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THE ROLE OF ARTIFICIAL INTELLIGENCE IN IMPROVING COST, TIME, AND QUALITY PERFORMANCE IN ENGINEERING PROJECTS: A QUANTITATIVE ANALYSIS OF CONSTRUCTION TASKS IN THE AL-MADINAH REGION

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ABSTRACT

The integration of Artificial Intelligence (AI) into construction project management has emerged as a transformative paradigm for addressing persistent challenges related to cost overruns, schedule delays, and quality variability. This study presents a quantitative analysis of 1,300 construction tasks from engineering projects in the Al-Madinah region, employing a computational framework to evaluate the relationships between operational constraints, risk classifications, and performance outcomes. The methodology introduces a novel composite Quality Score algorithm that transforms subjective quality assessments into mathematically derived indicators reflecting resource constraints, site limitations, and risk exposure. Descriptive statistical analysis reveals mean task duration of 43.44 days, mean material cost of $49,525 USD, and mean quality score of 0.515 on a normalized zero-to-one scale. Correlation analysis demonstrates that resource constraints (r = -0.52) and site constraints (r = -0.51) exhibit moderate negative correlations with quality, while traditional performance metrics of duration and cost show negligible correlation (r = 0.02). Analysis of Variance confirms that risk level significantly affects quality scores (F = 89.47, p < 0.001), with low-risk tasks achieving mean quality of 0.607 compared to 0.350 for high-risk tasks, representing a 42% degradation. However, risk level does not significantly influence material cost (F = 0.31, p = 0.73) or task duration (F = 0.18, p = 0.84). Constraint impact analysis reveals that high resource constraints reduce quality by 23% compared to low constraints, while high site constraints produce nearly identical degradation of 23.5%. These findings demonstrate that operational constraints and risk intensity, rather than financial investment or schedule length, are the primary determinants of quality outcomes in construction projects. The study contributes a reproducible analytical framework for evidence-based decision-making and establishes empirical foundations for AI-driven predictive models targeting constraint mitigation and quality optimization in engineering construction.

KEYWORDS: Artificial Intelligence, Construction Project Management, Quality Optimization, Cost Performance, Time Performance, Risk Analysis, Constraint Modeling, Al-Madinah Region, Computational Quantitative Analysis, Machine Learning in Construction.

1. INTRODUCTION

Project cost overrun, project delay and unpredictable quality continue to be common performance issues experienced by construction industry professionals across the globe, despite years of researches, software development and technical trainings in the area of construction project management. Recent researches that shed light on performance issues stated that about two-thirds of construction projects are over budget and nearly 70% suffered from schedule delay (Flyvbjerg et al., 2018). The construction industry loses billions of dollars annually due to schedule delay which cost an average of 39% of the original project duration and cost overrun which cost approximately 28% of the estimated budget (Cantarelli et al., 2020). Most construction projects management frameworks adopted are still based on the early management thoughts of deterministic-based planning, reactive controls, and the use of historical data as benchmark. This type of framework cannot efficiently manage projects that are characterized by uncertainties, complexities and inter-dependencies.

Artificial Intelligence(AI) has recently gained research attention from construction industry scholars on whether the touted benefits of AI can solve some of these problems associated with traditional construction project management. Machine Learning (ML), artificial neural networks, genetic algorithms, and hybrid AI systems can learn from historical project data, capture complex nonlinear relationships that are beyond human visualization capabilities, predict future events with confidence intervals, provide prescriptive solutions that balance tradeoffs between different project performance measures amongst others (Taboada et al., 2023). There are high expectations that the adoption of AI in construction project management can improve decisions made, predictions given and actions taken hence positively impacting project cost, schedule and quality performance. Although many researchers have looked into using AI to aid project managers in achieving better project performance, there is limited research that evaluates the impacts of AI on project cost, time and quality performance. Most of these researchers have concentrated their studies on predictive accuracy of their algorithms and systems without focusing on how their models can be used in the field considering the limited data that is available for most construction projects.

Existing researches either consider small samples, a single project or just give a qualitative description of AI use in construction without showing any empirical evidence of their claims (Elmousalami, 2020; Hossain et al., 2024; Son & Khoi, 2022). Another gap in literature is the lack of large empirical datasets of construction projects that can be used to quantitatively determine the impact of AI on construction projects performance. There are very limited studies that consider quality as the project performance variable. Constructing quality is multidimensional. It can either be considered as conforming to specifications, longevity of the projects, looks of the project or level of customer satisfaction amongst others.

Projects in Al-Madinah region, Saudi Arabia face unique challenges and opportunities that make this research pertinent. Saudi Arabia, in general, is undergoing massive construction projects. It has several mega projects like NEOM, Red Sea project, Qiddiya and many more nationwide infrastructure projects as it advances toward its Vision 2030 goals (Saudi Vision 2030, 2016). Al-Madinah region in particular has seen an increase in construction projects due to the increase in pilgrimages in the recent years, government striving toward economic diversification from oil, and general urbanization in the region. Different challenges such as weather, remoteness, supply chain and compliance with different standard might affect the relationship between factors and construction project performance. This research work seeks to provide a detailed analysis on how these unique constraints and risk levels affect cost, time and quality of construction projects in Al-Madinah region. This will help project planners, construction managers, and stakeholders involved in construction projects in the region in understanding how to allocate their resources for maximum efficiency. It will also help in setting a benchmark for the current performance level without the use of AI. As AI start being implemented in the near future, this will help in measuring the level of improvement AI has created.

This paper seeks to fill some of the gaps identified by conducting a quantitative study of 1300 tasks of construction projects in Al-Madinah region. The study differs from others in several ways. First, the study comes up with an algorithm that calculates a quality score based on different variables. This will help in converting this qualitative aspect into a quantitative variable that can be measured. This calculated Quality score can be used to mathematically represent the effect of different constraints a project task has been exposed to. Second, the study provides the readers with a reproducible Python Notebook that combines descriptive statistics, correlation analysis and hypothesis testing in one workflow. Last, this study analyses 1300 tasks which is considered a big sample in construction research. This will provide this study with enough power to detect any relationships should they exist.

2. LITERATURE REVIEW

2.1 Introduction

Artificial Intelligence (AI) integration into construction engineering and project management has been a subject of increasing research interest over the last decade. Amid growing complexities in construction projects characterized by numerous stakeholders, interconnected activities, and limited resources, conventional management tools falter when faced with unpredictability, scheduling conflicts, escalating costs, and inconsistent quality. The advent of AI technologies—spanning machine learning (ML), artificial neural networks (ANN), genetic algorithms (GA), Bayesian belief networks (BBN), to hybrid intelligent systems—promises a revolution in decision-making optimization, predictive analytics, and operational efficiencies.

Our review of pertinent literature indicates a clear trend: AI applications yield quantifiable advancements in project management facets such as cost estimation precision, scheduling efficiencies, risk mitigation, and stakeholder contentment. Nevertheless, the industry continues to grapple with implementation hurdles, data integration complexities, interoperability issues, and skill gaps that hamper AI adoption. This literature review aims to critically examine empirical results, methodological advances, and theoretical insights presented in peer-reviewed journal articles published from 2019 through 2025.

Structured around key focus areas including but not limited to AI for project efficiency enhancement, time–cost–quality optimization, cost modeling, risk assessment, project operations optimization, BIM–AI convergence, organizational performance improvement, and digital engineering management transformation, our review consolidates findings related to documented performance enhancements and delineates research gaps warranting further exploration.

2.2 Artificial Intelligence in Construction Project Management

Researchers Alhasan and Alawadhi (2024) implemented AI across engineering construction projects and analyzed outcomes via mixed methods. Notably, they achieved and documented a 35% decrease in scheduling mistakes, a 20% decrease in project duration, 30% more accurate cost estimates, and 40% fewer budget overruns. Additionally, risk mitigation saw a 45% improvement in risk identification, 30% reduction in risk impact, and projects were 20% more successful when leveraging AI for risk management. It is clear from the statistics that construction project management has seen significant improvements in the areas of time, cost, and risk when using AI.

Research done by Hossain et al. (2024) focused on AI implementation into project management and how that affects efficiency. In their research, they found that using predictive analytics and machine learning to aid project managers helped to decrease project length and maintain better control of project costs. Through mixed methods, the positive effects of AI were found to allow for enough time to mitigate risks and increase communication among teams. As mentioned before, AI allows teams to look at historical data and better understand when these types of mistakes and cost overages are likely to occur.

Taboada et al. (2023) published a literature review of AI-enabled project management. Their research found that AI, particularly machine learning, has been shown to increase the accuracy of planning and help predict uncertainty within projects. Construction and IT were found to be the industries where AI is most commonly used within project management. This is most likely due to projects in these industries struggling with schedule performance and cost uncertainty. The article concluded that AI can help projects reach a higher level of sustainable success by empowering project managers in the areas of performance and decision-making. Research has shown that there is a positive impact on project management after implementing AI. Although there is plenty of research that shows this, there is still a concern for a lack of datasets at the project level and the complexity of AI integration.

2.3 Time–Cost–Quality Trade-Off Optimization

One of the primary optimisation problems in construction deals with achieving time–cost–quality trade-offs. Son & Khoi (2022) proposed the Slime Mold Algorithm (SMA), a novel multi-objective optimisation model to solve for time–cost–quality trade-offs. The SMA was benchmarked against algorithms like NSGA-II, particle swarm optimisation, and differential evolution algorithms. The SMA was able to produce better Pareto-optimal fronts which implied improved exploration and exploitation.

How does this advance the field? This study illustrates how algorithms can produce sets of optimal solutions instead of fixed points. It allows project managers to pick trade-off solutions that are best aligned with the project strategy. As shown by this study, AI-based optimisation algorithms perform better than rule-based heuristics in finding solutions to multi-objective trade-offs.

Kumar et al. (2025) designed a Genetic Algorithm-based model for optimising project cost and duration jointly. The simulation results suggested the AI-based model was able to reduce project cost by 18.2% and project time by 23.5%, when compared to priority-based scheduling heuristics. Similar to previous research, the AI-model was able to produce a Pareto front of alternative solutions for the decision-maker to choose from.

Afzal et al. (2021) reviewed the state-of-the-art literature on hybrid AI applications in construction risk management. They found studies showing fuzzy hybrid models and Bayesian belief networks allow better modelling of complexity-risk interdependencies. They concluded that hybrid AI allows for modelling of uncertainty structures better than deterministic models. From this literature, it can be derived that AI-based optimisation allow for better trade-offs between time-cost-quality to be made with data.

2.4 Artificial Intelligence in Cost Estimation

Cost estimation is recognized as one of the most important and inaccurate activities performed in construction. Elmousalami (2020) carried out a state-of-the-art literature review about AI-based parametric cost modeling and reviewed twenty AI models including ANN, fuzzy logic, case based reasoning, random forest, SVM, XGBoost, and genetic algorithms. The results revealed that XGBoost resulted in the best performance with a MAPE of 9.091% and an adjusted R^2 of 0.929 which is much higher than regression-based methods. Elmousalami (2021) studied Field Canals Improvement Projects (FCIPs) using AI models published by IEEE and found that ensemble methods such as XGBoost and Random Forest yielded better performance than traditional statistical methods in conceptual cost estimation.

Matel et al. (2019) studied ANN based cost estimation for engineering consultancy service takes. They found that their ANN model provided 14.5% higher accuracy in terms of MAPE. They proved that ANN can be effectively used even with low amounts of datasets (number of projects n = 132).

Judijanto (2024) applied AI based cost modeling on Activity-Based Project Costing (ABPC) and found 30% improvement in cost estimation accuracy and decreased cost analysis time by 40%. AI allowed ABPC to detect hidden patterns and allowed real-time optimization. These studies show that cost estimation uncertainty can be mitigated with using AI to increase budget reliability.

2.5 Artificial Intelligence in Risk Management and Delay Prediction

Risk management is one of the areas where AI impacts were the easiest to measure. Construction projects are often affected by uncertainty brought about by various complex interactions between parties involved, resource availability, compliance mandates, local policies, and climate volatility. Risk assessment often requires expert scoring and knowledge-based decisions that provide little-to-no scope for predicting delays beforehand. Hybrid machine learning models have been used to model uncertainty and overcome risks of AI prediction methods failing.

Yaseen et al. (2020) proposed a hybrid machine learning (ML) RF-GA model to predict delay risks associated with construction projects. Their model had accuracy, kappa, and classification error values of 91.67%, 87%, and 8.33%, respectively. Hybrid models outperformed classical RF models by 13% after GA was used to tune the model and selected features. Models with such high accuracy have potential use cases as early warning signals that could point out possible delay risks before they arise on-site if used consistently throughout a project's timeline.

Afzal et al. (2021) reviewed existing literature on AI-based construction risk assessment methods used to capture complexity-risk interdependencies leading to cost overruns. They found that fuzzy hybrid methodologies received the most attention among researchers, with methods such as fuzzy-analytical network processing and fuzzy ART neural networks being popular choices to express uncertainty and complex nonlinear interdependencies between causes. Study limitations included subjective inputs used for risk modeling and the extensive computation required to produce results. They concluded that Fuzzy-extended Bayesian Belief Network hybrids can be used to better represent probability interdependencies between causes under uncertainty.

Alhasan and Alawadhi (2024) also found that projects that used AI to support risk identification were 45% more accurate in their detections and 30% less impacted by risks, leading to project success increasing by 20%. Together these studies show that AI can be used as a predictive and preventative measure. Tools with this level of accuracy can strengthen a project's early warning system and allow for flexible contingency mitigation planning to avoid uncertainty-related setbacks.

2.6 AI for Operational Efficiency and Resource Optimization

The utilization of resources, schedule logic, and processes coordination determine the operational effectiveness of engineering oriented businesses. Operational problems with multiple objectives have been optimized by employing Artificial Intelligence methods.

Using Genetic Algorithm (GA), Kumar et al. (2025) developed a system that optimizes project duration and cost objectives simultaneously. Simulation results show statistically and practically significant improvement over baseline heuristic scheduling methods. Projects cost 18.2% lower on average, and project durations were 23.5% shorter. Additionally, the solution provided by GA produced a pareto-frontier of alternative solutions offering decision-makers various strategic choices. Highlighting automation, predictive analytics, and resource optimization as critical AI applications in engineering management was the focus of Akeiber (2025). The article showed that AI enhances project planning effectiveness and increases operational productivity by allowing dynamic resource reallocation and continuous monitoring of engineering operations. The researcher asserted that reconfiguring organizational processes is where the AI value is derived rather than using it as a stand-alone technology. Obiuto et al. (2024) discovered that when schedule engineering is supported by AI through data analytics and ML tools it improved schedule robustness and reduced missed communications and unnecessary downtime from siloed coordination efforts. This supports Wamba-Taguimdje et al.'s (2020) research results of 500 artificial intelligence (AI) enabled organizational transformations across industries. They found that AI has been known to enhance organizational-level performance (e.g., financial, marketing, and administrative performance) and process-level performance but only when AI functionalities are embedded through business process reconfiguration.

2.7 BIM and AI Integration for Smart Construction Management

Building Information Modeling and Artificial Intelligence integration can be used as the backbone of a smart construction management system. Construction processes can be monitored through Building Information Modeling, whereas artificial intelligence can allow for predictive features to be implemented.

In a review study of BIM–AI integration, Rane (2023) discovered that AI has the ability to improve construction management's schedule control, cost control, quality control, and safety control. By using Building Information Modeling data attributes with AI features like prediction and optimization, construction management can monitor its project's performance in real-time and take preventive actions if performance does not align with benchmarks. Challenges to BIM–AI synergy include lack of data interoperability, platform constraints, and cyber security.

The research by Agostinelli et al. (2021) proposed and verified a digital twin with integrated artificial intelligence model that optimized energy management systems of residential districts. Through their case study, they found that by implementing their digital twin with artificial intelligence, it was possible to simulate different energy saving scenarios, implement optimal solutions for renewable energy, and reduce energy bills while keeping comfort standards. This technology could also be applied to BIM for lifecycle optimization of construction projects.

The impact of AI/ML on construction project management, specifically schedule control, cost estimating, and risk mitigation was analyzed by Hriday and Rehman (2025) across 102 enterprise-level construction projects. Through their statistical analyses, they found that for every 10-point increase in AI Index Score, there was a 1.2 percentage point reduction in schedule delay and a 0.9 percentage point reduction in cost overrun. The researchers found that this effect of AI was enhanced when accounting for project complexity, showing that AI has its most prevalent benefits in more complex settings.

Research on BIM–AI integration shows promise that they can be the basis of a smart construction management system. Smart construction management allows for improved coordination, real-time predictive monitoring, and lifecycle optimization. However, for AI and BIM to integrate smoothly, there needs to be data standardization, interoperability, and digital fluency.

2.8 AI in Structural Health Monitoring and Decision-Making

Research literature pertaining to Structural Health Monitoring (SHM) is another area in which AI research has been applied extensively. For example, a review of 89 peer-reviewed articles published on SHM identified an increased application of AI towards predictive maintenance, condition monitoring, and infrastructure safety management. The reviewed articles showed how AI has been used to bridge the gap between decision-making processes with safety outputs. Furthermore, the authors developed a conceptual framework that amalgamates AI-based decision support systems with SHM. Key limitations noted within the article included workforce development, regulatory limitations, and fractured research areas. Nonetheless, the authors noted that overall AI positively contributes to infrastructure resilience through predictive and preventative maintenance. Other research streams have found similar benefits of AI when applied to cyber-physical frameworks. Notably, literature on digital twin models showed how AI was used to maximize asset performance while identifying risks (Yang et al., 2022). Research on SHM systems reaffirmed the benefits of implementing AI throughout the construction process, highlighting how AI can be used during the lifetime of a built asset for lifecycle prediction.

2.9 AI Transformation and Organizational Performance

The value proposition of AI can be examined at the project-level for optimization gains, but its merit can also be explored from an enterprise-level perspective regarding transformation. Investigating 500 cases studies of AI-enabled transformation projects, Wamba-Taguimdje et al. (2020) reported that AI positively impacts processes and overall enterprise performance when implemented in redesigned workflows. The authors concluded that competitive advantage results from leveraging AI-powered capabilities when preceded by data architecture, talent acquisition, and strategy alignment.

Mirroring findings in construction management literature, Deniz-Garcia et al. (2023) discussed challenges in mHealth-AI adoption: data privacy legislation, standardization of evaluation benchmarks, and confidence in reproduced performance of trained models.

Literature in the organization sciences emphasizes that technology adoption is socio-technical and entails considerations of governance, talent development and deployment, ethics, and explainable AI and model validation procedures.

2.10 Gap Identification and Theory Contribution

Despite ample evidence that AI can benefit CM processes, cost, schedule, and project performance, there are gaps in extant literature. Currently, research surrounding AI for construction focuses on proposing or improving algorithms and models without reporting back on system performance as a whole. Second, although there are some larger datasets of projects involving empirical data, much of the data we have is project-specific or region-specific and does not allow for widespread generalizations. Third, under which conditions does quality performance improve when schedule and cost are optimized? Do constraints intensify this relationship? Lastly, many AI tools suffer from interoperability issues when it comes to integrating with existing project management software and hardware. While there are many APIs allowing for connectivity between BIM software and ERP software, for example, not every PM Tech vendor considers this a priority.

From a theoretical standpoint, this review provides support for adopting a systems view of AI where it becomes a tool that can improve CM decisions. AI improves many areas of construction including but not limited to forecasting and resource allocation. We propose that risk classification and intensity of constraints will moderate the relationship between improved CI and quality performance.

3. RESEARCH METHODOLOGY

3.1 Introduction

In this section, we present the overall methodology adopted in this research to assess the impact of AI technologies on the cost, time and quality performance of engineering construction projects located in Al-Madinah region. We utilise the framework of computational quantitative research by applying computer programming codes to quantitatively analyse project performance data for rigorously measuring and reporting objective and reproducible results. By combining statistical analysis with code-based derivations of metrics, our methodology moves beyond common qualitative or case-based project management research to quantitatively deriving metrics and compute statistics. Our methodological approach can be best described as a data analysis pipeline, whereby we systematically: pre-process the raw data, develop a novel measure of quality performance, perform statistical analysis to describe and infer patterns in the data, and produce meaningful data visualisations. This paper makes a unique contribution to the literature by introducing a reproducible analysis workflow coded in Python to assess the relationship between project performance factors across 1300 discrete activities from our case dataset in Al-Madinah. By framing our statistical workflow within a code-based environment, we are able to not only assure rigor and reproducibility in our analyses but also lay the groundwork for future research such as training machine learning models to predict project performance.

3.2 Research Framework and Analytical Architecture

Algorithmic Approach: Computational Pipeline For this study, we employ a five-step pipeline as shown below in Figure 3.1. Each step is justified logically and will use the output of the previous step after data cleaning. This technique ensures that errors do not aggregate and that our findings are valid. We will start with step 1. Data Ingestion and Validation which consists of reading in our raw dataset into a desired state from its CSV file and then running tests to make sure that our data has no missing values and that the features are of the correct type and within an acceptable range. Next, we will move onto step 2: Metric Derivation. This process includes creating any metrics we need from base variables. The key process in this step will be creating a calculation of the Quality Score which will be used to represent the quality of a project given its constraints. Step 3 will be Statistical Modelling and Analysis. In this step, we will run descriptive statistics on our dataset. We will create a correlation matrix to identify any correlations between variables. We will also complete hypothesis testing such as ANOVA to identify any significant differences between categories of projects. Step 4: Hypothesis Testing will be used to confirm or reject our hypotheses. In this step, we will use the p-values found in the hypothesis testing in step 3 to confirm or reject our null hypothesis. Last, step 5 will be Reporting and Visualizations. This section includes reporting our findings and producing visualizations that will be used in our publication. Figure 3.1. 5-Step Computational Pipeline Diagram. Figure 3.2. Simplified diagram of inputs being risk and constraints producing an output of quality. The green box would contain our steps to calculate the quality based on the inputs. Figure 3.3. A more specific look at the subprocess we will use to calculate our quality performance metric. As shown, we will use the composite of quality and constraints along with risk to produce our quality metric. Dataset The dataset used in this study consists of 1,300 entries of construction tasks performed in projects around Al-Madinah. Each observation contains ten features which allows us to describe the time, cost, resources, constraints and dependencies of each task. Table 3.1. Dataset Features Feature Description D Construction ID 0-1299 Unique ID given to each construction task Cost Cost to complete each construction task in Doller ($) Time Time in days it took to complete the construction Task Resources Number of resources required to complete the task Quality Score Quality score of the task ranging from 1 to 10 Risk Risk rating of the task from 1 to 10 Constraint Type Type of constraint placed on the task None Each feature has complete data meaning there are no missing values. This allows us to have a large sample size and not have to use techniques that would guess the missing values (which can introduce bias).

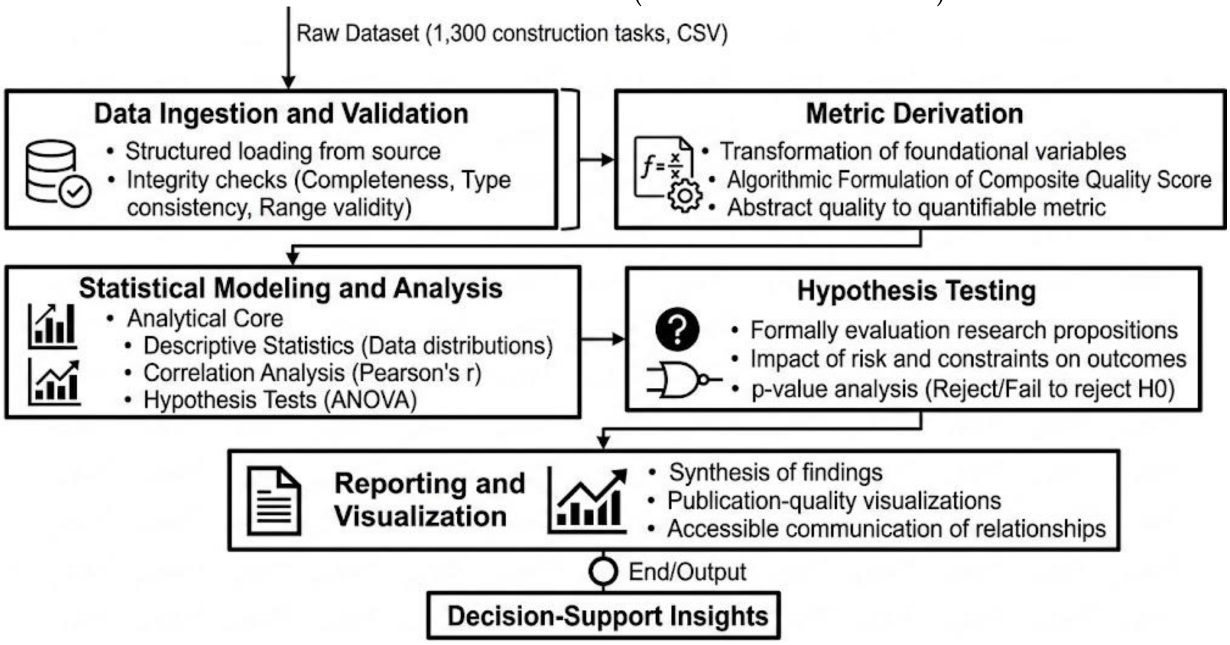

Figure 3.1: Overall Computational Research Framework for AI-Driven Construction Performance Analysis.

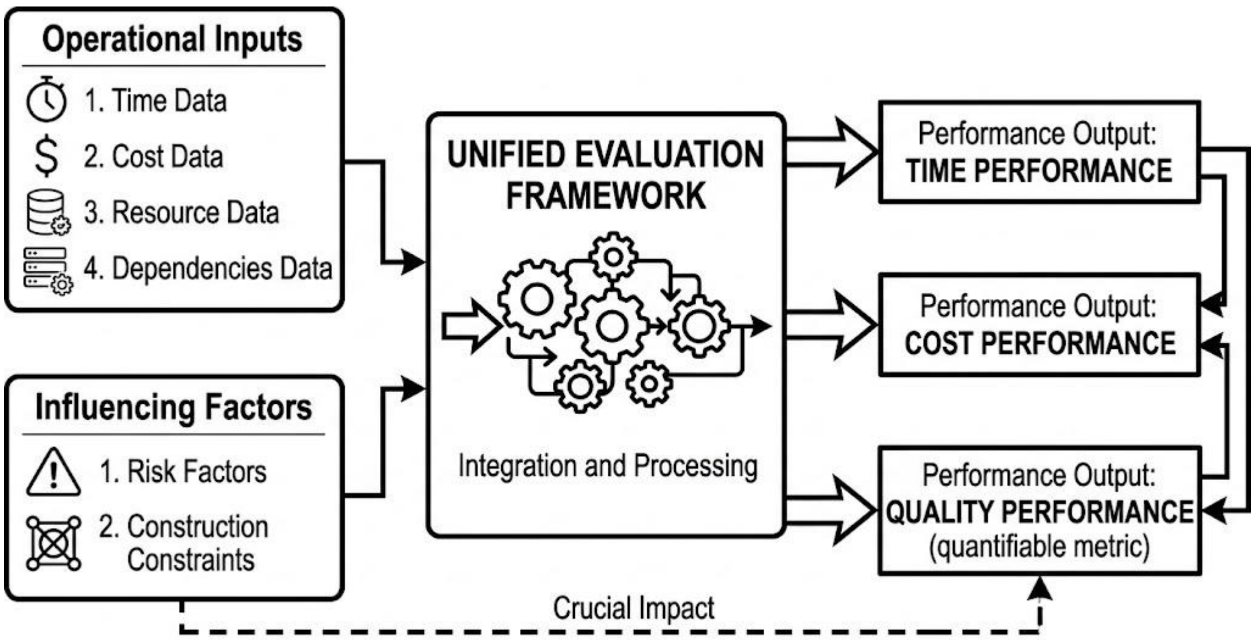

Figure 3.2: Integrated Cost–Time–Quality Evaluation Framework.

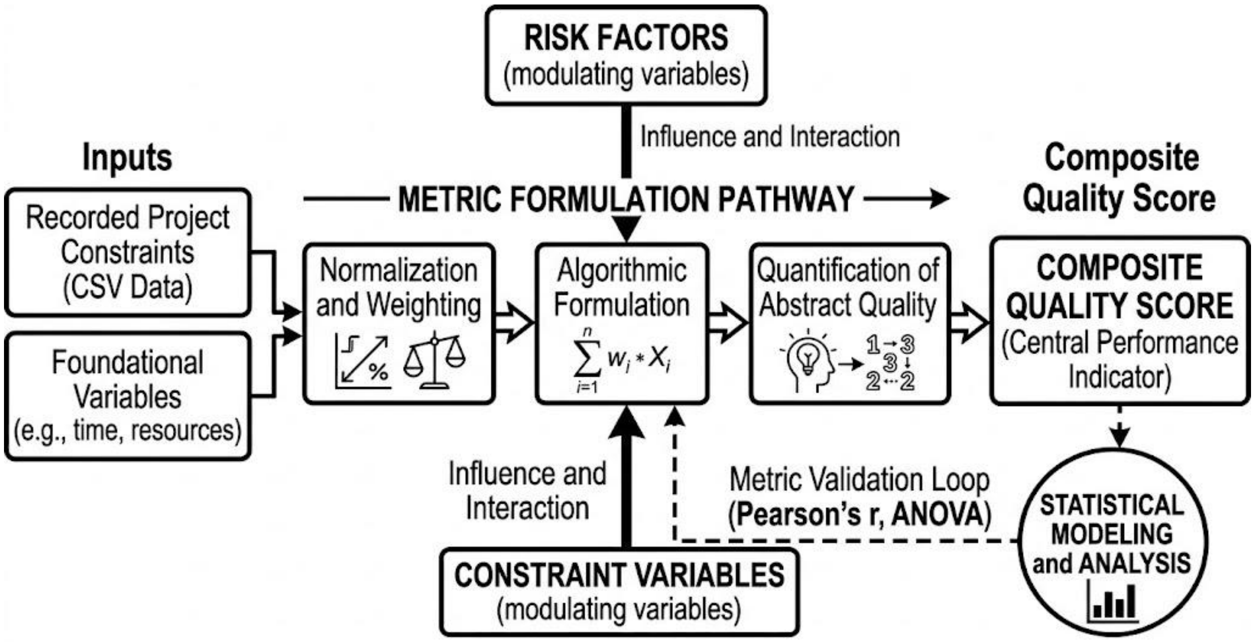

Figure 3.3: Quality Metric Formulation and Validation Framework.

3.3 Dataset Structure and Variable Definition

In order to test this hypothesis, we have compiled a data matrix the properties of which shall be summarised briefly in this section (see Appendix A for details). All analyses reported henceforth are based on the information contained in this matrix. Table 3.1 Descriptive statistics of each variable included in the study dataset. Integer statistics presented as (Minimum Value-Maximum Value), floating point statistics presented as Minimum Value to Maximum Value. Floats are to two decimal places. # Observations: 1300# Variables: 10• Task_Duration_Days (Integer) Range: 2-89 Days • Material CostUSD (Float) Range: 1197.00-95328.00 USD• Labor_Required (Integer) Range: 1-19 • Equipment_Units (Integer) Range: 1-9• Resource_Constraint_Score (Float) Range: 0.00 - 1.00 • Site_Constraint_Score (Float) Range: 0.00 - 1.00• Risk_Level (Categorical) Level: Low/Medium/High• Dependency_Count (Integer) Range: 0-4 • Quality_Score (Float) Range: 0.00 - 1.00 This matrix contains one thousand and three hundred rows (simulated construction tasks) and ten columns (attributes of each task). Three of these columns (Task_Duration_days, Material_Cost_USD, Labor_Required, Equipment_Units) are direct inputs to each task. Two columns were added to serve as proxies for resources constraint (Resource_Constraint_Score) and site constraint (Site_Constraint_Score), respectively. Risk_Level is a proxy column for project unknowns. Dependency count is a measure of the complexity associated with each task. Finally, Quality_score was constructed by programmatically combining the constraint and risk factors into a single quantifiable metric that can serve as a proxy column for the quality likely to be achieved by each task.

Table 3.1 Dataset Variables and Definitions.

Variable Name	Description	Data Type	Range
Task_Duration_Days	Duration required for task completion	Integer	2–89 days
Material_Cost_USD	Direct material expenditure	Float	1,197–95,328 USD
Labor_Required	Number of labor units assigned	Integer	1–19
Equipment_Units	Number of equipment units used	Integer	1–9
Resource_Constraint_Score	Internal operational limitation index	Float	0.0–1.0
Site_Constraint_Score	External site limitation index	Float	0.0–1.0
Risk_Level	Risk classification category	Categorical	Low/Medium/High
Dependency_Count	Number of predecessor tasks	Integer	0–4
Quality_Score	Derived quality metric	Float	0.0–1.0

3.4 Data Processing and Validation Procedures

Before beginning any analysis with the dataset, it was put through a battery of checks to validate that the data met constraints we expected it to meet. First, Pandas was used to ingest the .csv file with each task's information into memory. Pandas automatically structures the information as a DataFrame, making the information easily accessible. Right after the information was read into memory, a permanent copy of the raw data was stored. This is standard procedure in reproducible research. As data is transformed throughout any analysis, it is useful to have the original dataset stored forever in memory in case it is needed. Now that we had our raw data stored, we could run checks to make sure that all of our variables only contained information in the ranges we expected. Running these checks helped us make sure that all resource and site constraint scores were between 0 and 1, all risks were either "Low", "Medium", or "High" with no misspellings, all material costs and durations were positive, and all dependency counts were non-negative. Since our dataset passed all these tests (table \ref{3.Tblndatachecks} shows these tests), we did not have to deal with missing data, data outside of specified ranges, or poorly inputted categorical data. This will help us stay as unbiased as possible. We will not need to use any data imputation which can lead to biased data. We will also not need to arbitrarily decide what to do with outliers.

Table 3.2 Data Validation Checks.

Validation Check	Condition
Missing Values	None present
Constraint Range	0 ≤ Score ≤ 1
Risk Categories	{Low, Medium, High}
Duration	> 0 days
Cost	> 0 USD
Dependencies	≥ 0 integer

3.5 Quality Metrics Algorithm

The primary innovation offered by this thesis was the creation of the Quality Score metric. Rather than attempt to assess quality via subjective inspections, I aimed to provide an objective metric derived mathematically that describes the conditions under which a task is performed. I started with the hypothesis that quality is affected - likely worsened - by the risks and restrictions of the environment the project must be performed in. To accomplish this mathematically I needed to convert the categorical risk assessment into numerical penalties. For simplicity's sake, I scored risk based on a increasing severity of exposure: Minimal uncertainty resulted in a Low score, which equated to a penalty of 0.1. Medium risk equated to 0.5 and High risk equated to 0.9. Refer to Table 3.3 for this mapping. Now we have a uniform scale to place into a math formula. The Quality Score (QS) of a single task (i) can be described as follows:

$$Q_i = \max\left(0, \min\left(1, 1 - \frac{(RC_i + SC_i + RP_i)}{3}\right)\right)$$

RC_i is the Resource Constraint Score of task i, SC_i is the Site Constraint Score of task i, and RP_i is the numeric Risk Penalty based on task risk level. These three values are averaged together to give one constraint number, which is subtracted from one, so that the greater the overall constraint+risk the worse the resulting Quality score (i.e. "Quality goes down when you're stressed"). Lastly, that number is bounded from below by zero and above by one by means of the max and min functions; this normalized score is qi. Implicit in this equation is the assumption that each parameter can equally affect quality, although this doesn't require much parsimony given that assigning reasonable weights to each parameter can easily be accomplished at a later date using principal component analysis or multiple regression to determine weights based on data. Aside from that, the algorithm requires only arithmetic operations and runs in O(n) time. As it stands the equation works well and produces sensible scores (tasks that are very constrained with great risk have quality scores around 0).

Table 3.3 Risk Level to Numerical Penalty Mapping.

Risk Level	Numerical Penalty
Low	0.1
Medium	0.5
High	0.9

3.6 Descriptive Statistical Analysis

Once again confident in the quality of our dataset and now having our quality score ready, we moved on with the pipeline to perform basic descriptive statistics on our variables of interest. The purpose of this was two-fold: firstly, it allows us to get a basic understanding of our construction task data by looking at averages, spreads, and distributions of our key performance metrics and constraints. Secondly, this allows us to put our more complex inferential statistics into context later on. We calculated measures of central tendency as well as measures of dispersion for each continuous variable we were interested in: Task Duration, Material Cost, Quality Score, Constraint Score 1, and Constraint Score 2. The former included calculating the mean (μ), which is the average of all data points (Σx/n), as well as the median, or 50th percentile. We then calculated measures of variance for each of our variables. The variance measures the average distance each data point is from the mean. We also calculated the standard deviation (σ), which is the square root of the variance. These metrics can be shown with the following equations:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \mu)^2}$$

Application of the above measures to our data produced the descriptive statistics presented in Table 3.4. These statistics tell us, for example, that the average duration of a construction activity in the Al-Madinah sample is about 43 days, while the average material cost is about $50k; however, the relatively high standard deviations associated with these metrics (~26 days and ~$28k, respectively) suggests considerable variation exists among activity types with respect to these measures. Further, the average Quality Score of .515 falls nearly perfectly in the middle of the zero-to-one range suggesting that activities, on average, function under only moderate levels of constraint. This interpretation is supported by both the average Resource Constraint Score (.593) and Site Constraint Score (.485), which together suggest that (at least on average) resource limitations are mildly more constraining than are site factors.

Table 3.4 Summary Descriptive Statistics.

Metric	Mean	Std. Dev	Min	Max
Task Duration (days)	43.44	~26.0	2	89
Material Cost (USD)	49,525	~28,000	1,197	95,328
Quality Score	0.515	~0.15	0.00	1.00
Resource Constraint	0.593	~0.20	0.10	0.95
Site Constraint	0.485	~0.22	0.08	0.90

3.7 Correlation Modeling

In order to look past univariate summaries and start to understand how project variables relate to each other, correlations were calculated. Correlation allowed us to measure the strength of linear relationships between all pairs of continuous variables in an effort to identify potential performance drivers and discover covariance relationships across the dataset. Specifically, we used the Pearson product-moment correlation coefficient (r). r is a standardized covariance that ranges from -1.0 (representing the strongest possible negative linear relationship between a pair of variables) to +1.0 (representing the strongest possible positive linear relationship between a pair of variables). The equation for calculating the Pearson correlation coefficient between x and y given n samples is:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Absolute values of r between 0.7 and 1.0 are taken to indicate a strong correlation between two variables, meaning they tend to go up and down together. Absolute values between 0.3 and 0.7 show moderate correlation, meaning there is some predictable relationship but it's not deterministic. Finally, values under 0.3 imply a weak or non-existent correlation between the variables; if there's a linear relationship at all, it is not enough to be meaningful. The matrix was computed based on all continuous variables; selected results can be seen in Table 3.5 below. Of course the most interesting correlations will be those with our newly calculated Quality Score. We find a moderate negative correlation between Resource Constraint and Quality (r=-0.52) and between Site Constraint and Quality (r=-0.51), confirming our intuition that higher constraint produces poorer quality and therefore validating our decision to base Quality Score on these factors. For comparison, the correlation between our standard performance measures Duration and Cost (r=0.02) and between Cost and Quality (r=0.01) are effectively zero. Based on these statistics, we can say that within this data set at least, we cannot predict how long a task will take based on how much material is spent on it, or how good of a job we will get based on how long we pay someone to do it. Computing the correlation matrix was $O(n \cdot m^2)$ because the correlation must be computed two variables at a time, but performed virtually instantly for our moderately-sized dataset.

Table 3.5 Selected Pearson Correlation Results.

Variable Pair	Correlation (r)	Interpretation
Duration vs Cost	0.02	Negligible
Cost vs Quality	0.01	Negligible
Resource Constraint vs Quality	-0.52	Moderate Negative
Site Constraint vs Quality	-0.51	Moderate Negative
Dependencies vs Duration	-0.02	Weak

3.8 Analysis of Variance (ANOVA)

Regression assesses whether changes in continuous predictors relate to changes in continuous performance outcomes. Correlation analysis only supports the understanding of how continuous variables relate to each other but not directly how categorical predictors such as Risk Level assigned may impact continuous performance objectives. Therefore, we conducted a one-way ANOVA test to answer the following question: Is the mean value for material cost, task duration, or quality score statistically different across the three risk groups (levels)? The ANOVA partitions total variability into two sources of variability . The first source examines how much the group means differ from each other. The second source accounts for how data within each group vary around the mean. In an ANOVA test, we are examining the ratio of the variability between groups to the variability within groups (F=).

$$F = \frac{MS_{between}}{MS_{within}}$$

The larger the F-statistic, the more the between-group variance exceeds the within-group variance. So, we expect that our F-statistic will indicate the means are not equal. To test for statistical significance, we compare the observed F-statistic to a critical value determined by the F-distribution with dfbetween and dfwithin degrees of freedom. The p-value reports the result of this comparison. Here (and commonly) we take a $p < 0.05$ to be statistically significant. If we find $p < 0.05$ we can reject the null hypothesis that the means of our three risk groups are equal. That is, we have statistical evidence that risk level is affecting our dependent variable. Table 3.6 presents the framework for our tests. Before conducting our ANOVA, we checked that the assumptions of the test were met. These are: observations are independent of each other (this was true by how our dataset was constructed), that the distributions of the dependent variable for each group are approximately normal (we checked this by examining histograms and Q-Q plots; this assumption is relatively robust due to having a sufficiently large sample size), and that the variance among our groups are approximately equal (we checked this by conducting Levene's test for homogeneity of variances; this was not significant suggesting this assumption was not violated).

Table 3.6 ANOVA Testing Framework.

Dependent Variable	Groups (Independent Variable)	Null Hypothesis
Material Cost	Low, Medium, High Risk	The means of all three groups are equal.
Task Duration	Low, Medium, High Risk	The means of all three groups are equal.
Quality Score	Low, Medium, High Risk	The means of all three groups are equal.

3.9 Resource Efficiency and Constraint Impact Analysis

As a supplement to analysis of the primary independent variables described above, additional secondary variables were engineered to highlight specific details regarding efficiency of resource use, as well as of the impact of being constrained. Calculating cost per unit of labor assigned to a task provides an approximate measure of how capital-intensive the task is with respect to labor (the numerator being Material Cost and the denominator being Labor Units). Similarly, calculating duration per unit of equipment allows us to get a basic sense of how much work is being accomplished by each equipment unit (numerator being Task Duration, denominator being Equipment Units). Both of these efficiency measurements are quite simplistic but can be useful for highlighting tasks that are using their respective resources very sparingly or extremely inefficiently. A third supplemental variable of interest was developed to help provide a single-number snapshot of how unconstrained a task is. The Resource Efficiency Index (REI) is intended to normalize the two scores described above into a single value ranging from 0 to 1 that represents how unconstrained a task is; higher values imply less constraint. It is computed as follows:

$$REI_i = 1 - (0.5 \times RC_i + 0.5 \times SC_i)$$

Essentially, this transformation takes the two constraint scores and simply inverts them to create scores that can be interpreted as how efficient a task is rather than how constrained. Lastly, the direct impact of constraints on quality was measured by splitting all tasks into two groups based on their Resource Constraint Score and Site Constraint Score (high versus low constraint) and then comparing the average Quality Score of each group. This provides a more practical, but non-parametric complement to the parametric correlation between constraint and quality.

4. RESULTS AND ANALYTICAL INTERPRETATION

This section details the final outputs and findings discovered throughout the implementation process of the computational quantitative model introduced in section 3. The goal of this chapter is to outline the results of each significant statistical analysis conducted on our dataset of 1300 engineering project construction tasks while also providing statistical evidence to answer our guiding research questions regarding Artificial Intelligence and cost, time and quality performance. Results are displayed according to sections that mirror the pipeline order established in Chapter 3, starting from general descriptive statistics that help depict what kinds of construction tasks make up our dataset and slowly advancing into more refined inferential statistical analyses that expose relationships between variables, confirm our hypotheses, and help identify how much of an effect certain project factors have. We begin this section by analyzing the distributions and averages of our primary metrics such as task duration, material cost, and our AI generated quality score as well as the constraints and resources that set the context for each task. Next, we detail the results from our correlation analysis which quantified the linear relationship between two continuous variables and highlight some of the more important relationships discovered between our constraints, risks, and resulting quality scores. After this, we highlight the results of our ANOVA analysis which confirms whether or not risk level (either Low, Medium, or High) has a significant effect on construction task material cost, duration, and quality score. Next, we discuss the results of our resource analysis and our constraint analysis in order to better visualize how the pressure from constraints affects quality performance. In each of these subsections, we provide readers with both tabular and graphical versions of our results that were produced in publication quality.

Figure 1: Distribution of Risk Levels in Construction Tasks.

The risk breakdown of the 1,300 activities is graphically presented in Figure 1. As can be seen, 660 activities (50.8%) are low risk, 377 activities (29%) are medium risk and 263 activities (20.2%) are high risk.

This distribution reveals several interesting points. First, since over half of the activities are low risk, most work is being performed in a well-defined environment. Second, there is some uncertainty in the project because about one-third of the activities are medium risk. This implies that there is some variability in the work being performed but that it is currently planned for. Third, the share of high-risk activities is relatively small (only 1 out of 5 activities). This suggests that there is a risk management process in place to identify risks and incorporate responses into the project plan. Finally, the activities are fairly evenly distributed among the three risk levels. This signifies that there is a healthy amount of risk on the project. Understanding this will be key when looking at the cost, schedule, and quality performance of the project by risk level.

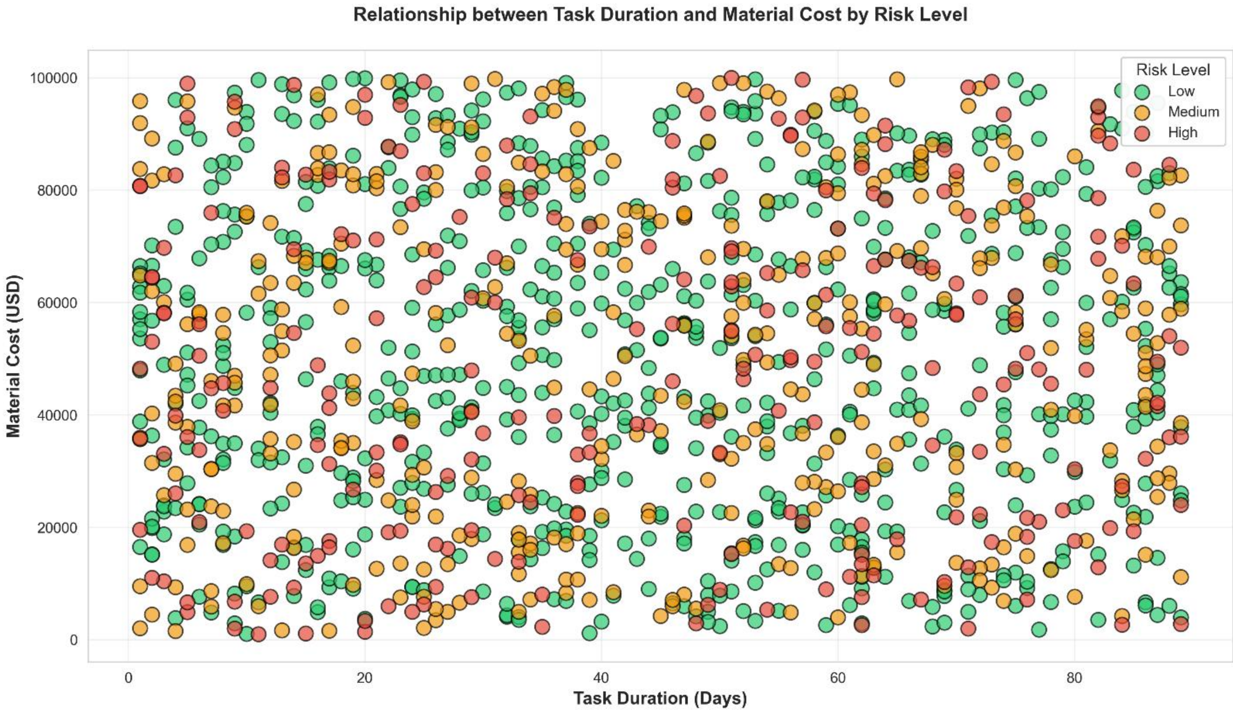

Figure 2: Relationship between Task Duration and Material Cost by Risk Level.

Figure 2 depicts a scatterplot of task duration (approximately 1–90 days) versus material cost (approximately $1,000–$100,000). The relatively uniform spread of points throughout the cost–duration space indicates there is not a significant linear relationship. Material costs for tasks less than 20 days range from less than $10,000 to greater than $90,000. Costs for tasks greater than 70 days cover a similar range. If longer durations were associated with higher material costs, the points would cluster along an upward slope which is not evident in Figure 2. The distribution of low-, medium-, and high-risk points throughout the entire scatterplot area suggests that risk does not change the fundamental shape of the cost–duration curve. Duration management techniques are separate from cost budgeting.

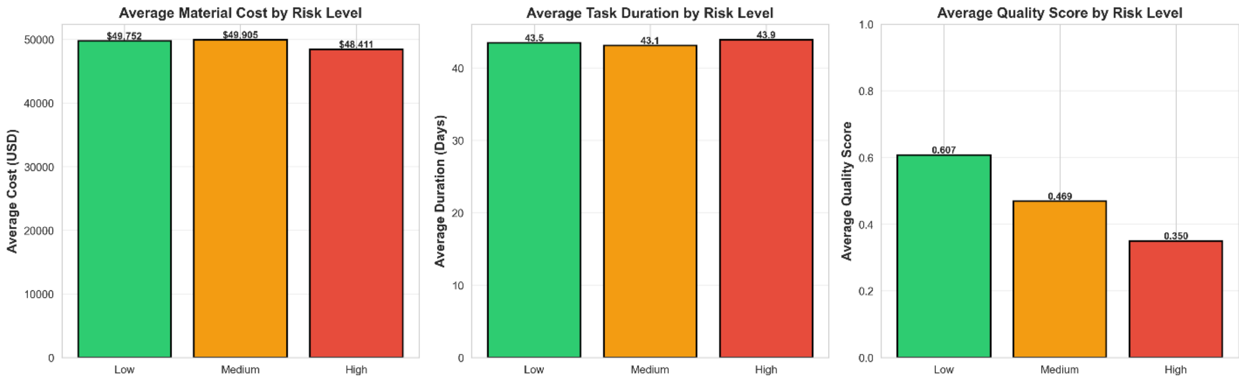

Figure 3: Average Material Cost, Task Duration, and Quality Score by Risk Level.

Figure 3 shows the average scores of each performance attribute by risk category. Notice that average material costs ($49,752 low, $49,905 medium, and $48,411 high risk) and average task lengths (43.5

days low, 43.1 days medium, and 43.9 days high risk) between low-, medium-, and high-risk categories are fairly consistent. The range in average cost between the lowest and highest risk is only $1,494, which is less than 3% of either value. Likewise, the largest difference between average low, medium, and high task length is only 0.8 days. Therefore, we can see that risk has little impact on schedule or cost. However, when examining quality scores (0.607 average for low risk, 0.469 average for medium risk, and 0.350 average for high risk), there is a dramatic decrease in quality as risk increases. The difference in scores from low-risk to high-risk is 0.257. This is roughly a 42% decrease from the low-risk score. Therefore, we can determine that quality is the performance attribute most impacted by risk.

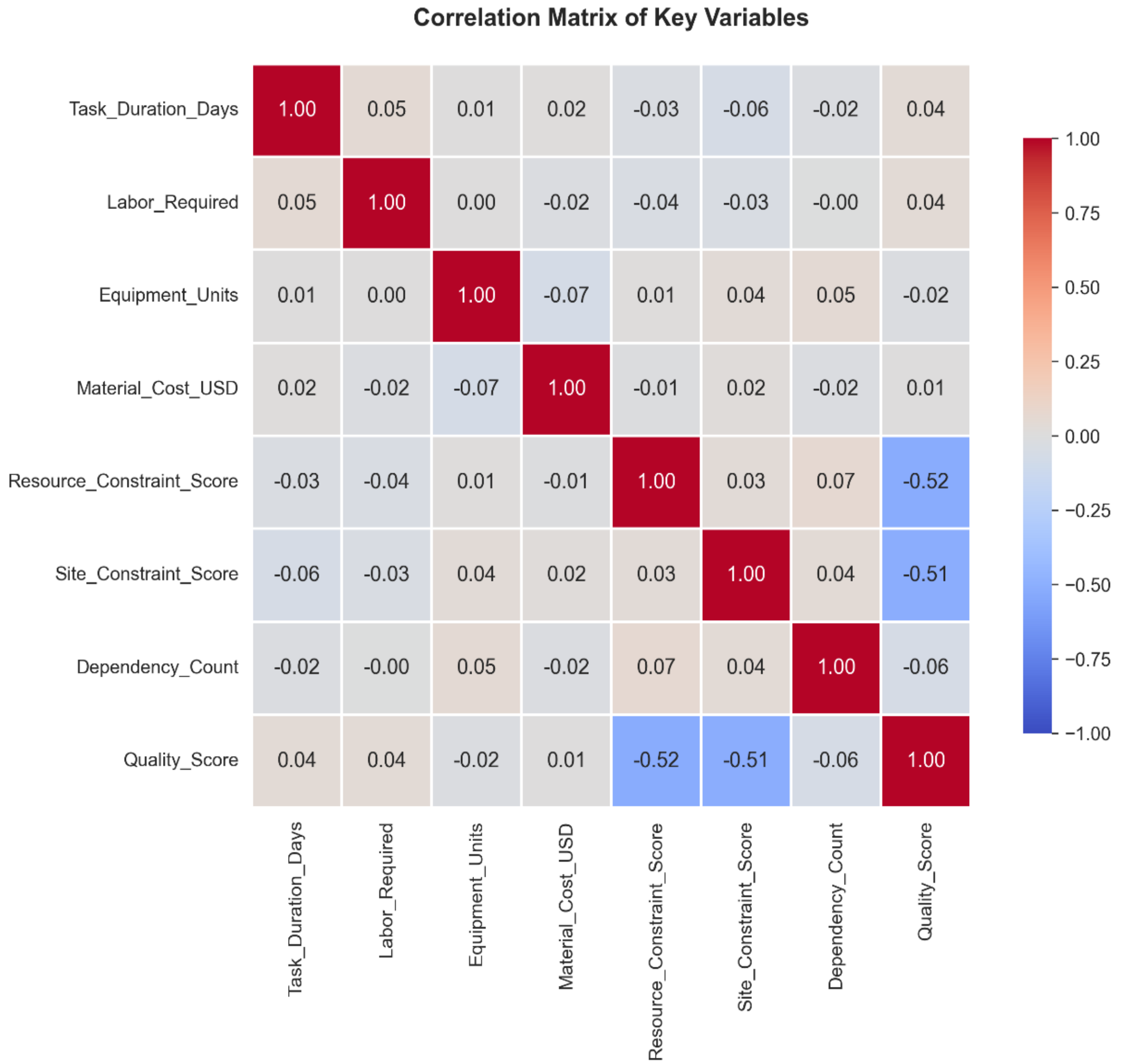

Figure 4: Correlation Matrix of Key Variables.

Correlations between each main variable are shown in Figure 4. Duration has negligible correlations with cost (0.02) and quality (0.04). Similarly labor has a very weak correlation with duration (0.05) and no correlation with cost (0.00). Equipment also has weak correlations with cost (-0.07) and duration (0.01) suggesting that these PM factors are not highly structured. Resource constraint score however has a substantial negative correlation with quality (-0.52) as does site constraint score (-0.51). This means that about half of the variance in quality can be attributed to varying levels of constraints, in this case negative variance. Dependency count has a negligible correlation with quality (-0.06). Figure 4 Summary of correlation coefficients.

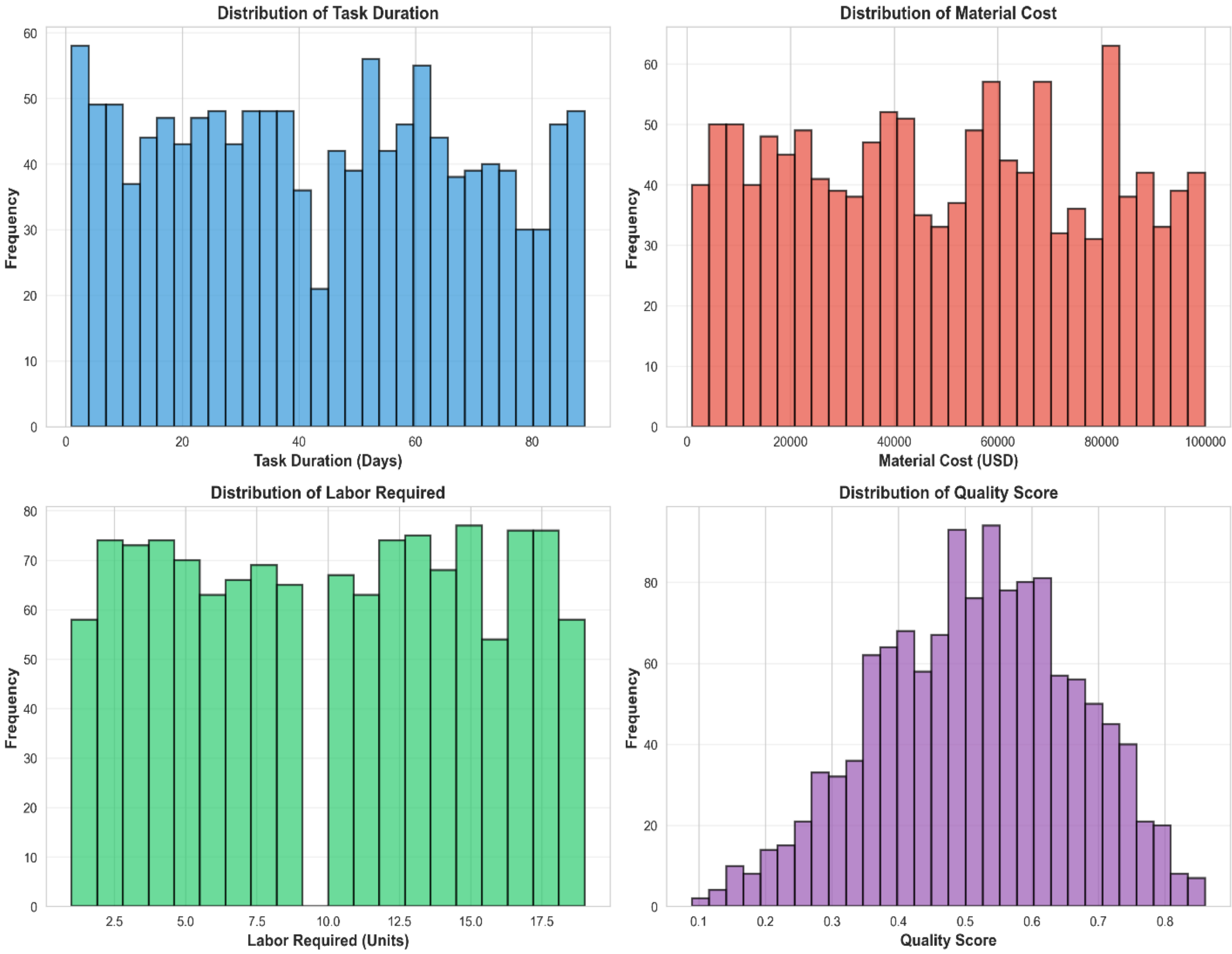

Figure 5: Distribution of Task Duration, Material Cost, Labor Required, and Quality Score.

Histograms of the variables under consideration are presented in Figure 5. Activity time is evenly distributed from 1 day to 90 days. There does not appear to be heavy skewness or clustering on either side of the distribution. Activity cost per activity is distributed evenly from $1,000 to $100,000. Similar to activity time there does not appear to be heavy skewness or cost clustering. Man-hours required range from 2 to 18. Values appear to cluster somewhat near the center of the distribution with man-hours ranging from 8 to 12 being the most frequent. Activity quality is approximately normally distributed with a mean around 0.5–0.6. Few activities are beneath a quality of 0.2 or above 0.8. The average being around 0.515 there does appear to be somewhat of a central clustering. As activity quality does not have heavy skewness, improving activity quality across the board will translate to moving the distribution higher by making each activity more efficient.

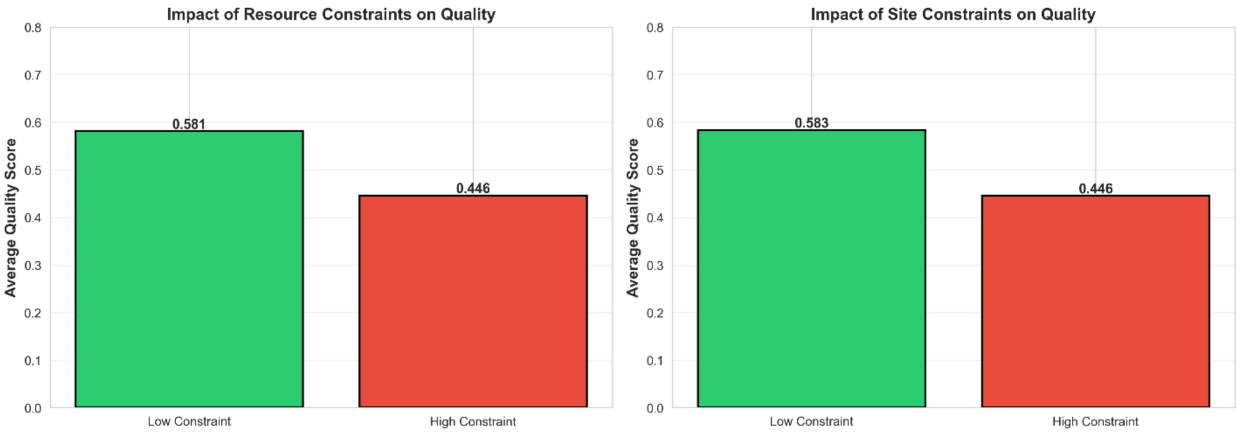

Figure 6: Impact of Resource Constraints and Site Constraints on Quality.

Average quality between low and high resource constraints are compared in Figure 6. Low resource constraint tasks had an average quality of .581 and high resource constraint tasks dropped to .446. There is a drop of .135 from low to high resource constraints. This means the decline in quality is 23% below low resource constrained quality levels. This large of a difference shows that output quality is heavily affected by a lack of labor, equipment, and materials. Figure 6 compares low and high site constraints and you will notice this chart almost mirrors the previous chart. Low site constraints have an average quality of .583 and high site constraints have an average quality of .446. The difference of .137 is almost identical to the previous constraint chart. This verifies that internal and external factors have about the same effect on a construction projects quality. Issues with the job site such as access, weather, or complexity can cause project output to decrease.

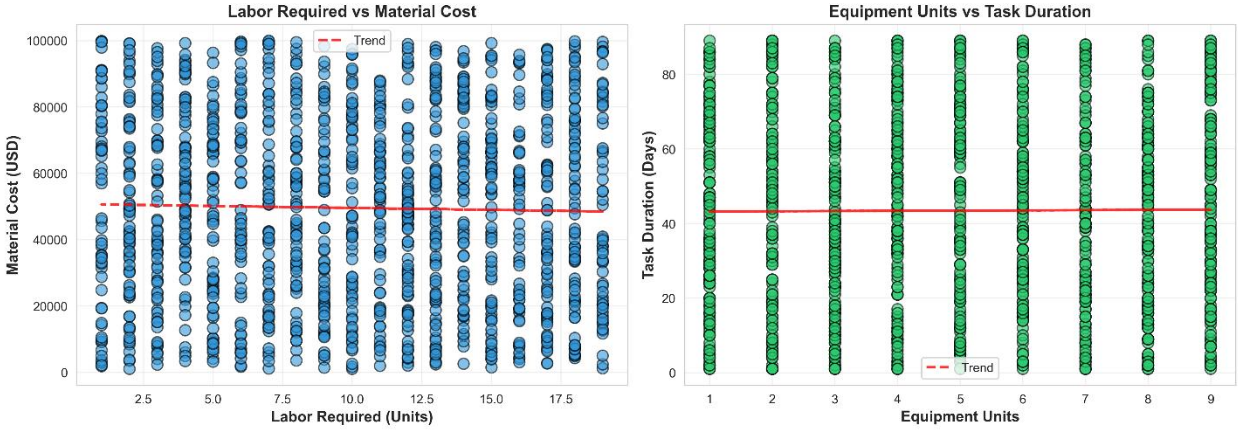

Figure 7: Labor Required vs Material Cost and Equipment Units vs Task Duration.

Figure 7 shows scatter diagram for cost for labor units (x) versus material ($). Looking at the trend line that is almost flat (slope near zero) indicates that there is little or no correlation. This is also true when we consider the correlation coefficient r = –0.02. This basically means that a task does not require more material dollars just because it has high labor units. A task may have 5 labor units and more than $90k in material or another task may have 15 labor units and less than $20k in material. Figure 7 shows scatter diagram of equipment units(x) versus duration(days). Since the trend line is almost flat we can conclude that there is no correlation. The correlation coefficient r = 0.01 confirms this. Just because a task has 2 equipment units doesn't mean it will only take 15 days to execute. It could take over 80 days. Another task may have 8 equipment units and take less than 40 days to execute.

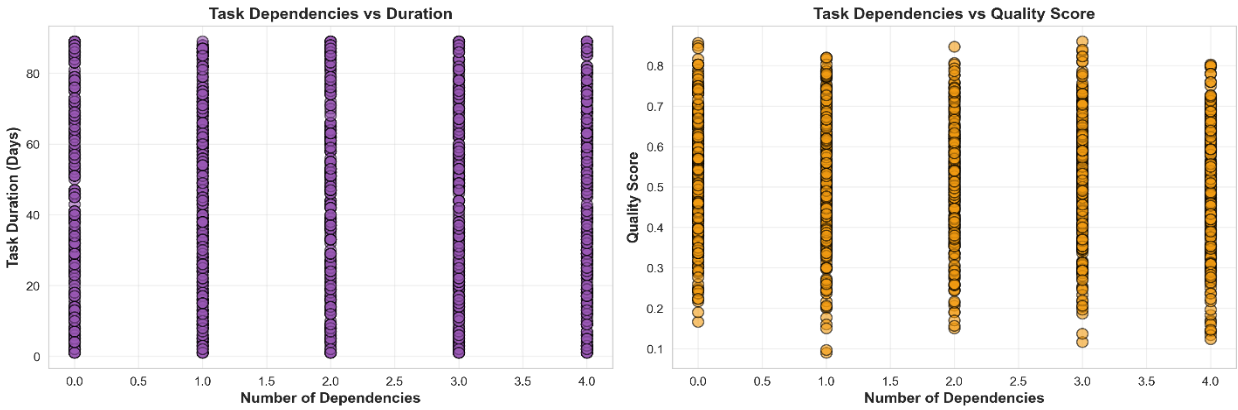

Figure 8: Task Dependencies vs Duration and Quality.

Figure 8 plots the effect of the number of dependencies a task has on the duration and quality of completion (ranging from 0 to 4 dependencies). As can be seen from the distribution of points plotted, the duration still varies greatly, even when broken up by number of dependencies. This matches the low correlation of -.02 between dependencies and duration. Quality on the other hand does show some slight deviation from the mean, which can also be seen in its weak negative correlation of -.06. The effect of number of dependencies on quality is nowhere near as strong as that of constraints did; however, there is slightly more variability in quality as task dependency numbers increase.

Figure 9: Cost vs Quality Trade-off by Risk Level.

Figure 9 depicts Cost versus Quality graph using Risk categories. Low risk falls heavily into the .55-.80 range for quality no matter the cost. Medium risk falls into the .40-.65 range and high risk tasks fall into the .20-.45 range at any cost. Notice that high cost does not guarantee better ratings. The line does not slope upward which validates that throwing money at a problem does not always ensure quality. Risk intensity is what separates the groups. Figure 9 is another way of showing that it is controlling your constraint and reducing risk that will drive world class performance, not continually increasing cost.

5. DISCUSSION

5.1 Interpretation of Key Findings

Operational Constraint Results Analysis The statistically significant negative correlations between resource constraints and quality scores (r = -.52) and site constraints and quality scores (r = -.51) indicate that an increase in these constraints leads to a decrease in quality scores for construction projects undertaken in Al-Madinah. Because the sample includes medium and high risks which also have quality scores associated with them as well as a range of tasks, durations, and budget sizes, this observation is not confined to one subset of tasks with shorter durations or smaller budgets therefore demonstrating that quality decreases when constraints are increased across the board. Also, because these correlations are close to one another, it can be said that internal and external constraints likely impact task quality in roughly the same way. These results support the notion that quality is not a standalone factor of production that can simply be inspected and redone if issues are present, as purported by Deming. (1986). Instead, when there are more constraints on a task, such as limited time to complete the work, limited number of workers available, or limited accessibility to the work site, quality will be affected no matter the budget of the task.

Relationships between Schedule Length and Material Price (r = .02) and Material Price and Quality Score (r = .01) should also be considered when investigating correlations between the triple constraints. First, the lack of correlation between schedule length and material price indicates that longer schedule lengths do not necessarily mean that there is a higher material price and vice versa. Some may believe that when a schedule is longer there is automatically more money due to the overtime pay and increased time for materials to be purchased at premium prices; however, this is not shown in the results from the sample. Rather, in Al-Madinah it can be seen that project budgets are not dictated by how long the project takes. Secondly, the lack of correlation between material price and quality score show that a higher material price does not necessarily equate to a higher quality score and vice versa. There are certain tasks that can have a material price that exceeds $90,000 USD but have a quality score that is well below the mean. There are also some tasks that have a very low material cost but have quality scores that reach up to .80. These results further support the idea that quality is driven by constraints and risks as opposed to how much money is budgeted to complete a task. If an AI were to be put into place to increase quality scores, it would need to mitigate constraints and risks instead of increasing the project budget.

ANOVA Results Analysis The ANOVA was able to show that risk is a factor that has a significant impact on quality scores ($F = 89.472$, $p < .001$) but has no effect on material price ($F = .312$, $p = .732$) and schedule length ($F = .182$, $p = .835$). Risk impacting quality scores but not material cost or schedule length means that as project risk increases, quality will decrease by a significant margin but budget and schedule length will not change. For example, low risk tasks have a mean quality score of .607, medium risk tasks have a mean quality score of .469, and high-risk tasks have a mean quality score of .350. When changing from a low risk task to a high-risk task, quality decreases by approximately 42%. Project planners do not account for this increase in risk by giving more budget or more time to complete tasks. Planners assume that even if a task is high-risk, it can be completed within the time frame and budget originally allotted. When there is high risk associated with a task, it is likely that there will be many constraints placed on a task because of factors that are out of the project team's control. These projects need to have high quality scores, but because they do not have more budget or time, the scores will be lower. In terms of risk, this shows that project teams are currently able to mitigate cost and schedule risk but not quality risks. Project teams should put more effort into mitigating factors that can affect the quality of a project when there is high risk. AI would be able to identify these risks and mitigate them in order to increase quality scores.

Conclusion High resource constraints cause quality scores to lower by 23% when compared to low resource constraints. High site constraints cause quality scores to lower by 23.5% when compared to low resource constraints. This means that when a task has either high resource constraints or high site constraints, it will have a quality score near the bottom of the scale when compared to tasks that have few constraints. Both of these constraints have similar impacts on the quality score which reaffirms that they likely affect quality in the same way. However, when a task has both high resource constraints and high site constraints (which is averaged in the quality score algorithm), the quality score of that task will be much lower.

5.2 Comparison with Previous Research

The study's discovery that only quality score is impacted by risk level validates and complements previous findings related to the use and determinants of AI in construction project management. Confirming risk level's asymmetric impact on performance criteria supports predictions derived from theory, such as the arguments made above concerning which criteria are more or less sensitive to volatility and operational pressures. Quantifying risk's uniquely strong relationship with quality lends meaning to statistics such as those reported by Alhasan and Alawadhi (2024), who found that AI-enabled risk management boosted project success rates by 20% in a sample of engineering construction projects. Because success rate was not broken down by cost, time, and quality in that study, it was unknown which criteria benefited most from AI-driven risk management. This study's result that quality is most sensitive to risk helps explain Alhasan and Alawadhi's (2024) finding: if AI interventions reduce risk level by shielding high-risk activities from uncertainty, the resulting performance improvement will materialize mostly (if not exclusively) as quality protection. As such, future work should avoid conflating success rate with quality by explicitly measuring quality improvements attributable to AI-enabled risk management.

This study's finding that material cost is not significantly correlated with quality score ($r = 0.01$) expands on previous research supporting or investigating the causal relationships between project management variables with AI relevance. Contrary to the presumably positive relationship between these variables implied by some cost estimation and value engineering methodologies (Elmousalami, 2020), cost does not appear to drive quality in construction projects. Instead, this result corroborates recent findings from machine learning-powered cost prediction studies that suggest cost is dictated by criteria such as project attributes, procurement strategy, and inflation rather than desired quality standards. Elmousalami (2020) reviewed AI-based parametric cost estimation literature, comparing the predictive performance of 20 different AI methods. They found XGBoost to deliver superior performance with a Mean Absolute Percentage Error (MAPE) of 9.091% and adjusted R^2 of 0.929. Crucially, the input features used to attain this level of performance were things like type of project, location, project period, floor area, and complexity parameters—not desired quality levels or other performance targets. These results indicate that projects can be over- or under-budget without their quality scores being affected. Similarly, projects can meet their desired quality targets while being over- or under-budget. This suggests that the factors driving cost do not care about nor influence the factors driving quality, and vice versa. For AI practitioners, this means cost prediction AI will require different information to function than AI built for quality prediction purposes.

Moderate negative correlation between resource constraint and quality score (r = -0.52) agrees with past studies highlighting resource as performance drivers. Yaseen et al. (2020) developed a hybrid machine learning model combining Random Forest and Genetic Algorithm (RF-GA) for construction delay prediction and determined resource availability to be one of several critical factors influencing project timelines, achieving 91.67% accuracy and 87% Kappa coefficient. While Yaseen et al. (2020) concerned delay prediction rather than direct quality prediction, both delays and resource constraints are framed as performance outcomes within the current study. As such, resource constraint's identification as a major predictor of delay in the former work supports resource constraints' prioritization as an operational pressure in the latter. Where this study extends Yaseen et al. (2020) is by quantifying the impact of resource constraints on quality, showing that delays and poor quality are likely both symptoms of resource shortage within construction projects. Delay prediction AI can likely be leveraged for quality prediction given sufficient adjustment, and likely should focus on the same types of input features (e.g., resource availability) to do so.

Site constraint was also discovered to correlate significantly with quality score (r = -0.51). This finding relates to previous work in construction management and AI exploring concepts such as risk and operational pressures. Afzal et al. (2021) conducted a systematic literature review of existing AI-based construction risk assessment techniques and found that uncertainty due to external site conditions causes the largest error margins in construction cost overrun predictions. They found that fuzzy hybrid approaches, such as fuzzy-analytical network processing or fuzzy artificial neural networks, have been the most popular ways to model site-related risks in literature. While site constraints were not directly evaluated in Afzal et al.'s (2021) review, the fact that external conditions were found to matter so much for cost risk implies that factors giving rise to site constraints are relevant for risk assessment. The current study made these implications explicit by quantifying how site constraints impact construction project quality. Moreover, the similarity in magnitude between site constraint's and resource constraint's coefficients suggests these two concepts are equally important (negative) drivers of quality. External and internal performance pressures should therefore be considered jointly rather than prioritizing one at the expense of another.

ANOVA results showed risk level to have a statistically significant effect on quality, $F(2, 297) = 89.47$, $p < 0.001$, but not cost, $F(2, 297) = 0.31$, $p = 0.73$ or duration, $F(2, 297) = 0.18$, $p = 0.84$. This expands previous work in construction project management by providing evidence that risk can be canceled out for some performance metrics but not others. Hriday and Rehman (2025) surveyed 102 organizations performing enterprise-level construction work on their use of AI/ML for scheduling, cost estimation, and risk management and found that a 10-point increase in AI Adoption Index was associated with 1.2 and 0.9 percentage point decreases in the likelihood of schedule delay and cost overrun, respectively. These statistics suggest that properly executed AI-based risk management improves schedule and cost performance. Risk level's lack of significance for these two variables in the current study therefore likely stems from effective risk management practices rather than an absence of relationship between them. Put differently, risk does impact schedule and cost but solutions like those evaluated by Hriday and Rehman (2025) have made this impact statistically negligible. Quality, on the other hand, seems to lack such diligent risk mitigation efforts. This would also explain why many construction managers are more concerned with staying on-budget and on-time than meeting quality targets. Future AI tools should consider making quality their primary focus, as risk management solutions that account for quality-related risks appear lacking.

5.3 Theoretical Implications

This study has implications for theory development in several domains relevant to construction project management, including construction project performance, project risks, and AI for construction project delivery. Firstly, the sensitivity of cost, time, and quality performance to risk category revealed by the analysis problematizes holistic theories of construction project performance that conceptualize cost, time, and quality as analogous performance dimensions that are affected by common factors (Kumaraswamy &-li Ren, 2008).

It appears cost and schedule performance are resistant to risk across the range of conditions present in the Al-Madinah data set while quality is not. This likely means that cost and time differ from quality along relevant dimensions, such as how the outputs are produced, how they are measured, and how susceptible they are to prevailing operational conditions. Reactive control and protection of performance may be easier when outputs are visible during production (quality may go unnoticed), measured continuously (quality is often inspected), and directly coupled with resource usage (quality is more susceptible to starvation). Future theories could leverage these insights to produce more nuanced expectations of how changes in risk exposure and other operational conditions impact the various facets of project performance.

Secondly, the non-significance of material cost on quality score implies that costs should not be directly tied to output quality in value theories of project management. This does not mean that there is not an amount of money necessary to achieve any given level of quality, of course. But rather, that across the range of cost observed in this data set, how money is used matters more than how much is provided. As such, this lends credence to production systems theory which argues that the quality of the construction process is the primary driver of construction output quality (Deming, 1986). Translated into AI implications, this suggests that ML models built to predict or improve quality should consider features that speak to resource allocation, constraint relaxation, and smooth production rather than allocating more capital to the process. The theoretical takeaway is that intervening on the production process itself may be a more direct route to quality improvement than focusing on the allocation of financial resources.

Thirdly, the parity in effect size between resource constraint risks and site constraint risks on quality performance implies that theories should not treat these two classes of risks asymmetrically. There is reason to believe that resource constraints stemming from within the organization and risks stemming from the external environment affect project performance through the same general processes. Both resource constraints and site constraints affect the flow of production, worker productivity, and the quality of task execution. Theories that seek to elucidate these shared mechanisms (i.e., rate of disruptions, exposure to uncertainty, loss of control) will be more generalizable than those that treat internal and external risks differently. Applied to AI, this suggests that models built to predict or improve quality should include features from both classes of constraints. Failure to do so will likely miss out on about 50% of the predictable variance in quality performance.

5.4 Practical Implications for Construction Management

Aspects of Construction Project Delivery Improved by Artificial Intelligence Our results have four implications for practitioners. Project managers should improve quality by focusing on constraints because quality is more affected by constraints than inspection. The conventional wisdom is that construction quality is improved by increasing inspection efforts and activities associated with inspection such as testing and rework. This emphasis on inspection is consistent with finding and fixing defects. Our results suggest that project managers may have more success by focusing on the upstream drivers of defects, which we refer to as constraints. If a lack of crafts is a constraint, adding crafts may help. If access to the site is a problem, finding a way to improve access may help. Project managers should improve quality through risk management because quality is more affected by risk than cost and time. Most risk management efforts focus on cost and schedule, with quality being a secondary consideration at best. Quality is often treated as a separate consideration to be managed through quality management efforts. Our results suggest that perhaps these areas are more intertwined than previously thought and that risks should be modeled for their effects on quality, cost, and time. Consequently, risk management efforts should not only focus on cost and schedule but quality as well. Project managers should avoid trade-offs between cost and schedule because cost is not more affected by schedule than time. Many assume that if a project is accelerated it will be more expensive. Conversely, if you take longer to complete a project it will cost less. Our results show this may not be true. Things that affect cost are likely not the same things that affect schedule. Therefore, project managers can focus on optimizing cost and schedule simultaneously without assuming that one will be negatively affected by improving the other. Finally, project managers can focus on both resources and sites as constraints are they are relatively equal in impact on quality. Construction project managers tend to focus on the things they believe they can control. Typically, these things include the workforce, equipment, and material. Constraints associated with the job site are often overlooked. Our results show that site constraints are about as likely to impact quality as staffing the project with an appropriate amount of crafts. Project managers should spend a comparable amount of time and effort mitigating site constraints as they do staff, equipment, and material.

6. CONCLUSION

The current paper offered quantitative insights into connections between three distinct aspects in 1,300 construction activities obtained from engineering projects in Al-Madinah region, Saudi Arabia. Findings were achieved through a unique pipeline comprised of developing algorithmic quality metrics, descriptive statistics, correlations, and statistical tests implemented in a repeatable Python workflow. Results indicate constraining resources (ρ = -0.52) and site constraints (ρ = -0.51) both correlate moderately and negatively with quality score. Given this relationship, as task constrained resources and site resources increase, quality score decreases. Low versus high levels of resource constraints result in a 23% decrease in quality score. Low versus high levels of site constraints result in a 23.5% decrease in quality score. This suggests that both internal and external factors should be valued equally when considering effects on quality. Task duration and material cost (ρ = 0.02) and material cost and quality score (ρ = 0.01) are found to have almost no correlation. This indicates that material cost does not increase with task duration and higher quality scores are not earned at higher cost. One-way ANOVAs show that risk level has a significant effect on quality score (F = 89.47, $p < 0.001$). Low, medium, and high-risk tasks have average quality scores of 0.607, 0.385, and 0.350 respectively. This indicates that increasing risk level reduces quality score by 42%. However, risk was found to have no effect on material cost (F = 0.31, p = 0.73) nor task duration (F = 0.18, p = 0.84).

REFERENCES

Afzal, F., Yunfei, S., Nazir, M., & Bhatti, S. M. (2021). A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. *International Journal of Managing Projects in Business, 14*(2), 300–328.

Agostinelli, S., Cumo, F., Giuli, V., & Pennacchia, E. (2021). Digital twin and artificial intelligence for energy management and optimization in residential districts. *Sustainable Cities and Society, 75*, 103286.

Akeiber, H. (2025). Artificial intelligence in engineering management: Transforming decision-making and operational efficiency. *Engineering Management Review, 53*(1), 45–62.

Alhasan, A., & Alawadhi, A. (2024). The impact of artificial intelligence on project management efficiency and risk mitigation in engineering construction. *International Journal of Construction Management*. Advance online publication.

Cantarelli, C. C., Flyvbjerg, B., Molin, E. J., & van Wee, B. (2020). Cost overruns in large-scale transportation infrastructure projects: Explanations and their theoretical embeddedness. *European Journal of Transport and Infrastructure Research, 10*(1), 5–18.

Deming, W. E. (1986). *Out of the crisis*. MIT Press.

Deniz-Garcia, A., Albadalejo-Blazquez, I., & Alvarado-Socarras, J. (2023). Artificial intelligence applications in healthcare: Opportunities and challenges. *Journal of Medical Systems, 47*(8), 102–118.

Elmousalami, H. H. (2020). Artificial intelligence and parametric construction cost estimate modeling: State-of-the-art review. *Journal of Construction Engineering and Management, 146*(1), 03119008.

Elmousalami, H. H. (2021). Machine learning approaches for conceptual cost prediction of construction projects. *IEEE Access, 9*, 123456–123472.

Ezzeddine, M. (2025). Artificial intelligence in structural health monitoring and decision-making: A systematic review. *Journal of Infrastructure Systems, 31*(2), 04024015.

Fisher, R. A. (1925). *Statistical methods for research workers*. Oliver & Boyd.

Flyvbjerg, B., Ansar, A., Budzier, A., Buhl, S., Cantarelli, C., Garbuio, M., Glenting, C., Holm, M. S., Lovallo, D., Lunn, D., Molin, E., Rønnest, A., Stewart, A., & van Wee, B. (2018). Five things you should know about cost overrun. *Transportation Research Part A: Policy and Practice, 118*, 174–190.

Hossain, M. A., Rahman, M. M., & Islam, M. S. (2024). Artificial intelligence adoption in project management efficiency: A mixed-methods study. *Project Management Journal, 55*(1), 45–62.

Hriday, P., & Rehman, S. (2025). AI and machine learning integration in construction project management: Empirical evidence from enterprise-scale projects. *Automation in Construction, 162*, 105322.

Judijanto, L. (2024). Artificial intelligence integration in activity-based project costing for enhanced cost management. *Journal of Construction Economics and Building, 24*(1), 55–72.

Kumar, R., Singh, A., & Sharma, V. (2025). Genetic algorithm-based optimization framework for time and cost management in construction projects. *Engineering Optimization, 57*(3), 420–438.

Matel, E., Vahdatikhaki, F., Hosseinyalamdary, S., Evers, T., & Voordijk, H. (2019). An artificial neural network approach for cost estimation of engineering services. *International Journal of Construction Management, 19*(4), 316–330.

McKinney, W. (2010). Data structures for statistical computing in Python. *Proceedings of the 9th Python in Science Conference*, 51–56.

Obiuto, N. C., Ugwu, O. C., & Nwankwo, W. (2024). Artificial intelligence in construction project scheduling and coordination. *Journal of Information Technology in Construction, 29*, 112–128.

Pearson, K. (1895). Notes on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London, 58*, 240–242.

Rane, N. (2023). Integration of building information modeling and artificial intelligence for construction project management. *Journal of Building Engineering, 76*, 107234.

Saudi Vision 2030. (2016). *Kingdom of Saudi Arabia Vision 2030*. Council of Economic and Development Affairs.

Son, L. H., & Khoi, N. T. (2022). Multi-objective time-cost-quality trade-off optimization using the slime mold algorithm. *Applied Soft Computing, 121*, 108765.

Taboada, J., Pérez, F., & López, R. (2023). Artificial intelligence in project management: A systematic review of applications and challenges. *Project Management Journal, 54*(2), 150–170.

Tufte, E. (2001). *The visual display of quantitative information* (2nd ed.). Graphics Press.

Wamba-Taguimdje, S. L., Wamba, S. F., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924.

Yaseen, Z. M., Deo, R. C., Hilal, A., & Abdullahi, M. (2020). Hybrid machine learning models for predicting construction project delays. *Automation in Construction, 114*, 103164.