural local government projects remain underrepresented.

3. **Perceptual Performance Metrics**: Project performance outcomes were evaluated using validated survey scales completed by project engineers and managers. Future studies could combine self-reported survey data with objective financial cost audits and empirical schedule records.

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Future Research Directions

To expand upon this study, future research should consider the following avenues:

1. **Longitudinal Impact Studies on Mega-Projects**: Conduct multi-year longitudinal tracking of major transport mass-transit and bridge projects to measure the real-world ROI of AI analytics from pre-construction through operations.
2. **Autonomous Site Robotics and Agentic AI**: Evaluate the integration of autonomous site vehicles, spot-robot inspectors, and agentic AI systems in active construction environments.
3. **Cross-ASEAN Comparative Analysis**: Perform comparative research across ASEAN economies (e.g., comparing the Philippines, Vietnam, Indonesia, and Malaysia) to analyze how varying regulatory environments affect digital technology adoption and project delivery outcomes.

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