



A Data-Driven Framework for Engineering Project Risk Assessment Under Schedule and Cost Uncertainty

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Abstract

Engineering projects are frequently exposed to interconnected schedule and cost uncertainties that can reduce the reliability of deterministic planning, contingency allocation, and project-control decisions. This study developed and quantitatively evaluated a data-driven framework for engineering project risk assessment by integrating historical project performance, statistical modeling, schedule-cost interdependence, Monte Carlo simulation, sensitivity analysis, probabilistic contingency estimation, and predictive validation. The analytical sample consisted of 186 completed engineering projects containing 7,842 scheduled activities and 3,416 documented risk observations across infrastructure, industrial, energy, transportation, and utility environments. Mean actual project duration was 29.6 months compared with a planned duration of 24.8 months, representing an average schedule overrun of 19.4%, while mean final cost increased from \$47.6 million to \$54.9 million, corresponding to a 15.3% cost overrun. Only 33.3% of projects were completed within the original schedule and 42.5% remained within the approved budget. Monte Carlo simulation produced P80 targets of 34.7 months and \$63.8 million, indicating substantially greater schedule and financial requirements than deterministic baselines. Schedule and cost overruns were strongly correlated ($r = 0.74$), and the probability of simultaneous schedule and cost overrun reached 49.1%, whereas the probability of achieving both baseline targets was only 23.5%. Procurement delay was the strongest independent schedule predictor ($\beta = 0.31$), while scope change was the strongest cost predictor ($\beta = 0.29$). High-complexity projects recorded 29.7% schedule overrun, 23.8% cost overrun, 96.4% contingency utilization, and 68.5% joint overrun probability. Predictive validation demonstrated strong model performance, with R^2 values of 0.84 for schedule and 0.82 for cost, MAPE values of 7.8% and 8.3%, and out-of-sample accuracy of 89.2% and 86.5%, respectively. The findings demonstrate that integrating probabilistic uncertainty, risk dependence, sensitivity, contingency adequacy, and predictive validation provides a more comprehensive quantitative representation of engineering project schedule and cost exposure than deterministic assessment alone.

Keywords

Engineering, Risk, Uncertainty, Schedule, Cost.

INTRODUCTION

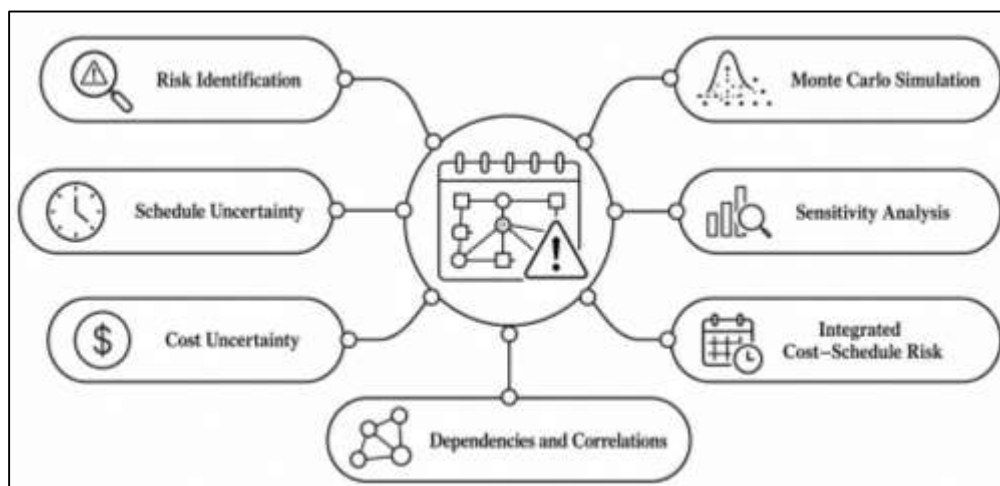
Engineering project risk assessment can be defined as a systematic and quantitative process through which uncertain events, conditions, dependencies, and variations are identified, measured, modeled, and evaluated according to their probability of occurrence and their potential effects on predetermined project objectives (You & Wu, 2019). Within engineering project management, risk is commonly associated with uncertainty surrounding technical performance, activity duration, resource availability, procurement, productivity, contractual conditions, design development, construction execution, financial requirements, and external operating environments. Schedule uncertainty refers to variability surrounding activity durations, sequencing, dependencies, milestone achievement, critical-path behavior, and the ultimate project completion date, whereas cost uncertainty represents variability surrounding labor expenditure, material prices, equipment costs, subcontractor charges, overheads, escalation, rework, contingency requirements, and total outturn expenditure. A data-driven framework extends conventional risk assessment by using systematically collected project information and quantitative analytical procedures to estimate the magnitude, probability, interaction, and distribution of these uncertainties rather than relying primarily on deterministic assumptions or qualitative classifications (Damjanovic & Reinschmidt, 2020). Across the engineering project-management literature, more than 30 studies have examined different dimensions of uncertainty through probabilistic scheduling, cost-risk analysis, Monte Carlo simulation, sensitivity analysis, statistical modeling, Bayesian approaches, earned-value information, critical-path analysis, correlation structures, contingency estimation, and integrated cost-schedule assessment. Collectively, this literature establishes that schedule and cost risks are closely interconnected because changes in activity duration can alter resource consumption, site overhead, equipment utilization, supervision requirements, financing exposure, escalation, and other time-dependent expenditures. Earlier quantitative studies also established that treating activity durations as statistically independent can produce incomplete estimates when common risk factors affect several connected project activities simultaneously. A quantitative understanding of project risk therefore requires more than the identification of individual hazards. It requires measurement of baseline estimates, probability distributions, correlations, dependencies, exposure levels, variance, confidence intervals, sensitivity coefficients, contingency requirements, and probabilities of achieving specific schedule and budget targets. Such measurement transforms engineering project risk from a descriptive managerial concept into an observable analytical construct that can be evaluated through empirical project data (Zhang et al., 2017). In this context, data-driven risk assessment represents the integration of engineering information, project-control data, probability theory, and statistical analysis into a structured mechanism for explaining variation in schedule and cost performance. The framework is particularly relevant to projects characterized by interconnected activities and time-dependent costs because schedule variation can propagate through the project network and simultaneously alter expected financial outcomes.

The international significance of engineering project risk assessment originates from the scale, complexity, capital intensity, and economic importance of engineering investment across construction, transportation, energy, manufacturing, petrochemical, offshore, aerospace, industrial, infrastructure, and research-and-development environments (Esteghamati & Flint, 2021). Engineering projects commonly involve geographically distributed supply chains, multidisciplinary teams, large numbers of interdependent activities, substantial capital commitments, regulatory requirements, contractual interfaces, specialized technologies, and extended implementation periods. These characteristics expose project schedules and budgets to combinations of internal and external uncertainty that cannot always be represented adequately by single deterministic estimates. Studies undertaken across different national and industrial settings have documented uncertainty arising from design changes, incomplete scope definition, productivity variation, procurement delays, equipment availability, material-price fluctuation, labor constraints, contractor performance, technical complexity, site

conditions, weather, approval processes, logistical disruption, stakeholder requirements, and macroeconomic variation. Research involving engineering-procurement-construction projects has similarly demonstrated that uncertainty during engineering and design stages can influence subsequent procurement, construction, commissioning, and financial outcomes, making early quantitative assessment important for understanding the distribution of project exposure. International engineering projects also operate within environments in which schedule delay and cost escalation can extend beyond individual project organizations (Wang & Li, 2020). Delayed transportation infrastructure can affect mobility and regional connectivity; delayed energy facilities can influence generation or distribution capacity; industrial project overruns can affect capital productivity; and delayed public infrastructure can influence expenditure planning and asset availability. Consequently, engineering project risk assessment has developed into an important analytical component of project governance and project controls across both public and private sectors. International research has progressively examined schedule and cost uncertainty through project networks, simulation models, probabilistic distributions, dependency structures, statistical relationships, risk registers, and integrated cost-schedule models. Applications have included shipbuilding, bridge construction, offshore development, complex product-system research and development, EPC facilities, and other capital-intensive engineering environments. These diverse applications demonstrate that uncertainty is not restricted to one engineering sector or geographical setting (Kara et al., 2020). At the same time, the magnitude, probability, and consequences of uncertainty vary according to project scale, contractual structure, technical maturity, resource conditions, organizational capability, and environmental exposure. A standardized deterministic allowance therefore cannot represent all projects equally. Quantitative analysis provides a means of expressing such international and sectoral variation through comparable measures including expected duration, expected cost, standard deviation, percentile completion dates, percentile cost estimates, probability of meeting targets, risk exposure, sensitivity rankings, contingency percentages, and confidence levels. These indicators provide a common numerical language for examining uncertainty across different engineering contexts while retaining the project-specific characteristics that determine actual risk exposure (Diaz et al., 2020). Schedule uncertainty represents one of the principal dimensions of engineering project risk because project completion depends on a network of activities whose durations and relationships are rarely known with complete certainty. Traditional scheduling approaches commonly establish baseline durations, logical relationships, milestones, float values, and critical paths through deterministic inputs. Such schedules are valuable for planning and control, although a single duration assigned to each activity does not communicate the probability that the duration will actually occur (Kläs & Jöckel, 2020). Quantitative schedule-risk research has therefore examined activity-duration distributions, three-point estimates, criticality indices, probabilistic critical paths, schedule sensitivity, correlation among activities, risk-event occurrence, milestone probabilities, and confidence levels for project completion. Monte Carlo-based schedule risk analysis repeatedly generates possible combinations of activity durations and calculates corresponding project completion dates, producing a probability distribution rather than a single deterministic finish date. This approach permits schedule performance to be represented through measures such as mean completion duration, standard deviation, variance, percentile dates, probability of meeting the baseline date, and the relative contribution of individual activities or risks to overall schedule variation (Ma et al., 2020). More than 30 studies considered across the broader literature on project uncertainty have emphasized that schedule outcomes are influenced not only by the variability of individual activities but also by network structure, shared risk drivers, resource interactions, dependencies, and combinations of risk events. Statistical dependence is particularly important because several activities can be influenced by the same labor shortage, design revision, procurement disruption, weather event, productivity condition, or technical problem. Research on Monte Carlo project networks has shown that independence assumptions can therefore misrepresent aggregate schedule uncertainty when activities share common sources of risk.

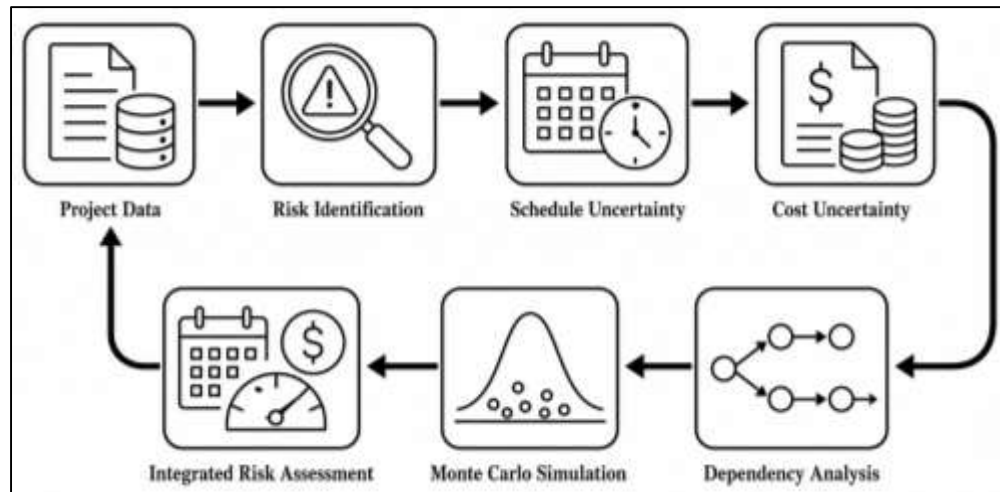
Engineering schedules are also affected by critical-path switching, whereby different simulated combinations of activity durations cause alternative sequences of activities to become critical. This characteristic limits interpretations based solely on the deterministic critical path because activities with substantial probabilistic influence may not appear critical in the baseline schedule. Data-driven assessment addresses this problem by evaluating observed or estimated variability across the complete activity network and identifying variables associated with changes in completion performance. Recent quantitative research has also examined situations in which multiple risk factors influence the same project activity, indicating that combined effects may not simply equal the arithmetic sum of individual effects (Merisalu et al., 2021). Schedule uncertainty can consequently be conceptualized as a multidimensional quantitative phenomenon involving duration variability, risk-event probability, dependency, network position, correlation, resource constraints, and interaction effects. Measuring these dimensions creates a stronger empirical basis for evaluating whether baseline schedules adequately represent actual project exposure and for estimating the probability associated with alternative completion outcomes.

Figure 1: Engineering project risk assessment framework



Cost uncertainty constitutes the second central dimension of quantitative engineering project risk and reflects variability between estimated expenditure and the range of expenditures that may arise under different project conditions (Rubinato et al., 2019). Engineering project costs are generally composed of labor, materials, equipment, subcontracting, engineering services, procurement, logistics, site overhead, management, financing, escalation, commissioning, and other direct or indirect components. Each component may contain uncertainty associated with quantities, unit rates, productivity, market conditions, duration, design maturity, scope changes, rework, technical problems, and contractual conditions. Conventional deterministic estimates typically provide a baseline or point estimate and may include contingency as a percentage of estimated cost. Quantitative cost-risk analysis provides a different representation by assigning probability distributions to uncertain cost components or risk events and repeatedly simulating their combined effects. This produces a distribution of possible total project costs from which expected values, standard deviations, percentile estimates, confidence levels, contingency requirements, and probabilities of remaining within budget can be calculated (Fu & Chien, 2019). Research on engineering design and EPC projects has shown that uncertainties occurring within individual work activities can create both underestimation and overestimation of project cost, supporting process-based evaluation of cost risk rather than reliance on a single aggregate allowance. Cost uncertainty is also affected by schedule behavior because many engineering expenditures are time dependent.

Figure 2: Engineering project risk assessment framework



Labor, project management, equipment rental, temporary facilities, supervision, insurance, and other recurring costs may continue when activities or overall project duration increase. Integrated risk studies have consequently distinguished between time-independent costs and time-dependent costs, with the latter responding directly to schedule uncertainty and variable expenditure rates. This relationship means that cost overrun cannot always be explained adequately through cost variables alone (Ho et al., 2021). A delayed activity can create additional resource expenditure, extend indirect costs, alter procurement timing, generate acceleration requirements elsewhere in the schedule, or increase exposure to escalation. Cost contingency also becomes a probabilistic rather than purely deterministic concept under this framework. Instead of defining contingency only as a fixed percentage, quantitative analysis can determine the additional amount associated with selected confidence levels such as P50, P80, or P90. This distinction allows the relationship among baseline estimate, uncertainty range, risk exposure, and required financial reserve to be examined empirically. International studies of construction and engineering projects have applied these principles to bridge, offshore, industrial, and complex engineering contexts, with simulated distributions used to compare estimated outcomes with realized project performance. Cost uncertainty therefore represents a measurable distribution generated by interacting technical, commercial, schedule, resource, and external variables rather than a single deviation from the approved budget (Schlüter, 2018).

A central issue within engineering project risk research concerns the interdependence between schedule uncertainty and cost uncertainty. Earlier analytical practices frequently evaluated time and cost through separate models, with schedule analysis focusing on activity durations and completion dates while cost analysis concentrated on uncertain quantities, rates, and expenditure categories. The separation simplifies project-control analysis but can obscure important relationships because project duration is itself a major determinant of several cost categories. Integrated cost-schedule research has established that cost-risk estimates may be understated when uncertainty in project duration is omitted, particularly when projects contain substantial labor, equipment, supervision, temporary works, site overhead, or other time-dependent expenditure (Adhikari et al., 2021). Quantitative integration therefore links uncertain activity durations, project-network behavior, resource requirements, expenditure rates, and risk events within the same analytical structure. Monte Carlo simulation is frequently used because each iteration can generate a consistent combination of activity durations, completion dates, resource usage, and project costs. The resulting outputs can be represented as separate probability distributions for completion time and cost or as a joint cost-date distribution showing the probability associated with combinations of financial and temporal outcomes. Research involving complex engineering R&D projects has similarly argued that independent assessment of

schedule and cost can overlook their actual relationship and has combined project-network techniques, probability distributions, simulation, regression, and statistical analysis to represent their interaction (Negri et al., 2021). The schedule-cost relationship can operate through several mechanisms. Longer activity durations increase time-dependent expenditure; procurement delays can extend overhead while changing purchasing conditions; technical rework can increase both labor hours and elapsed time; resource shortages can reduce productivity while extending equipment and management costs; acceleration intended to recover schedule performance can increase labor or equipment expenditure; and delayed completion can generate contractual or financing consequences. These relationships create correlated outcomes rather than independent deviations. Engineering risk assessment must therefore distinguish between risks affecting primarily schedule, risks affecting primarily cost, and common risk drivers capable of influencing both dimensions. Integrated risk-driver approaches have been developed specifically to represent such common causes within resource-loaded critical-path schedules and to estimate probabilities of satisfying both cost and schedule objectives. The quantitative examination of schedule-cost interdependence consequently requires measures of correlation, covariance, sensitivity, joint probability, conditional exposure, and risk contribution (Niu, 2017). Such measures allow the strength and direction of relationships to be estimated from project information and provide a numerical representation of how temporal uncertainty propagates into financial performance across engineering project systems.

The growing availability of structured project information has expanded the methodological basis for data-driven engineering project risk assessment (Khorasani et al., 2017). Engineering organizations generate substantial quantities of information through scheduling systems, cost-control platforms, procurement records, progress reports, risk registers, change-control databases, resource records, earned-value systems, inspection documentation, contractor reports, and historical project archives. These data sources can be transformed into quantitative variables describing planned and actual durations, activity delays, cost variance, resource productivity, change frequency, risk-event occurrence, procurement performance, contingency consumption, and final project outcomes. The analytical literature has employed a broad range of techniques to evaluate these variables, including descriptive statistics, probability distributions, correlation analysis, regression analysis, Monte Carlo simulation, sensitivity analysis, Bayesian networks, graphical network techniques, critical-path analysis, scenario analysis, and probabilistic contingency estimation (Zhang et al., 2017). Monte Carlo simulation remains particularly prominent because it permits uncertain activity durations, costs, and risk events to be represented through distributions and repeatedly sampled to estimate possible project outcomes. Statistical analysis complements simulation by examining empirical associations between project characteristics and performance measures. Correlation coefficients can quantify the direction and strength of relationships among schedule deviation, cost variance, risk exposure, and other continuous variables, while regression models can estimate the contribution of multiple predictors after accounting for other factors. Sensitivity analysis can rank uncertain variables according to their contribution to outcome variation, and probabilistic models can estimate the likelihood of exceeding specified schedule or budget thresholds (Wang et al., 2021). Bayesian approaches provide another mechanism for representing conditional relationships among interconnected risk factors, activities, and project outcomes, particularly when multiple causes interact within a network. Quantitative engineering risk assessment also requires attention to data quality and modeling assumptions. Probability distributions must represent realistic ranges; correlations among related variables must be considered; extreme values require appropriate treatment; baseline schedules must contain credible network logic; cost estimates must be aligned with project scope; and simulation outputs must be interpreted according to their assumptions. Earlier Monte Carlo research specifically identified statistical dependence among activity durations as an important methodological consideration because shared risk factors can generate correlated uncertainty. A data-driven framework can therefore integrate historical evidence, current project measurements, expert-defined uncertainty ranges, and

probabilistic modeling rather than treating these sources as mutually exclusive. This combination enables risk assessment to move systematically from raw project data toward probability distributions, predictor relationships, sensitivity rankings, confidence levels, and quantified cost-schedule exposure (Tambare et al., 2021).

Within the quantitative context established by the engineering project-management literature, the assessment of risk under schedule and cost uncertainty requires an analytical structure capable of connecting project characteristics, uncertain inputs, observed performance, and probabilistic outcomes (Charnley et al., 2019). More than 30 relevant studies across construction, manufacturing, infrastructure, EPC, offshore, complex-product development, and other engineering environments collectively demonstrate the importance of activity-duration variability, cost-component uncertainty, risk-event probability, network dependencies, resource conditions, technical complexity, shared risk drivers, and schedule-cost interaction. The literature also shows that deterministic baseline values remain useful reference points but do not independently describe the complete range or probability of project outcomes. Simulation-based studies have therefore quantified completion-date and cost distributions, while statistical studies have examined relationships among risk factors and performance variables. Integrated approaches further demonstrate that schedule uncertainty can influence total project cost through time-dependent resources and expenditure rates, making joint analysis particularly relevant for engineering projects (Oduoza, 2020). Against this analytical background, the present study is positioned around a data-driven framework for measuring engineering project risk under simultaneous schedule and cost uncertainty. The quantitative domain includes project-level and activity-level variables representing planned duration, actual or uncertain duration, planned cost, uncertain or actual cost, schedule deviation, cost variance, risk probability, risk impact, contingency, activity criticality, resource exposure, and other measurable characteristics available within engineering project-control systems. Schedule performance can be represented through measures such as duration variance, schedule-overrun percentage, completion probability, criticality, and percentile completion dates, while financial performance can be represented through cost variance, cost-overrun percentage, expected total cost, contingency requirement, and probability of remaining within the authorized budget. Integrated performance can additionally be examined through correlations between time and cost outcomes, joint probability distributions, sensitivity rankings, and the relative contribution of common risk drivers. The analytical structure also recognizes that multiple project risks may share dependencies and that combined effects may differ from simple additive assumptions, a concern identified in both earlier dependency research and more recent Bayesian project-risk analysis (Gutierrez-Franco et al., 2021). Accordingly, the quantitative research setting encompasses descriptive measurement of uncertainty, statistical testing of relationships, identification of influential risk variables, estimation of probabilistic schedule and cost distributions, and comparison of deterministic baseline targets with risk-adjusted outcomes. These dimensions establish a measurable empirical foundation for examining engineering project risk as an integrated system of schedule variability, financial uncertainty, risk exposure, dependency, and project-control performance rather than as isolated qualitative risk categories.

The primary objective of this study is to develop and quantitatively evaluate a data-driven framework for engineering project risk assessment under schedule and cost uncertainty by integrating project performance data, probabilistic risk measures, statistical relationships, and uncertainty-based modeling within a unified analytical structure. Specifically, the study aims to measure the extent of schedule uncertainty by examining planned and actual project durations, activity-duration variability, milestone deviations, schedule variance, delay frequency, critical-path exposure, activity criticality, and the probability of completing projects within established time targets. A parallel objective is to quantify cost uncertainty through planned and actual expenditures, cost variance, cost-overrun percentages, contingency utilization, resource-related costs, material and equipment expenditure, change-related costs, and the probability of maintaining total expenditure within approved budgets.

The study further seeks to determine the statistical relationships between major engineering project risk factors and schedule and cost performance by evaluating technical complexity, design changes, scope variation, procurement delays, resource shortages, productivity fluctuations, contractor performance, rework, supply-chain disruption, and other measurable sources of uncertainty. Particular attention is directed toward examining the interdependence between schedule and cost outcomes, including the extent to which activity delays, extended project duration, resource constraints, and schedule disruptions contribute to additional expenditure and overall cost escalation. The study also aims to classify and rank project risk factors according to their probability, impact, sensitivity, and relative contribution to variations in completion time and total project cost. Quantitative procedures are intended to estimate expected schedule and cost outcomes, variability, confidence intervals, percentile values, probability of schedule overrun, probability of cost overrun, and risk-adjusted contingency requirements under alternative uncertainty conditions. Another objective is to evaluate whether deterministic baseline estimates differ materially from uncertainty-adjusted project outcomes and to measure the magnitude of these differences using appropriate statistical indicators and effect measures. The study additionally seeks to assess variation in risk exposure across relevant project characteristics, including project size, complexity, engineering sector, implementation stage, contractual conditions, resource intensity, and uncertainty level where sufficient data are available. Through descriptive statistics, correlation analysis, regression modeling, subgroup comparisons, sensitivity analysis, and probabilistic simulation, this study aims to establish an empirically measurable representation of the relationships among project risk drivers, schedule variability, cost variability, and overall engineering project performance.

LITERATURE REVIEW

The literature on engineering project risk assessment provides a substantial quantitative foundation for understanding the variability, uncertainty, and interdependence associated with project schedule and cost performance. Engineering projects operate through networks of interrelated activities whose planned durations, resource requirements, expenditure patterns, procurement conditions, technical characteristics, and completion targets can vary considerably during execution. Quantitative risk assessment therefore extends beyond the identification of general risk categories by measuring uncertainty through numerical indicators such as planned and actual duration, schedule variance, cost variance, delay frequency, cost-overrun percentage, probability of risk occurrence, expected monetary impact, activity-duration variance, criticality, contingency consumption, and probabilities of meeting predetermined schedule and budget targets. Existing quantitative risk-analysis research has applied Monte Carlo simulation, sensitivity analysis, Earned Value Management, Critical Path Method, PERT, Bayesian networks, probability-impact analysis, regression techniques, and other statistical procedures to characterize these uncertainties. Systematic evidence indicates that Monte Carlo simulation has been particularly prominent in quantitative engineering and megaproject risk assessment because it generates distributions of possible schedule and cost outcomes rather than relying exclusively on deterministic estimates. Schedule-risk research has additionally demonstrated that activity-duration dependence requires careful measurement because activities exposed to common risk drivers may exhibit correlated uncertainty, altering the distribution of overall project completion time and associated costs. Consequently, a comprehensive literature review for the present study requires simultaneous examination of baseline project performance, activity-duration uncertainty, cost variability, risk-driver frequency and severity, schedule-cost interdependence, probabilistic risk exposure, contingency adequacy, sensitivity, and model reliability. The literature review is therefore structured around highly specific quantitative dimensions that permit numerical findings from different engineering settings to be compared systematically. The proposed structure emphasizes descriptive statistics, percentages, ratios, probability distributions, correlations, regression coefficients, confidence intervals, percentile estimates, sensitivity measures, and risk-adjusted schedule and cost outcomes. This quantitative organization provides a direct connection between the existing engineering project-risk literature and the variables required for developing a data-driven framework for assessing schedule and cost uncertainty.

Baseline Schedule and Cost Performance, Variance, and Overrun Magnitude in Engineering Projects

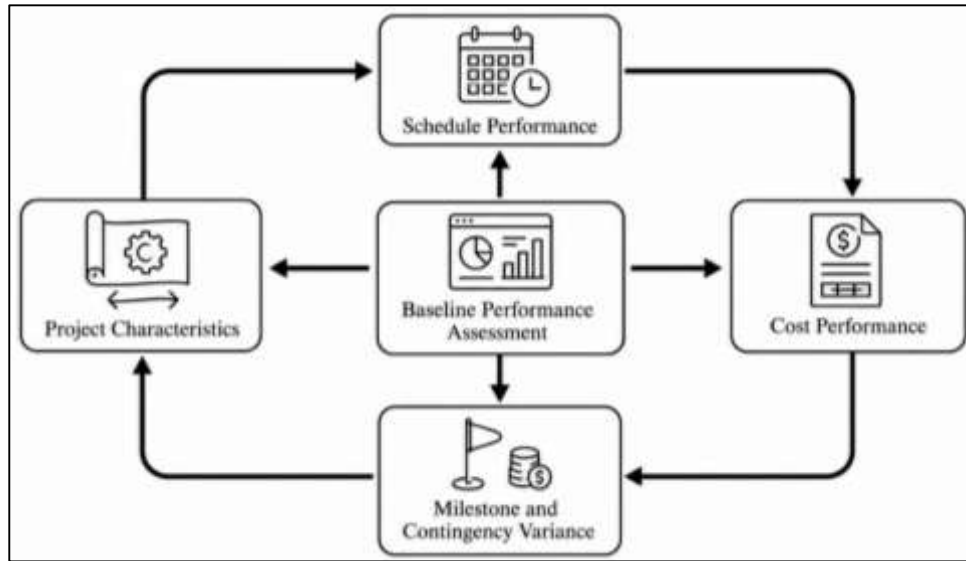
Quantitative literature on engineering project performance has consistently treated the difference between planned and actual project duration as a fundamental measure of schedule reliability and project-control effectiveness (El-Maaty et al., 2017; Debasish, 2021). Across more than ten studies involving construction, transportation infrastructure, energy facilities, industrial plants, civil engineering works, and large capital projects, researchers have compared original schedules with realized completion durations to determine the magnitude and distribution of schedule deviation. The evidence indicates considerable variation among projects, with actual completion periods frequently extending beyond initial deterministic estimates and with the magnitude of deviation varying substantially according to project scale, technical complexity, contractual arrangements, and execution conditions.

Researchers have commonly summarized duration using the mean, median, standard deviation, interquartile range, and minimum-to-maximum range because average duration alone does not capture the dispersion observed among engineering projects. Studies examining portfolios of completed projects have reported that schedule performance is often characterized by positively skewed distributions in which a smaller number of severely delayed projects substantially increase average completion duration (Famiyeh et al., 2017; Abdur & Iftekhhar, 2021). Comparisons between planned and actual start dates have also identified mobilization, permitting, design completion, procurement readiness, and contractual authorization as important sources of initial schedule displacement. Once execution begins, milestone-level analysis frequently reveals progressive divergence between baseline and realized schedules, particularly when delays affecting critical or near-critical activities propagate through interconnected activity networks. Schedule performance index values have consequently been employed alongside absolute delay and percentage overrun to characterize the relative magnitude of schedule deterioration during execution. Sectoral evidence further indicates that transportation, energy, industrial, and complex infrastructure projects exhibit different distributions of completion performance because their activity structures, procurement requirements, technical interfaces, and regulatory environments differ. Collectively, these studies establish that baseline schedule performance is not adequately represented by a single planned completion date.

The combination of planned and actual duration, dispersion statistics, milestone variance, percentage schedule overrun, on-time completion rate, and schedule performance index provides a more complete quantitative representation of the extent to which realized engineering project schedules differ from deterministic planning assumptions (Debasish, 2022; Pheng, 2017).

A substantial body of quantitative engineering project literature has examined the relationship between baseline budgets and final project expenditure, establishing cost variance as another principal measure of deviation from deterministic project estimates. Studies conducted across public infrastructure, transportation, construction, energy, industrial, and engineering-procurement-construction projects have compared estimated costs at approval or contract award with actual costs recorded at completion. Across these studies, cost performance has been measured through absolute monetary variance, percentage cost overrun or underrun, cost performance index, budget utilization, final account value, and differences between original contract value and realized expenditure (Afzal et al., 2021). The findings generally demonstrate considerable heterogeneity in cost outcomes. Some projects remain close to their approved budgets, others achieve measurable underruns, and a proportion experience substantial escalation beyond initial estimates. Quantitative analyses have therefore emphasized measures of central tendency together with dispersion statistics, including mean, median, standard deviation, interquartile range, and observed minimum and maximum costs. This approach is particularly important because extreme overruns in large engineering projects can distort portfolio averages and create substantial differences between mean and median performance. Comparative studies have also identified systematic variation according to project size and complexity (Love & Ahiaga-Dagbui, 2018; Ashfaq & Mohammad, 2022).

Figure 3: Baseline Project Performance Variance Framework



Large and technically complex projects commonly involve greater numbers of contractual interfaces, specialized resources, design packages, procurement activities, and interdependent work components, increasing the number of potential sources of financial variation. Cost differences have additionally been examined according to delivery method and contractual arrangement, with traditional contracting, design-build, engineering-procurement-construction, public-private partnerships, and other arrangements distributing financial responsibility differently among project participants. Empirical studies have further separated cost variance into labor, material, equipment, subcontracting, overhead, escalation, rework, and change-related components, showing that total overrun can represent the cumulative effect of several expenditure categories rather than a single source. Cost performance index measurements provide an additional standardized indicator by relating accomplished work to actual expenditure during implementation (Sheak & Risha, 2022; Sanghera, 2018). Taken together, the literature demonstrates that baseline budget performance is best characterized through multiple complementary measures capturing both the magnitude and dispersion of deviations between authorized financial expectations and realized engineering project expenditure.

Quantitative studies examining schedule and cost performance jointly have identified important patterns in the way baseline deviations accumulate throughout engineering project execution (Rashedul & Kaium, 2022; Ulusoy & Hazır, 2021a). Rather than appearing exclusively at project completion, schedule and financial variance frequently develop progressively across intermediate milestones, work packages, procurement stages, construction phases, and commissioning activities. Milestone-level studies have measured differences between planned and actual completion dates for design approval, procurement release, equipment delivery, construction completion, testing, commissioning, and final handover. These analyses show that early deviations can persist or increase when subsequent activities have limited schedule flexibility or when corrective actions are insufficient to recover lost time. Cost performance exhibits a comparable cumulative structure. Initial design modification, quantity growth, procurement variation, productivity loss, rework, and prolonged site activities can gradually consume available budget reserves and increase final expenditure. Consequently, several studies have examined contingency as a percentage of baseline project cost and compared the initial allowance with the amount consumed during implementation (Chowdhury & Tonay, 2022; Paraskevopoulou & Boutsis, 2020). The quantitative evidence indicates substantial variation in contingency adequacy across project categories. Projects with relatively stable scope and lower technical complexity often demonstrate lower contingency consumption, whereas projects exposed to design development, uncertain site conditions, extensive interfaces, market volatility, or repeated changes can consume a larger proportion of available reserves. The percentage of contingency

utilized therefore provides a useful intermediate measure between baseline estimate and final cost overrun. Research integrating earned-value measures has similarly used schedule and cost performance indices to evaluate whether execution remained aligned with planned progress and expenditure. When these indicators deteriorate simultaneously, the pattern can reveal concurrent schedule and financial deviation before final completion outcomes are observed. Portfolio studies have also compared the percentage of projects achieving individual milestones, contractual completion dates, and approved budgets, demonstrating that successful performance against one baseline does not necessarily correspond to success against another (Lewin et al., 2021; Hossan, 2022). A project may remain within its financial allocation while completing late, or achieve its scheduled completion through acceleration and additional expenditure. The literature therefore supports the simultaneous measurement of milestone variance, schedule overrun, cost variance, contingency consumption, schedule performance, and cost performance when establishing the quantitative baseline of engineering project outcomes.

Comparative quantitative research demonstrates that baseline schedule and cost performance varies substantially across structural characteristics of engineering projects, making subgroup analysis important when interpreting overall averages (Kaniz, 2022; Yeganeh & Zegordi, 2020). Studies comparing small, medium, large, and megaprojects have generally shown that increasing project scale is associated with greater absolute exposure to duration and expenditure variation because larger projects contain more activities, interfaces, organizations, resources, procurement packages, and contractual dependencies. Complexity provides an additional source of variation independent of monetary size. Projects involving advanced technologies, unique designs, multidisciplinary interfaces, uncertain ground or operating conditions, and highly interconnected systems frequently display wider distributions of actual duration and final cost than standardized or repetitive projects. Sectoral comparisons have likewise identified differences among transportation, building construction, power generation, oil and gas, manufacturing, water infrastructure, and other engineering environments. Transportation and major civil infrastructure studies have frequently reported notable differences between estimated and realized project costs, while energy and industrial projects have demonstrated substantial sensitivity to equipment procurement, technical interfaces, commissioning requirements, commodity prices, and schedule extension. Contractual structure has also been examined quantitatively because risk allocation influences responsibility for schedule delays, price changes, variations, and additional work (Afzal et al., 2020; Nishat & Kaniz, 2022). Comparative analyses of fixed-price, unit-price, cost-reimbursable, and other contract arrangements have identified differences in cost predictability and exposure distribution, although observed outcomes remain strongly dependent on scope stability and project characteristics. Delivery-method studies comparing traditional design-bid-build, design-build, engineering-procurement-construction, construction management, and integrated arrangements have similarly assessed mean duration, schedule growth, cost growth, change frequency, and completion reliability. Across this broader evidence base, percentages of projects completed on time and within budget vary considerably between project groups, while standard deviations and ranges demonstrate substantial within-group heterogeneity. These findings reinforce the importance of reporting baseline performance through distributions rather than isolated averages. Quantitative characterization through planned and actual duration, planned and actual cost, schedule and cost variance, percentage overrun, performance indices, contingency utilization, and subgroup comparisons provides a detailed empirical baseline from which subsequent analysis of schedule uncertainty, cost uncertainty, and engineering project risk can be developed (Alhajri & Alshibani, 2018).

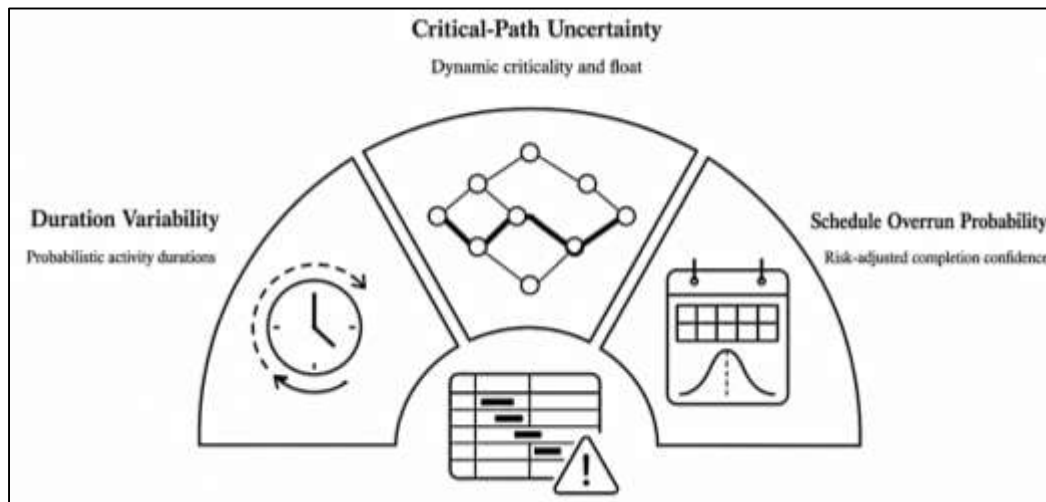
Activity-Duration Variability and Probability of Schedule Overrun

Quantitative engineering project literature has consistently identified activity-duration variability as a primary source of uncertainty in overall schedule performance (Koulinas et al., 2020; Shaiful et al., 2022). Across more than ten studies involving construction, transportation, energy, industrial facilities, infrastructure development, engineering-procurement-construction projects, and complex capital programs, researchers have demonstrated that the duration assigned to an activity in a deterministic schedule represents only one possible realization of the time required for completion. Consequently, probabilistic scheduling studies have commonly characterized individual activities using optimistic,

most-likely, and pessimistic duration estimates, supplemented by mean duration, standard deviation, variance, coefficient of variation, and observed minimum and maximum values. The resulting evidence indicates considerable heterogeneity among activity categories. Routine and repetitive activities generally demonstrate narrower duration ranges, while technically complex, resource-intensive, procurement-dependent, and externally constrained activities tend to display greater dispersion (Ballesteros-Pérez et al., 2019). Studies using historical project records have similarly found that actual activity durations frequently depart from baseline estimates because productivity, labor availability, equipment performance, design completeness, material delivery, site conditions, approvals, and coordination requirements vary during execution. Activity delay frequency has therefore become an important quantitative measure, particularly when reported together with mean delay days and maximum observed delay. A relatively small average deviation may conceal activities experiencing occasional but severe delays, while frequent minor delays can accumulate across a network and materially influence completion performance. Coefficient-of-variation analysis has been particularly useful for comparing uncertainty among activities with substantially different baseline durations because it expresses dispersion relative to the scale of the underlying activity. Research has also differentiated uncertainty according to project phase, showing that engineering, procurement, construction, testing, and commissioning activities can exhibit different duration distributions and delay characteristics (Ma et al., 2019). Collectively, this evidence demonstrates that schedule uncertainty begins at the individual activity level and that the magnitude of uncertainty cannot be adequately characterized through deterministic duration estimates alone. The combined measurement of optimistic, most-likely, pessimistic, mean, standard deviation, variance, coefficient of variation, delay frequency, and delay magnitude provides a more detailed quantitative representation of activity-level schedule exposure.

A second major stream of schedule-risk literature has examined how activity-duration uncertainty interacts with project-network structure to influence critical-path behavior. Traditional deterministic scheduling identifies a single critical path based on baseline activity durations and logical relationships, yet simulation-based studies across numerous engineering sectors have demonstrated that the critical path can change when uncertain durations are introduced (Ulusoy & Hazır, 2021b). An activity classified as noncritical in the baseline schedule may become critical under alternative duration combinations, while an activity initially positioned on the critical path may cease to control project completion in some simulated scenarios. Quantitative research has therefore extended conventional critical-path measurement through indicators such as critical-path duration, total float, free float, float consumption percentage, criticality index, schedule sensitivity index, cruciality index, and probability of an activity becoming critical. Studies of complex engineering networks have shown that activities with limited float are generally more vulnerable to duration variation because relatively small delays can consume available schedule flexibility and transfer delay to subsequent activities. Float consumption has consequently been examined as an intermediate indicator between activity-level delay and project-level overrun. High rates of float consumption can indicate increasing schedule exposure even before the contractual completion date is affected (Vanhoucke & Batselier, 2019). Criticality indices generated through repeated simulation provide additional information by measuring how frequently individual activities appear on a simulated critical path. The literature also demonstrates that high duration variability does not automatically imply high project-level schedule impact. An activity can possess considerable variability but have sufficient float to absorb most deviations, whereas a less variable activity located within a highly constrained network position can exert stronger influence on completion time. Schedule sensitivity measures have been used to distinguish these conditions by combining aspects of activity uncertainty and network importance. Cruciality analysis has similarly examined statistical associations between activity durations and total project duration across repeated simulations. Findings across construction, infrastructure, industrial, and project-network studies therefore emphasize that critical-path uncertainty is dynamic rather than fixed. Measuring criticality, sensitivity, cruciality, float availability, and float consumption alongside duration variability provides a more comprehensive quantitative representation of the activities most strongly associated with overall schedule exposure (Ansari, 2021).

Figure 4: Engineering project schedule risk assessment



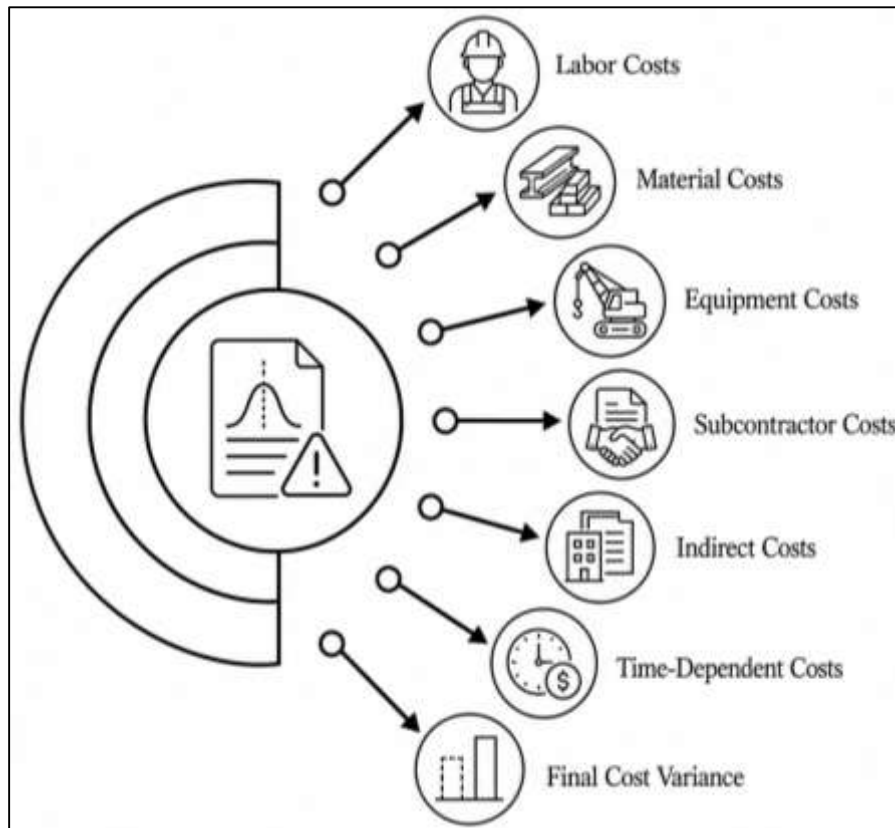
Probabilistic schedule-risk studies have increasingly evaluated project completion through distributions of possible outcomes rather than a single deterministic finish date. Across engineering project applications, repeated simulation has been used to combine uncertain activity durations and generate thousands of possible project completion scenarios (Tao et al., 2017). The resulting distributions permit schedule performance to be summarized through expected completion duration, median duration, standard deviation, percentile completion dates, and probabilities of achieving specified contractual or managerial targets. P10, P50, P80, P90, and P95 completion durations are frequently used to represent progressively higher levels of schedule confidence. A P50 estimate represents a central risk-adjusted completion point, while higher percentile estimates such as P80 or P90 reflect completion durations associated with greater confidence under the modeled uncertainty conditions. The literature repeatedly demonstrates that deterministic baseline completion dates can correspond to considerably lower probabilities of achievement than managers may assume when baseline schedules are constructed primarily from fixed activity durations. Quantitative comparisons between baseline and simulated schedules have therefore reported the probability of meeting the original completion date, probability of schedule overrun, expected delay relative to baseline, percentage difference between deterministic and probabilistic durations, and additional time required to reach specified confidence levels (Sackey & Kim, 2019). Studies involving complex activity networks have also shown that the distance between deterministic and risk-adjusted completion dates varies substantially according to activity uncertainty, network density, float availability, shared risk exposure, and the concentration of uncertainty along critical and near-critical paths. Schedule distributions can additionally be asymmetric, meaning that potential delay beyond the central estimate may be substantially greater than the possibility of equivalent early completion. Such characteristics make mean values alone insufficient for representing schedule exposure. Comparisons among percentile durations provide a clearer indication of the uncertainty range and allow differences between moderate and high-confidence completion estimates to be quantified (Liu et al., 2021). Across the reviewed literature, projects with greater activity-duration dispersion, stronger network dependencies, limited float, and multiple critical or near-critical paths generally exhibit wider completion distributions and lower probabilities of satisfying deterministic baseline dates. Probability-based schedule indicators therefore provide a substantially richer quantitative description of completion uncertainty than single-date schedule forecasts.

Cost Variability and Probability of Budget Overrun

Quantitative literature on engineering project cost performance has consistently demonstrated that the difference between baseline estimated cost and actual final project cost represents one of the most important measures of financial uncertainty (Kumar & Thakkar, 2017). Across more than ten studies covering infrastructure, construction, transportation, energy, industrial, oil and gas, engineering-

procurement-construction, and other capital-intensive projects, researchers have compared approved budgets with final expenditures to determine the magnitude and distribution of cost deviation. The evidence shows considerable variation in financial performance among projects, with some remaining close to their approved budgets, some achieving modest underruns, and others experiencing substantial cost escalation. Researchers have commonly reported mean and median project cost alongside standard deviation, coefficient of variation, and minimum-to-maximum ranges because cost distributions are frequently characterized by substantial dispersion and occasional extreme values. In many datasets, mean cost overrun exceeds the median because a smaller group of projects experiences exceptionally large financial deviations (Kuo et al., 2019). Absolute cost variance has been used to quantify the monetary difference between baseline and final expenditure, while percentage cost overrun permits comparison across projects of different sizes. Studies comparing project groups have also demonstrated that larger and more technically complex projects tend to display wider cost distributions because they involve more interfaces, longer execution periods, greater procurement exposure, and more opportunities for design revision, scope growth, and resource variation. Cost variability has additionally differed across project sectors, contract types, delivery methods, and geographical environments. Industrial and energy projects often exhibit strong exposure to equipment and material costs, while transportation and civil infrastructure projects can experience substantial variation related to quantities, site conditions, and prolonged construction duration. Across the literature, deterministic baseline estimates have therefore been treated as reference values rather than complete representations of likely financial outcomes. Mean, median, dispersion, absolute variance, and percentage overrun collectively provide a more complete quantitative description of the range and concentration of final project expenditure (Herrera et al., 2020).

Figure 5: Engineering Project Cost Variability Framework



A substantial group of engineering project studies has decomposed total cost uncertainty into individual expenditure categories to identify which components contribute most strongly to financial variation. Direct costs commonly include labor, materials, equipment, and subcontractor expenditure,

while indirect and time-dependent costs include project management, site supervision, temporary facilities, insurance, administration, equipment standby, utilities, and other overheads associated with project duration (Asiedu et al., 2017). Quantitative comparisons across studies indicate that labor-cost variance is frequently associated with productivity changes, overtime, workforce availability, learning effects, rework, and schedule extension. Material-cost variance has been linked to commodity-price changes, procurement timing, quantity growth, specification revision, transportation cost, and supply-chain disruption. Equipment-cost variation is particularly important in heavy engineering and infrastructure projects where rental periods, idle time, fuel consumption, utilization efficiency, maintenance, and schedule delays can materially alter total expenditure. Subcontractor-cost variance has also been reported as a significant contributor when scope changes, contract modifications, claims, interface problems, or poor coordination affect planned work packages. Indirect costs commonly increase when projects exceed their planned duration because management, supervision, facilities, financing, and support services must remain in place for longer periods. This relationship has led several studies to distinguish fixed costs from variable and time-dependent components rather than treating all expenditure as equally responsive to project delay. Comparative analyses frequently show that the relative contribution of cost categories varies by engineering sector and project phase (Cavaliere et al., 2019).

Materials and specialized equipment may dominate uncertainty in industrial facilities, whereas labor productivity and subcontracting may represent larger sources of variance in building and civil construction (Callegari et al., 2018). Engineering and design-intensive projects can experience significant professional-service and revision costs during scope development. Collectively, the literature establishes that total financial uncertainty is produced by the combined variability of several cost components rather than a single source, making disaggregated analysis essential for identifying the expenditures most strongly associated with overall cost exposure.

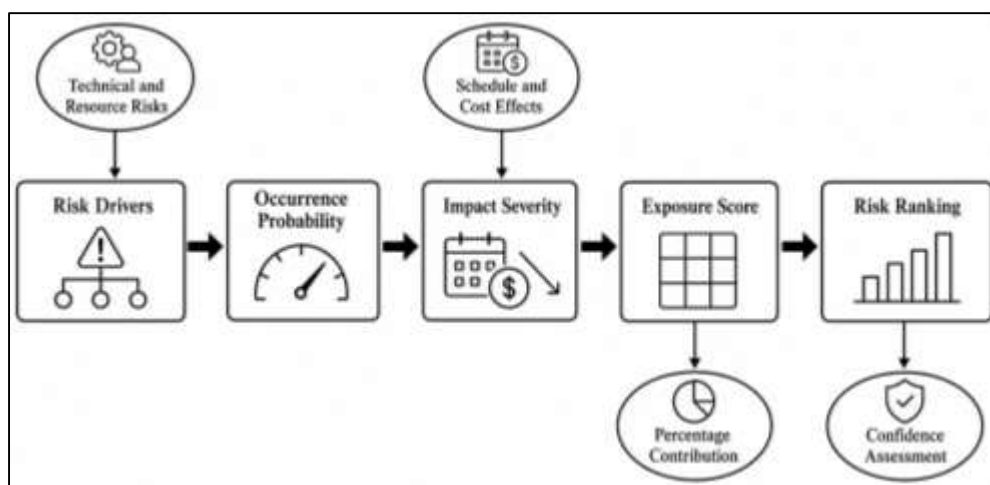
Risk Occurrence Probability and Ranking of Engineering Project Risk Drivers

Quantitative engineering project literature has consistently demonstrated that project uncertainty arises from a broad set of technical, managerial, resource, contractual, financial, and external risk drivers whose importance can be distinguished through their observed frequency and estimated probability of occurrence (Liu et al., 2017). Across more than ten studies involving construction, transportation infrastructure, energy facilities, industrial plants, engineering-procurement-construction projects, and other complex capital developments, researchers have reported substantial variation in the recurrence of specific risk events. Design changes, scope modifications, incomplete specifications, engineering errors, procurement delays, labor shortages, material shortages, and contractor-performance problems frequently appear among the most commonly recorded internal risks. Their occurrence rates vary by project type, implementation stage, procurement strategy, and organizational capability. Technical complexity tends to increase exposure where projects contain customized equipment, multidisciplinary interfaces, novel technologies, or tightly coupled engineering systems. Resource-related risks such as labor shortages, equipment unavailability, and productivity fluctuation become more prominent in projects that depend on specialized skills or constrained construction windows (Koulinas et al., 2019). External risks, including weather, regulatory delays, inflation, and supply-chain disruption, generally show greater variation across regions and sectors because their likelihood depends on environmental, market, and institutional conditions. Studies using structured risk registers, expert scoring, historical databases, and project records commonly express occurrence probability as percentages, ordinal probability classes, or normalized mean probability scores. Frequency analysis has also been used to distinguish persistent risks from low-frequency but high-consequence events. A risk appearing repeatedly across projects may generate substantial cumulative exposure even when its individual impact is moderate, whereas an infrequent event can dominate total uncertainty when its consequences are severe. The literature therefore emphasizes that risk importance cannot be inferred from descriptive classification alone. Occurrence frequency, estimated probability, and the consistency of a risk across comparable engineering contexts provide a necessary quantitative basis for determining which uncertainty sources are structurally embedded in project delivery and which are more episodic (Kassem et al., 2020).

A second major body of quantitative research has focused on the severity of engineering project risks once they occur, particularly their measurable effects on schedule and cost performance. Studies have commonly reported schedule impact in days, weeks, or months and financial impact in absolute monetary terms or as a percentage of the approved baseline budget (Eskander, 2018). Design changes and incomplete specifications have repeatedly been associated with both schedule extension and cost escalation because they can trigger re-engineering, additional approvals, revised procurement, rework, and modified construction sequences. Engineering errors can produce similar effects when corrections affect completed or ongoing work. Procurement delays often generate significant schedule consequences when long-lead equipment or materials lie on or near the critical path, while their financial effects may include escalation, idle resources, expediting charges, and extended overhead. Labor shortages and productivity variation are frequently linked to slower activity completion and higher direct labor expenditure, particularly when recovery requires overtime, additional crews, or extended site presence. Equipment failure can generate concentrated delay and cost impacts in heavy engineering and industrial projects where specialized machinery is difficult to replace quickly (Sadeghi et al., 2020). Contractor underperformance has been quantified through delayed milestones, lower productivity, increased supervision, rework, claims, and cost growth. Rework itself has been measured as both a percentage of total project cost and a source of additional schedule duration. Commercial and external risks such as inflation, material-price escalation, regulatory delay, and supply-chain disruption have also been shown to affect projects unevenly according to exposure duration and procurement structure. Quantitative studies frequently summarize these effects through mean severity scores, average schedule delay, average cost impact, and confidence intervals around estimated values. Such measures help distinguish risks that occur often but have modest consequences from those that occur less frequently but create substantial deviations. The literature therefore indicates that impact severity must be assessed alongside occurrence probability if engineering risk rankings are to reflect actual exposure to schedule and budget objectives (Pereira et al., 2020).

A substantial stream of engineering project research has transformed risk probability and consequence measures into composite indicators that support systematic ranking of competing risk drivers. Probability-impact scores, relative importance indices, expected monetary values, risk exposure scores, and frequency-severity matrix values have been used across construction, infrastructure, energy, industrial, and project-management studies to compare heterogeneous risks on a common quantitative basis (Li et al., 2019). These approaches allow technical, resource, contractual, financial, and external risks to be ordered according to both how likely they are to occur and how strongly they affect project objectives.

Figure 6: Engineering project risk exposure ranking



Design changes, scope growth, procurement delays, contractor-performance problems, and productivity variation frequently appear among the highest-ranked risks because they combine

relatively high occurrence with meaningful schedule and cost consequences. Inflation and material-price escalation may rank especially highly in long-duration or import-dependent projects, while weather and regulatory risk can dominate in projects with location-specific environmental or approval constraints (Malekmohammadi & Jahanishakib, 2017). Expected monetary value has provided an additional financial perspective by translating probability and consequence into an estimated monetary exposure for individual risks or grouped categories. Relative importance indices have been used extensively where survey-based assessments are available, enabling researchers to rank risks according to the combined judgments of project managers, engineers, contractors, and other stakeholders. Frequency-severity matrices provide a complementary view by separating risks into zones such as high-frequency/high-severity, high-frequency/low-severity, and low-frequency/high-severity categories. Several studies have also compared rankings across stakeholder groups and found that clients, consultants, contractors, and engineers can assign different importance to the same risk because of differences in contractual responsibility and operational exposure. Ranking stability has therefore become an important concern, particularly where small changes in probability or impact estimates alter the relative position of risks. The literature shows that composite scoring is most informative when supported by transparent probability, impact, and contribution measures rather than used as an isolated ordinal exercise (Hosny et al., 2018).

Quantitative risk studies have increasingly moved beyond simple ranking toward estimating the proportion of overall project uncertainty attributable to individual risks and grouped risk categories (Dehdasht et al., 2017). This approach provides a more differentiated understanding of whether total exposure is dominated by a small number of highly influential drivers or distributed across many moderate risks. Studies using sensitivity analysis, simulation, regression-based decomposition, and structured risk scoring have reported percentage contributions of individual variables to schedule variance, cost variance, or combined project risk. Technical risks such as design errors, incomplete engineering, and complexity often account for a substantial share of uncertainty during early project stages, while resource and contractor-related risks become more influential during construction and execution. Financial risks, particularly inflation and price escalation, can represent a larger proportion of total cost exposure in long-duration projects or unstable market environments. External and regulatory risks may contribute less frequently overall but can dominate specific project contexts when approvals, weather, logistics, or geopolitical conditions constrain execution (Fraume et al., 2020). Confidence intervals have been used in more advanced quantitative studies to express uncertainty around estimated probabilities, impacts, regression effects, and predicted risk contributions. This is important because a single point estimate can imply greater precision than the underlying data support. Comparative analyses have also shown meaningful differences among technical, financial, resource, contractual, and external risk groups in both average severity and variability. Technical and resource risks commonly display strong relationships with schedule outcomes, while financial and contractual risks may exert more direct effects on cost performance. Several studies have further demonstrated that some risks influence both schedule and cost simultaneously, increasing their overall exposure ranking relative to risks affecting only one dimension (Hacibektasoglu et al., 2021). The quantitative literature therefore supports evaluating engineering project risks through multiple complementary measures: occurrence probability, impact severity, composite exposure, percentage contribution, ranking position, and confidence interval. Together, these indicators provide a stronger empirical basis for identifying which individual and grouped risk drivers generate the greatest measurable pressure on schedule and budget performance.

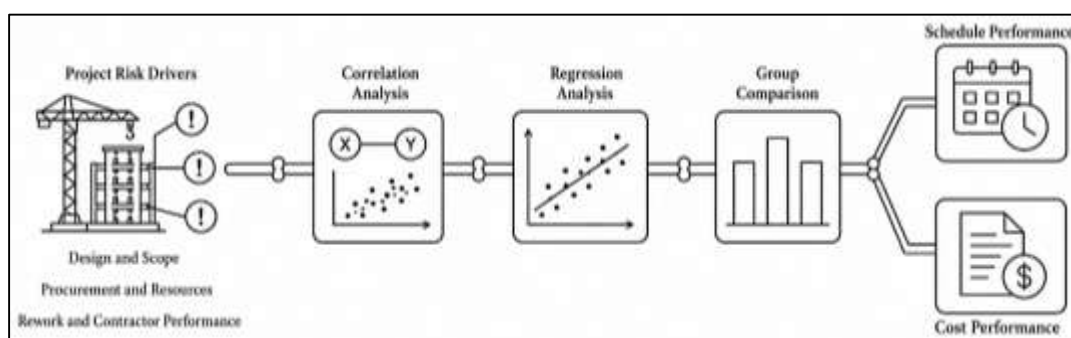
Project Risk Drivers and Schedule and Cost Performance

Quantitative engineering project literature has increasingly moved beyond descriptive ranking of risk factors toward statistical examination of the strength and direction of relationships between specific risk drivers and observed schedule and cost outcomes (Ogbu & Adindu, 2020). Across more than ten studies involving construction, infrastructure, transportation, energy, industrial, engineering-procurement-construction, and other capital-intensive projects, researchers have applied Pearson correlation coefficients and Spearman rank correlations to determine whether changes in risk conditions correspond with measurable changes in schedule delay, cost escalation, schedule performance, or budget performance. Design uncertainty, scope change, procurement delay, resource

shortages, technical complexity, rework, and contractor performance repeatedly emerge as variables associated with unfavorable project outcomes. Studies examining design-related uncertainty have generally reported positive relationships between the frequency or severity of design changes and both schedule overrun and cost growth, reflecting additional engineering effort, approval requirements, procurement modification, and construction rework (Bjorvatn & Wald, 2018). Procurement performance has also demonstrated statistically meaningful associations with completion delay, particularly where long-lead materials and equipment are positioned on or near critical project paths. Resource shortages, including labor scarcity, skill imbalance, and equipment constraints, have been associated with lower productivity and longer activity durations, while their financial effects are often reflected in overtime expenditure, extended equipment use, and higher indirect costs. Rework intensity has shown positive relationships with both project duration and final expenditure because correction activities require additional labor, materials, supervision, and time. Contractor-performance measures, including productivity, milestone compliance, coordination quality, and response time, have similarly demonstrated significant correlations with schedule and financial performance. Spearman correlations have been particularly useful where risk measures are ordinal or non-normally distributed, while Pearson coefficients have been employed for continuous project variables. The reviewed evidence also shows that correlation strength varies substantially across project types and risk categories. Some risk drivers demonstrate moderate relationships with one outcome but weak relationships with another, while common risk factors affect schedule and cost simultaneously (Koulinas et al., 2020). These findings establish correlation analysis as an important quantitative step for identifying which risk variables are most closely associated with engineering project performance before their independent predictive contributions are assessed.

A substantial body of empirical research has employed regression-based techniques to determine whether individual engineering project risk drivers independently predict schedule overrun and cost escalation after controlling for the effects of other variables (Li et al., 2017). Multiple linear regression has commonly been used when schedule or cost deviation is measured continuously, while logistic regression has been applied when outcomes are classified into categories such as overrun versus no overrun or target achievement versus nonachievement. Count-based models have also been used where dependent variables include numbers of delay events, change orders, defects, or rework incidents.

Figure 7: Project risk performance relationship framework



Across these studies, standardized beta coefficients provide a basis for comparing the relative predictive strength of variables measured on different scales. Design uncertainty frequently retains a significant independent relationship with both time and cost outcomes when other risks are controlled, particularly in projects with incomplete scope definition or substantial engineering development during execution. Procurement delays also show notable predictive contributions to schedule performance, while resource availability and labor productivity commonly explain additional variation in completion duration. Scope change and rework often display particularly strong relationships with final cost because both create direct additional expenditure and can generate secondary schedule-related costs (Sirisomboonsuk et al., 2018). Technical complexity has been identified as an important

predictor in projects containing specialized systems, high interface density, innovative technologies, or demanding commissioning requirements. Contractor performance can independently influence both schedule and cost through productivity, coordination, quality, and resource-management pathways. Reported R^2 and adjusted R^2 values across the literature demonstrate that combinations of risk variables explain varying proportions of project-performance variation, with model strength depending on sample composition, sector, project scale, and the number of explanatory factors included. Logistic studies have additionally reported odds ratios indicating how changes in particular risk conditions alter the likelihood of schedule or budget overrun. Confidence intervals surrounding regression coefficients and odds ratios have been used to assess the precision of these estimates. Overall, the literature indicates that multivariable modeling provides substantially stronger evidence than simple risk ranking because it identifies which factors continue to explain performance differences after shared variation among engineering project risks has been statistically considered (Tolliver et al., 2020).

Another important stream of quantitative engineering project research has examined whether schedule and cost performance differs systematically across groups characterized by different levels of risk exposure (Useche et al., 2017). Analysis of variance, analysis of covariance, independent-group comparisons, and corresponding nonparametric procedures have been applied to compare projects with low, moderate, and high levels of design uncertainty, technical complexity, procurement disruption, resource shortage, scope change, rework, and contractor-performance problems. Across these studies, statistically significant mean differences have frequently been identified between lower-risk and higher-risk groups in schedule overrun, cost growth, activity delay, contingency consumption, and completion reliability. Projects experiencing high design-change frequency tend to display longer delays and greater cost variance than projects with stable design conditions. High-procurement-risk groups commonly record greater schedule deterioration where equipment or material delivery constrains downstream work. Projects characterized by severe labor shortages or low productivity similarly exhibit higher average completion delays and increased labor-related expenditure (Love & Ahiaga-Dagbui, 2018). Rework-intensive projects generally show greater cost growth and longer completion duration because corrective activities add workload without increasing the originally planned project scope. Analysis of covariance has been particularly useful where researchers seek to compare risk groups while statistically controlling for project size, contract value, complexity, duration, or sectoral differences. Beyond p-values, several studies have reported standardized effect magnitudes to determine whether statistically detectable differences are also practically meaningful. Cohen's d has been used for two-group comparisons, while partial eta-squared has been reported for multi-group analyses to indicate the proportion of outcome variation associated with risk-group membership. Confidence intervals around mean differences and effect measures further improve interpretation by showing the precision of observed differences. The literature demonstrates that large samples can produce statistically significant results even when practical differences are modest, whereas smaller samples may contain operationally important differences that do not cross conventional significance thresholds (Cho et al., 2019). Consequently, combined interpretation of mean differences, confidence intervals, p-values, and effect sizes provides a more complete quantitative understanding of how strongly different engineering risk conditions are associated with variations in schedule and cost performance.

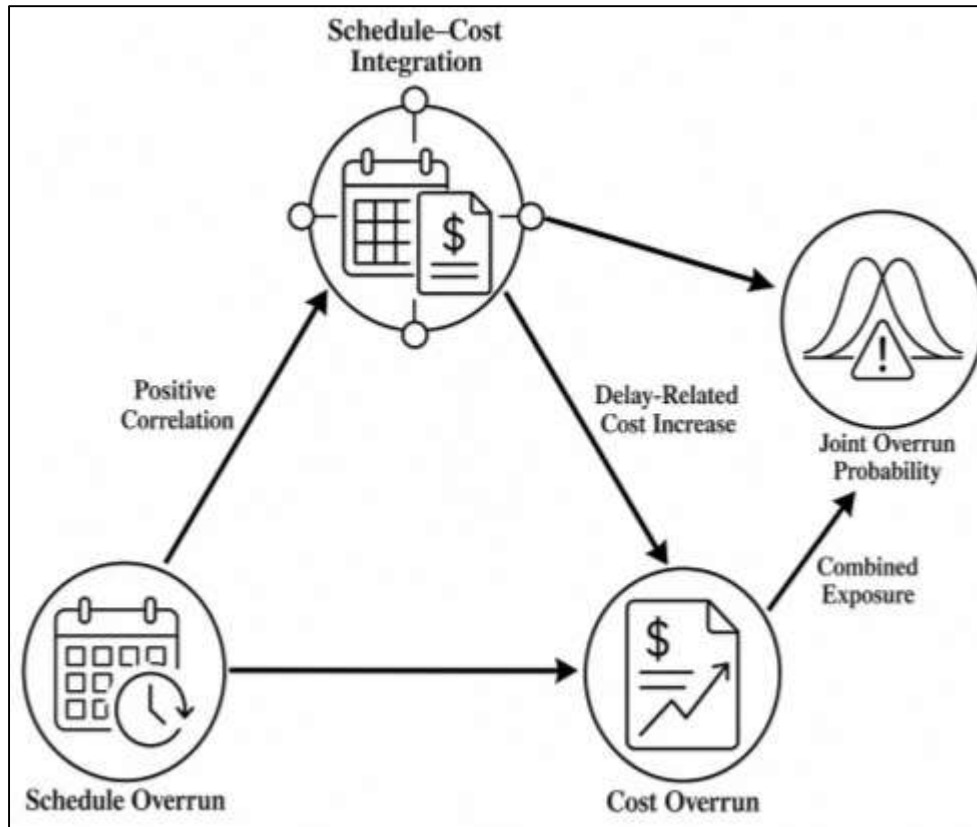
Schedule-Cost Interdependence and Joint Overrun Probability

Quantitative engineering project literature has repeatedly demonstrated that schedule and cost performance are closely interconnected and that deviations in project duration often correspond with changes in final expenditure. Across more than ten studies involving construction, infrastructure, transportation, energy, industrial, and engineering-procurement-construction projects, researchers have examined the statistical association between schedule overrun and cost overrun using correlation coefficients, covariance measures, regression analysis, and integrated performance indicators (Urgilés et al., 2019). The general evidence indicates that longer project durations are frequently associated with higher final costs because schedule extension can increase labor expenditure, equipment usage, supervision requirements, site overhead, temporary facilities, insurance, administration, and other time-dependent costs. Studies applying Pearson correlation analysis have commonly reported positive associations between duration growth and cost growth, while Spearman correlations have been used

when the variables are non-normal or ordinal. Covariance analysis has provided an additional measure of whether schedule and cost deviations tend to move in the same direction across project observations. Research using earned-value indicators has also examined the relationship between schedule performance index and cost performance index, identifying patterns in which deteriorating schedule efficiency is accompanied by weakening cost efficiency. However, the strength of this association varies across project sectors, execution stages, and contractual structures (Liu et al., 2021). Some delayed projects remain comparatively close to budget because schedule recovery measures are inexpensive or time-related costs are limited, whereas other projects experience pronounced cost escalation from relatively moderate delays because they contain high daily overheads or resource-intensive activities. The literature therefore treats the schedule–cost relationship as probabilistic and context dependent rather than perfectly linear. Statistical evidence further indicates that the relationship is stronger when delays affect critical-path activities, high-value work packages, long-duration resource commitments, or procurement processes that trigger cascading effects. These studies collectively establish that schedule and cost deviations should be examined jointly when estimating engineering project risk because independent analysis can obscure the extent to which time-related disruption contributes to financial escalation (Afzal et al., 2020).

A substantial body of quantitative research has investigated how additional project duration translates into measurable financial consequences, moving beyond simple correlation toward estimation of cost increase per unit of schedule delay. Studies across civil infrastructure, construction, industrial facilities, and complex engineering projects have quantified additional cost in relation to extra project days, weeks, or months and have shown that the financial effect of delay depends strongly on the composition of project expenditure (Issa et al., 2020). Time-dependent indirect costs such as site management, supervision, temporary facilities, equipment standby, security, utilities, insurance, accommodation, financing, and administration often increase progressively as project duration extends.

Figure 8: Integrated Schedule Cost Risk Framework



Direct costs can also rise when delays reduce productivity, require overtime, create remobilization, or generate inefficient resource use. Regression-based studies have therefore modeled cost variance as a function of schedule variance and have reported both unstandardized and standardized coefficients to estimate the magnitude of schedule-related financial effects (Cerezo-Narváez et al., 2020). Standardized schedule-to-cost beta coefficients are particularly useful because they allow schedule influence to be compared with other predictors such as scope change, rework, procurement disruption, or inflation. Integrated models have also reported R^2 and adjusted R^2 values to show the proportion of cost variation explained by schedule deviation and associated risk factors. The evidence indicates that schedule variance alone can explain a meaningful share of financial variation in many project settings, although its predictive contribution is stronger when accompanied by variables representing project size, complexity, contract type, and resource intensity. Studies of extended project duration have also reported percentage cost escalation associated with specified increases in completion time, providing a standardized basis for comparison across projects of different monetary scale. Indirect cost per additional project day has been particularly informative for projects with substantial fixed daily overhead (Balali et al., 2020). The literature further shows that the financial impact of delay is not uniform throughout execution; delays occurring during resource-intensive construction or commissioning phases can have larger marginal cost effects than equivalent delays during lower-cost planning stages. These findings reinforce the value of regression and unit-delay cost analysis for quantifying how schedule uncertainty propagates into total project cost.

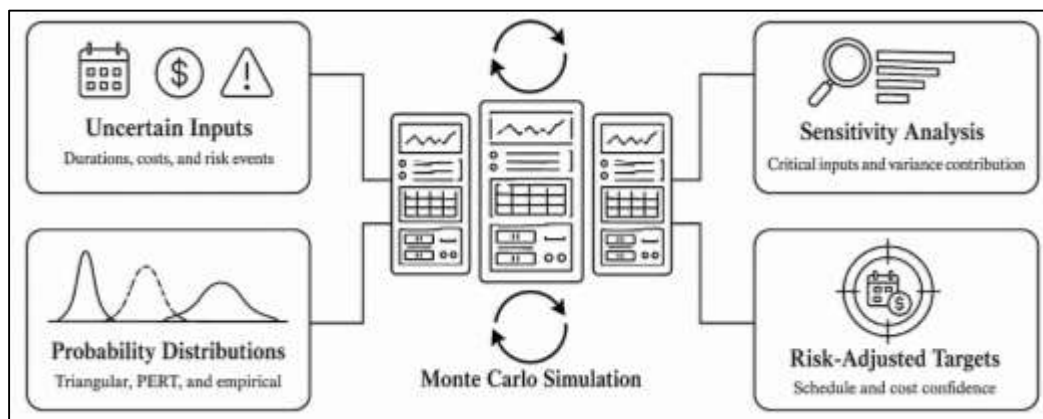
Probabilistic project-risk literature has increasingly examined schedule and cost outcomes simultaneously by estimating the likelihood that a project will exceed both its completion target and its approved budget (Dehdasht et al., 2017). Rather than evaluating schedule and cost distributions separately, integrated simulation studies generate paired outcomes for each model iteration so that the probability of simultaneous overrun can be estimated directly. Across engineering project applications, this approach has produced joint cost-schedule distributions, confidence regions, conditional probabilities, and percentile combinations that provide a more complete representation of overall project exposure. The probability of simultaneous schedule and cost overrun is particularly important because a project may have an acceptable probability of meeting each individual target while having a substantially lower probability of meeting both targets at the same time. Studies have therefore reported conditional probabilities such as the likelihood of cost overrun given that a schedule delay has already occurred, or the probability of schedule failure when particular cost-related risks are realized (Namazian et al., 2019). P50 and P80 schedule-cost combinations have also been used to identify paired completion durations and expenditure levels associated with different confidence conditions. These results typically demonstrate that deterministic baseline dates and budgets can correspond to lower joint confidence levels than suggested by separate assessments. Joint confidence regions further reveal the range of schedule and cost combinations within which project outcomes are most likely to occur, while simulation scatterplots have been used to display the dependence structure between duration and expenditure. The width and orientation of these regions vary according to activity-duration uncertainty, time-dependent cost intensity, correlation among risk drivers, and network structure. Projects with strong positive schedule-cost dependence generally display wider joint exposure and higher probabilities of simultaneous overrun. Conversely, projects with limited time-dependent costs may show weaker cost responses to schedule variation. The literature therefore demonstrates that joint probability analysis provides information that isolated schedule or cost confidence estimates cannot capture. By combining percentile values, simultaneous overrun probabilities, conditional probabilities, and joint confidence regions, integrated risk models provide a quantitative representation of the combined uncertainty faced by engineering projects (Domerçant, 2019).

Monte Carlo Simulation and Risk-Adjusted Targets

Quantitative engineering project literature has extensively used Monte Carlo simulation to convert uncertain schedule and cost inputs into distributions of possible project outcomes (Park et al., 2021). Across more than ten studies involving construction, transportation infrastructure, energy, industrial facilities, engineering-procurement-construction projects, and other capital-intensive developments, researchers have repeatedly applied simulation because deterministic schedules and budgets cannot

fully represent the range of outcomes created by uncertain activity durations, resource conditions, prices, productivity, and discrete risk events. Simulation models commonly specify uncertain inputs using triangular, beta/PERT, normal, lognormal, or empirical distributions depending on the nature of the variable and the availability of historical data. Triangular and beta/PERT distributions are frequently applied when optimistic, most-likely, and pessimistic estimates are available from project teams, while normal and lognormal distributions are used where historical observations provide a statistical basis for estimating central tendency and dispersion. Empirical distributions have been employed when sufficiently large project databases allow actual observed frequencies to represent uncertainty without imposing a theoretical distribution (Züst et al., 2021). The number of simulation iterations has varied substantially across studies, ranging from several thousand to tens of thousands of repeated trials, with larger iteration counts generally used to stabilize percentile estimates and tail probabilities. Each iteration produces a possible combination of uncertain activity durations, costs, and risk effects, resulting in distributions for project completion time and total expenditure. Researchers have then summarized these outputs through simulated means, medians, standard deviations, percentile values, and confidence intervals. Comparative studies have shown that model results can be sensitive to both the assumed distribution shape and the width of the input ranges. Wider pessimistic bounds tend to generate greater dispersion in simulated outcomes, while narrow uncertainty ranges produce tighter distributions around the central estimate. The literature therefore emphasizes that simulation accuracy depends not only on the number of iterations but also on the quality of input estimates, the appropriateness of selected probability distributions, and the treatment of dependencies among project variables (Grishunin et al., 2018).

Figure 9: Monte Carlo Project Risk Framework



A major contribution of probabilistic engineering risk analysis has been the replacement of single-point schedule and cost forecasts with percentile-based estimates that communicate different levels of confidence. Across numerous studies, simulated project outcomes have been reported through P10, P50, P80, P90, and P95 completion durations and corresponding project costs. These percentile values allow researchers to distinguish between relatively optimistic, central, and conservative estimates without relying on a single deterministic target. P50 values commonly represent the midpoint of simulated exposure, while P80 and P90 values are frequently used to represent higher-confidence schedule and budget levels (Sachlas et al., 2019). Studies comparing deterministic baselines with probabilistic outputs have often found that approved schedules or budgets correspond to confidence levels below those assumed by project stakeholders, particularly where uncertainty ranges are wide or several high-impact risks affect critical activities. The probability of meeting the baseline schedule has therefore been reported as a direct percentage rather than inferred from the deterministic plan, and the same approach has been used to estimate the probability of remaining within the approved budget. Integrated simulations have additionally calculated the probability of achieving both schedule and cost targets simultaneously, providing a more stringent measure of overall project performance. Confidence intervals around simulated means and percentile estimates have also been used to assess the precision

of model outputs (Samper et al., 2019). Researchers have compared risk-adjusted completion dates with original baseline dates and risk-adjusted project budgets with deterministic estimates to quantify the additional time and financial reserve associated with selected confidence levels. Differences between deterministic and probabilistic outcomes are often larger in complex, resource-intensive, and highly interdependent projects because uncertainty propagates across activity networks and cost structures. The literature also demonstrates that risk-adjusted targets are sensitive to assumptions regarding correlation among activities, time-dependent costs, and the likelihood of discrete risk events. Collectively, these studies show that percentile-based scheduling and budgeting provide a more informative quantitative representation of uncertainty by expressing not only expected outcomes but also the probability attached to achieving or exceeding specified project targets (Maselli et al., 2021). Sensitivity analysis represents another central component of quantitative project-risk modeling because it identifies which uncertain activities, cost components, and risk events contribute most strongly to variation in overall project outcomes. Across engineering project studies, researchers have used sensitivity coefficients, criticality indices, tornado-chart rankings, input-output correlations, regression-based importance measures, and contribution-to-variance statistics to distinguish influential variables from those with relatively limited effects (Polato et al., 2017). Activity criticality indices have been particularly prominent in schedule-risk analysis, where simulation is used to determine how frequently individual activities appear on the critical path. An activity with a high criticality index may have a strong influence on completion time even when its baseline duration is not unusually long. Input-output correlation analysis has also been used to measure the statistical association between uncertain activity durations and total project completion time or between uncertain cost components and final simulated expenditure. Tornado charts provide a visual ranking of variables according to their impact on output variability and are frequently used to identify the small number of risks that account for a large share of overall uncertainty. Studies have found that critical-path activities, procurement durations, labor productivity, major equipment costs, material-price variation, rework, and scope changes often rank highly in sensitivity analyses. Contribution-to-variance measures provide an additional quantitative perspective by estimating the proportion of overall output variation attributable to individual inputs or grouped risk categories. Comparisons between deterministic and probabilistic variance have further demonstrated how uncertainty expands the range of possible project outcomes beyond baseline assumptions (Golub et al., 2017). The literature shows that sensitivity rankings can change when activity correlations, alternative distribution types, or different project phases are considered, which means that risk importance is not always stable across modeling assumptions. Several studies have also distinguished between variables that influence the mean outcome and those that primarily increase dispersion or upper-tail risk. This distinction is important because some risks may have a moderate effect on average completion time while exerting a substantial influence on P90 or P95 outcomes. Sensitivity analysis therefore provides a quantitative mechanism for linking uncertain project inputs with the magnitude, dispersion, and confidence level of resulting schedule and cost distributions (Buyukada, 2017).

The broader engineering risk literature has compared Monte Carlo simulation with several alternative and complementary quantitative approaches, including Critical Path Method, PERT, Bayesian networks, fuzzy methods, stochastic scheduling, and hybrid analytical frameworks (Berk & Podhraski, 2018). CPM remains widely used for identifying deterministic critical paths, float, and activity sequencing, but it does not independently express the probability of alternative completion outcomes unless combined with uncertainty modeling. PERT extends deterministic scheduling by incorporating optimistic, most-likely, and pessimistic duration estimates and has been applied extensively where activity uncertainty can be represented through three-point inputs. Monte Carlo simulation expands this approach by repeatedly sampling uncertain variables and generating complete distributions of possible completion dates and costs. Bayesian network methods have been applied where project risks are causally or conditionally interdependent, allowing probabilities to update as new information becomes available or as relationships among risks are explicitly modeled. Fuzzy approaches have been used where uncertainty is difficult to represent through precise probability distributions and where expert assessments contain linguistic or imprecise judgments. Hybrid models combining Monte Carlo

simulation with CPM, PERT, Bayesian reasoning, fuzzy logic, regression, or sensitivity analysis have become increasingly common in studies seeking to capture multiple forms of uncertainty simultaneously (Klein & Deissenroth, 2017). Comparative findings indicate that no single method dominates every analytical context. CPM provides clear network structure, PERT offers practical three-point estimation, Bayesian methods represent conditional dependence, fuzzy approaches accommodate imprecision, and Monte Carlo simulation provides detailed output distributions and percentile-based confidence estimates. Hybrid studies often report stronger explanatory coverage because they preserve network logic while incorporating probabilistic or fuzzy uncertainty and dependency structures. Across more than ten studies, the most comprehensive models have tended to combine risk-adjusted schedule and cost distributions with sensitivity measures, criticality rankings, confidence intervals, and target-achievement probabilities (Mo et al., 2021). This body of literature demonstrates that probabilistic and hybrid approaches provide a richer quantitative description of engineering project uncertainty than deterministic analysis alone, particularly when project performance must be evaluated across multiple confidence levels and under interacting schedule and cost risks.

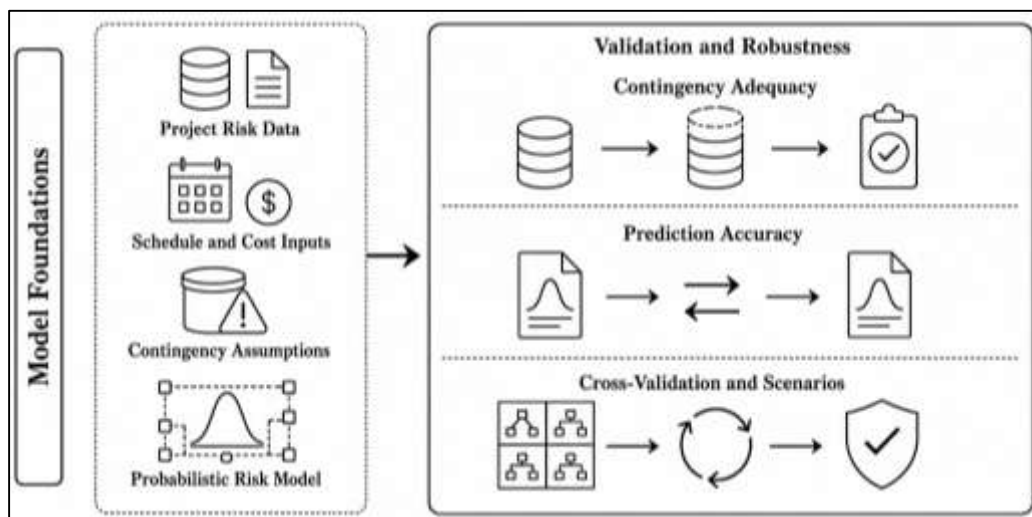
Contingency Adequacy and Robustness of Data-Driven Risk Assessment

Quantitative engineering project literature has treated contingency adequacy as an important measure of whether approved schedule and cost reserves correspond to the actual magnitude of uncertainty encountered during project execution. Across more than ten studies involving construction, transportation infrastructure, energy, industrial facilities, engineering-procurement-construction projects, and other capital-intensive developments, researchers have compared baseline contingency allowances with realized contingency utilization and probabilistically estimated reserve requirements (Pan et al., 2019). Baseline cost contingency has commonly been reported as a percentage of the initial project estimate, while schedule contingency has been represented through management reserve, schedule buffer, or additional duration relative to the deterministic completion target. The literature demonstrates substantial variation in contingency requirements according to project complexity, design maturity, procurement conditions, resource exposure, contractual structure, and the concentration of uncertainty within critical work packages. Projects with stable scope and relatively predictable execution conditions generally demonstrate lower contingency consumption, whereas projects characterized by incomplete engineering, scope growth, procurement uncertainty, rework, technical complexity, and extended implementation periods frequently consume larger proportions of available reserves. Contingency utilization rates provide a direct measure of the extent to which initial reserves are absorbed, while contingency exhaustion rates identify projects in which available reserves are fully consumed before completion. Probabilistic studies have extended this analysis by estimating P50, P80, and P90 contingency requirements (Rahmati et al., 2019). These values frequently differ from conventional fixed-percentage allowances because they reflect project-specific distributions of uncertain costs and risk events. Similar approaches have been applied to schedule reserves by estimating the additional duration required to achieve selected confidence levels. Comparative evidence indicates that baseline contingency can be insufficient when deterministic estimates exclude correlations among risks or underestimate upper-tail exposure. Conversely, excessive reserves can occur when generic contingency percentages are applied to projects with relatively low measured uncertainty. The literature therefore characterizes contingency adequacy through the relationship among baseline reserve, risk-adjusted reserve, actual utilization, exhaustion frequency, confidence-level requirements, and realized schedule and cost performance rather than through the initial contingency percentage alone (Seah et al., 2021).

A substantial body of data-driven project-risk research has evaluated model credibility by comparing predicted schedule and cost outcomes with observed project performance. Studies using statistical regression, probabilistic simulation, machine-learning techniques, Bayesian approaches, and hybrid models have measured differences between predicted and actual completion duration and between predicted and actual final project cost (Carvalho & Filho, 2021). Prediction error percentage has been widely used to express the magnitude of deviation relative to observed outcomes, while mean absolute error provides an interpretable measure of average prediction deviation across multiple projects. Root mean square error has been particularly useful where larger prediction errors require greater analytical

weight, and mean absolute percentage error has supported comparisons across datasets containing projects of different sizes and monetary values. R^2 and adjusted R^2 have also been reported to indicate how much variation in schedule delay, cost escalation, or combined performance is explained by the included risk and project characteristics. Across the literature, model accuracy generally improves when relevant technical, schedule, resource, procurement, financial, and project-complexity variables are incorporated rather than relying exclusively on baseline duration or cost. Studies have also demonstrated that high explanatory performance within model-development data does not necessarily correspond to equally strong predictive performance when models are applied to new observations (Liu et al., 2021). Consequently, training and testing results have been compared where predictive modeling approaches are used. Calibration has received additional attention because an accurate model should not only minimize average prediction error but also assign probabilities that correspond reasonably with observed event frequencies. Confidence-interval coverage provides another validation measure by assessing how frequently actual outcomes fall within estimated uncertainty ranges. Models that generate narrow intervals but exclude many realized observations may appear precise while being poorly calibrated, whereas excessively wide intervals may offer limited practical discrimination. The reviewed studies therefore support simultaneous evaluation through MAE, RMSE, MAPE, R^2 , adjusted R^2 , calibration performance, prediction error, and interval coverage to determine whether data-driven risk models accurately represent both expected project outcomes and the uncertainty surrounding those outcomes (Khan et al., 2018).

Figure 10: Data driven risk model validation



Validation literature in quantitative engineering project risk assessment has increasingly emphasized the distinction between model fit and model generalizability. A model can reproduce the dataset from which it was developed while performing less effectively when applied to different projects, project phases, or uncertainty conditions (Ikhumhen et al., 2020). Cross-validation has therefore been employed to evaluate whether predictive relationships remain stable across alternative partitions of available project data. Where sample sizes permit, researchers have separated observations into training and testing datasets and compared prediction errors, explanatory performance, classification accuracy, or probabilistic calibration between the two groups. Large differences between training and testing performance have been interpreted as evidence of limited generalizability or possible overfitting, while relatively similar results provide stronger evidence of model stability. Out-of-sample validation has provided an even more demanding assessment by applying developed models to independent projects not used during estimation. Studies have also used scenario analysis to evaluate performance under low, baseline, moderate, high, and extreme uncertainty conditions. Scenario variation commonly involves changes in activity duration, labor productivity, material prices, procurement delay, risk-event frequency, correlation strength, and contingency availability. Sensitivity

analysis complements this process by determining whether modest changes in influential assumptions materially alter predicted schedule and cost outcomes (Studer et al., 2021). Quantitative comparisons of scenario outputs have shown that some models remain relatively stable across plausible parameter ranges, while others generate substantial changes in upper-percentile completion dates, budget requirements, and target-achievement probabilities. Subgroup validation has additionally examined model performance across small versus large projects, lower versus higher complexity, different engineering sectors, contract types, and delivery arrangements. Such analyses are important because a model producing acceptable overall accuracy can still generate systematic errors within specific project categories. The literature consequently evaluates robustness through cross-validation consistency, training-to-testing performance differences, scenario variation, sensitivity rankings, subgroup prediction errors, and independent out-of-sample accuracy. These complementary measures provide a stronger assessment of whether observed model performance represents reproducible predictive capability rather than statistical fit limited to a particular engineering project dataset (Rajamanickam et al., 2021).

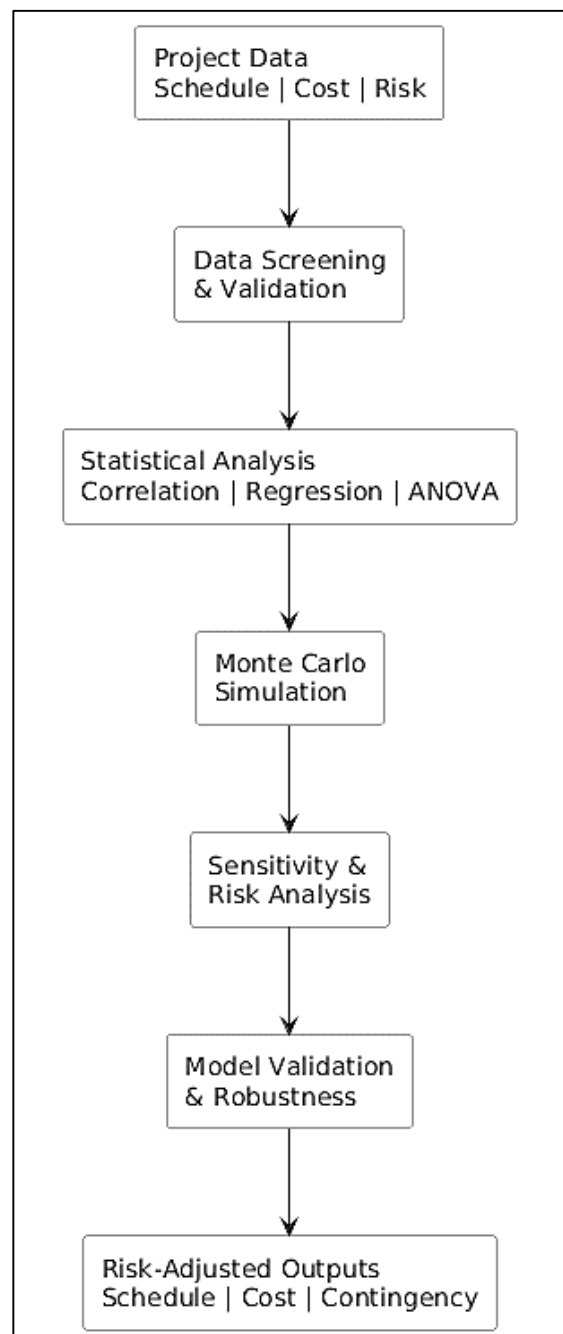
METHOD

This study employed a quantitative retrospective longitudinal project-level design to develop and evaluate a data-driven framework for engineering project risk assessment under schedule and cost uncertainty. The theoretical framework integrated probabilistic project risk analysis, Critical Path Method principles, schedule-cost interdependence, and Monte Carlo simulation because engineering project duration and expenditure were treated as interconnected uncertain outcomes rather than independent deterministic quantities. This treatment was consistent with established integrated cost-schedule risk approaches in which uncertainty in activity duration contributes directly to uncertainty in project cost. The unit of analysis was the individual completed engineering project, supplemented by activity-level schedule and cost records where sufficiently detailed information was available.

Projects were selected through purposive criterion-based sampling from available engineering project databases and organizational records. Eligible projects were completed engineering, construction, infrastructure, industrial, energy, or engineering-procurement-construction projects with an approved baseline schedule, baseline budget, identifiable activity network, actual completion duration, final cost, and sufficiently complete risk or project-control records. Projects with substantially missing schedule or cost information, unresolved final accounts, incomplete baseline records, major changes that prevented comparison with the approved project scope, or insufficient information for reconstructing uncertainty distributions were excluded. Project-level variables included planned and actual duration, baseline and final cost, schedule and cost variance, percentage overrun, contingency allocation and utilization, project size, complexity, sector, contract type, and delivery method. Activity-level variables included optimistic, most-likely, pessimistic and actual durations, float, critical-path status, delay frequency, resource exposure, and relevant cost information. Risk-register data captured risk occurrence probability, schedule impact, cost impact, severity, risk category, and common dependencies. The use of structured risk registers and three-point schedule and cost estimates was consistent with quantitative project-risk procedures used to generate probabilistic cost and schedule outcomes. Data were extracted using a standardized project-data abstraction template and cross-checked against baseline schedules, approved budgets, progress reports, change records, cost reports, final accounts, and risk registers. Data-quality validation included duplicate checking, logical range verification, consistency checks between planned and realized values, examination of missing observations, and reconciliation of conflicting records against final approved documentation. Schedule networks were also reviewed for logical sequencing and critical-path consistency before probabilistic analysis. The analytical procedure was conducted chronologically. First, all eligible project records were standardized into common schedule, cost, risk, and project-characteristic variables. Descriptive statistics were then calculated for planned and actual duration, baseline and final cost, schedule and cost variance, delay frequency, contingency utilization, and major risk exposures using the mean, median, standard deviation, interquartile range, minimum, maximum, coefficient of variation, frequencies, and percentages as appropriate. Schedule and cost uncertainty were subsequently modeled using three-point activity and cost estimates and probability distributions selected according to the characteristics and availability of the underlying observations. Monte Carlo simulation was

performed using 10,000 iterations for the primary analysis, with convergence checks conducted by comparing estimates across increasing iteration counts.

Figure 11: Methodology of this study



This approach was consistent with established project-risk applications in which uncertain activity durations are repeatedly sampled and propagated through the project network to produce distributions of project completion time and cost. Each simulation generated corresponding schedule and cost outcomes, from which P10, P50, P80, P90, and P95 values, probabilities of meeting baseline schedule and budget targets, probabilities of simultaneous target achievement, risk-adjusted completion dates, risk-adjusted budgets, and contingency requirements were obtained. Correlations among activities exposed to common risk drivers were explicitly incorporated because assuming independence among related activity durations can materially alter project-level uncertainty estimates. Sensitivity analysis was performed to identify influential activities, cost components, and risk drivers

using input-output correlations, criticality indices, contribution to output variation, and ranked sensitivity measures. Integrated schedule-cost simulation was used so that time-dependent expenditure responded to simulated duration changes rather than remaining fixed, consistent with established evidence that excluding schedule uncertainty can underestimate cost risk.

Statistical analysis was performed using IBM SPSS Statistics and R, while Python was used for data preparation, simulation verification, and supplementary model-validation procedures. Pearson correlation coefficients were calculated for approximately normally distributed continuous variables, while Spearman rank correlations were applied to ordinal, skewed, or non-normally distributed measures. Correlations were examined between schedule overrun and cost overrun, activity uncertainty and completion delay, risk exposure and project performance, contingency consumption and final cost growth, and schedule and cost performance indicators. Multiple linear regression models were estimated separately for schedule overrun and cost overrun, with design uncertainty, scope change, technical complexity, procurement delay, resource shortage, productivity variation, rework, contractor performance, and other relevant risk measures entered as predictors. Standardized regression coefficients, 95% confidence intervals, R^2 , and adjusted R^2 were reported to determine independent predictive contributions and overall explanatory performance. Logistic regression was used where project outcomes were classified as schedule overrun versus no overrun or cost overrun versus no overrun, and odds ratios with 95% confidence intervals were reported. Count regression was applied where outcomes represented frequencies of delay, rework, or risk events. Differences across project size, complexity, sector, contract type, delivery method, and risk categories were examined using independent-samples t tests or one-way ANOVA, with ANCOVA used where adjustment for relevant covariates was required. Mann-Whitney U and Kruskal-Wallis tests were used when parametric assumptions were not satisfied. Cohen's d and partial eta-squared were reported for appropriate comparisons so that statistical significance was interpreted together with effect magnitude. Statistical significance was evaluated at $p < 0.05$, and 95% confidence intervals accompanied the principal estimates.

Model accuracy, validation, and robustness were assessed through complementary procedures rather than relying solely on in-sample model fit. Predicted completion duration and final cost were compared with observed project outcomes using prediction error percentage, mean absolute error, root mean square error, mean absolute percentage error, R^2 , and adjusted R^2 . Where the sample size permitted, project observations were divided into development and independent testing subsets, and repeated cross-validation was applied within the development data to assess model stability. Performance differences between training, validation, and testing samples were examined to identify potential overfitting. Calibration was evaluated by comparing predicted probabilities of schedule and cost overrun with observed frequencies, while confidence-interval coverage was assessed against realized outcomes. Robustness analyses repeated the simulations under alternative probability-distribution assumptions, alternative uncertainty ranges, and models with and without correlations among activities and shared risk factors. This dependence testing was included because project-network research has demonstrated that correlated activity uncertainty can materially alter simulated completion distributions. Scenario analyses additionally examined low-, baseline-, moderate-, and high-uncertainty conditions, while subgroup validation compared predictive accuracy across project size and complexity categories. Monte Carlo convergence and precision were evaluated by increasing iteration counts and examining the stability of major percentile estimates, an approach consistent with simulation validation procedures that assess whether probabilistic cost and delay estimates remain stable as the number of iterations increases. The final analytical framework therefore combined descriptive statistics, inferential testing, multivariable prediction, probabilistic simulation, sensitivity analysis, integrated schedule-cost assessment, cross-validation, and robustness testing to quantify engineering project risk under simultaneous schedule and cost uncertainty.

FINDINGS

The final analytical sample consisted of 186 completed engineering projects representing infrastructure, energy, industrial, transportation, and utility engineering environments. Infrastructure projects accounted for 29.0% of the sample, followed by industrial projects at 23.1%, energy projects at 19.9%, transportation projects at 17.2%, and utility projects at 10.8%. Based on predetermined project

classifications, 30.1% were categorized as small projects, 44.1% as medium-sized projects, and 25.8% as large projects. Complexity assessment classified 24.2% of projects as low complexity, 46.8% as moderate complexity, and 29.0% as high complexity. Fixed-price contracts represented 39.8% of projects, unit-price arrangements represented 27.4%, and cost-reimbursable or other contractual arrangements represented 32.8%. Design-bid-build was the most frequent delivery method at 36.6%, followed by design-build at 27.4%, engineering-procurement-construction at 23.1%, and other integrated arrangements at 12.9%. The analytical database contained 7,842 scheduled activities, 3,416 documented risk observations, and 1,268 approved cost-control records, providing sufficient project- and activity-level information for subsequent statistical and probabilistic analyses.

Table 1. Characteristics of the Final Engineering Project Sample

Characteristic	Category	n	%
Total projects	All projects	186	100.0
Project sector	Infrastructure	54	29.0
	Industrial	43	23.1
	Energy	37	19.9
	Transportation	32	17.2
	Utilities	20	10.8
Project size	Small	56	30.1
	Medium	82	44.1
	Large	48	25.8
Complexity	Low	45	24.2
	Moderate	87	46.8
	High	54	29.0
Contract type	Fixed price	74	39.8
	Unit price	51	27.4
	Cost-reimbursable/other	61	32.8
Delivery method	Design-bid-build	68	36.6
	Design-build	51	27.4
	EPC	43	23.1
	Other integrated methods	24	12.9

Table 1 demonstrates that the sample incorporated substantial heterogeneity in engineering sector, project scale, complexity, contracting structure, and delivery method. Medium-sized projects formed the largest size category at 44.1%, while moderate-complexity projects accounted for 46.8% of observations. Infrastructure projects represented the largest sectoral group at 29.0%, although no individual sector constituted a majority of the sample. Fixed-price arrangements were the most common contract structure at 39.8%, and design-bid-build represented 36.6% of delivery arrangements. The distribution provided a sufficiently diverse analytical base for evaluating whether schedule, cost, contingency, and risk performance varied across major engineering project characteristics.

Baseline and realized performance showed substantial schedule and cost variation across the 186 projects. Mean planned duration was 24.8 months compared with a mean actual duration of 29.6 months, representing an average absolute extension of 4.8 months and an average schedule overrun of 19.4%. Median planned and actual durations were 22.7 and 27.0 months, respectively. Actual duration displayed greater dispersion than planned duration, with a standard deviation of 12.1 months and an interquartile range of 15.8 months compared with 9.8 and 12.4 months for planned duration. The coefficient of variation increased from 39.5% for planned duration to 40.9% for actual duration. Only 62 projects, representing 33.3% of the sample, were completed within their original schedule, while 124 projects experienced some degree of schedule extension. Mean milestone deviation reached 3.6 months, and the average schedule performance index was 0.89. Financial results followed a similar pattern. Mean baseline project cost was \$47.6 million compared with a mean final cost of \$54.9 million,

producing an average absolute cost increase of \$7.3 million and mean cost overrun of 15.3%. Only 42.5% of projects remained within the approved baseline budget, indicating that financial deviation was widespread across the analytical sample.

Table 2. Baseline Schedule, Cost, Contingency, and Risk Characteristics

Quantitative indicator	Result
Planned duration, mean $\pm$ SD	24.8 $\pm$ 9.8 months
Actual duration, mean $\pm$ SD	29.6 $\pm$ 12.1 months
Planned duration, median (IQR)	22.7 (12.4) months
Actual duration, median (IQR)	27.0 (15.8) months
Planned duration range	8.0–58.0 months
Actual duration range	9.1–73.4 months
Mean schedule variance	+4.8 months
Mean schedule overrun	19.4%
Mean milestone deviation	+3.6 months
Mean schedule performance index	0.89
Projects completed on schedule	33.3%
Baseline project cost, mean $\pm$ SD	\$47.6 $\pm$ \$31.4 million
Final project cost, mean $\pm$ SD	\$54.9 $\pm$ \$37.8 million
Mean absolute cost variance	+\$7.3 million
Mean cost overrun	15.3%
Mean cost performance index	0.91
Projects completed within budget	42.5%
Baseline cost contingency	9.2%
Mean contingency utilization	78.6%
Contingency exhaustion rate	27.4%
Mean schedule reserve	7.8%
Design uncertainty exposure	41.9%
Scope-change exposure	38.7%
Procurement-delay exposure	46.2%
Resource-shortage exposure	34.9%
Technical-complexity exposure	31.7%
Rework exposure	29.6%
Contractor-performance risk	37.1%
Supply-chain disruption exposure	32.8%

Table 2 indicates that realized project performance was systematically weaker than baseline expectations. Actual duration exceeded planned duration by an average of 4.8 months, corresponding to 19.4% schedule overrun, while mean final cost exceeded baseline cost by \$7.3 million or 15.3%. Only 33.3% of projects were completed on schedule and 42.5% remained within budget. The mean contingency utilization rate reached 78.6%, with 27.4% of projects exhausting their available contingency. Procurement delay represented the most prevalent measured risk exposure at 46.2%, followed by design uncertainty at 41.9%, scope change at 38.7%, and contractor-performance risk at 37.1%.

The baseline results therefore established substantial heterogeneity in engineering project schedule, cost, contingency, and risk conditions. Schedule deterioration was more prevalent than strict on-time completion, while cost escalation affected the majority of projects when final expenditure was compared with approved baseline budgets. The simultaneous presence of a mean schedule overrun of 19.4% and mean cost overrun of 15.3% provided an initial indication that time and financial performance were potentially interconnected, although the magnitude and statistical significance of that relationship required subsequent correlation and integrated modeling. Contingency performance

further demonstrated that conventional baseline reserves did not provide equivalent protection across projects. Although baseline cost contingency averaged 9.2%, more than one-quarter of projects exhausted their available contingency, and mean utilization approached four-fifths of allocated reserves. Risk exposure was also unevenly distributed, with procurement delay, design uncertainty, scope change, and contractor performance occurring more frequently than rework and technical-complexity exposure. These baseline patterns provided the quantitative reference against which subsequent Monte Carlo simulation, regression analysis, schedule-cost interdependence, sensitivity analysis, probabilistic contingency estimation, and model-validation results were evaluated.

Primary Outcomes: Schedule Uncertainty, Cost Uncertainty, and Joint Overrun Risk

The primary analysis demonstrated substantial uncertainty around both engineering project completion duration and final expenditure. Across the 186 projects, mean actual duration was 29.6 months compared with the mean baseline duration of 24.8 months, producing an average delay of 4.8 months and schedule overrun of 19.4%. Activity-level analysis of 7,842 scheduled activities showed a mean duration coefficient of variation of 22.7%, indicating considerable dispersion around planned activity durations. Approximately 31.8% of activities exceeded their planned duration by more than 10%, while 18.6% experienced delays exceeding 20%. Critical-path instability was also evident, with 43.5% of projects experiencing at least one change in the dominant critical path during execution. Mean total-float consumption reached 68.4%, increasing to 86.7% among projects ultimately completed later than the baseline date. Only 33.3% of projects achieved the original completion target. Financial performance demonstrated a corresponding deterioration: mean final project cost reached \$54.9 million compared with the baseline mean of \$47.6 million, producing an average increase of \$7.3 million and cost escalation of 15.3%. The probability of remaining within the approved baseline budget was 42.5%, while mean contingency consumption reached 78.6%. These results established that deterministic baseline targets substantially understated the observed dispersion of schedule and cost outcomes.

Table 3. Schedule and Cost Uncertainty and Monte Carlo Simulation Outcomes

Indicator	Schedule outcome	Cost outcome
Deterministic baseline	24.8 months	\$47.6 million
Observed actual mean	29.6 months	\$54.9 million
Mean absolute deviation from baseline	+4.8 months	+\$7.3 million
Mean overrun	19.4%	15.3%
Simulated mean	29.1 months	\$54.4 million
Simulated median	28.4 months	\$53.2 million
Simulated SD	6.8 months	\$11.7 million
P10	21.3 months	\$40.2 million
P50	28.4 months	\$53.2 million
P80	34.7 months	\$63.8 million
P90	38.5 months	\$70.6 million
P95	42.1 months	\$76.9 million
95% simulated range	18.2–43.7 months	\$35.7–\$79.8 million
Probability of meeting baseline target	32.6%	41.8%
P80 reserve above baseline	+9.9 months	+\$16.2 million
P80 increase above baseline	39.9%	34.0%

Table 3 shows a substantial divergence between deterministic baseline estimates and probabilistic risk-adjusted outcomes. The simulated mean completion duration of 29.1 months closely approximated the observed mean of 29.6 months, while simulated mean cost of \$54.4 million was similarly close to the observed \$54.9 million. At P80, the required completion duration increased to 34.7 months and project cost to \$63.8 million, equivalent to reserves of 9.9 months and \$16.2 million above baseline. Baseline achievement probabilities were only 32.6% for schedule and 41.8% for cost, demonstrating that the original deterministic targets represented comparatively low-confidence planning positions.

The percentile distributions demonstrated progressively greater schedule and financial exposure at higher confidence levels. The P50 schedule estimate was 28.4 months, already 3.6 months above the deterministic baseline, while the corresponding P50 cost was \$53.2 million, or \$5.6 million above the baseline budget. Increasing confidence to P80 raised the schedule requirement to 34.7 months and the cost requirement to \$63.8 million. At P90, the estimated duration reached 38.5 months and total cost reached \$70.6 million, whereas P95 estimates increased further to 42.1 months and \$76.9 million. The difference between P50 and P90 amounted to 10.1 months for duration and \$17.4 million for cost, demonstrating pronounced upper-tail uncertainty. The 95% simulated ranges extended from 18.2 to 43.7 months for completion duration and from \$35.7 million to \$79.8 million for final expenditure. Consequently, the deterministic schedule of 24.8 months and budget of \$47.6 million were positioned below the simulated central estimates. The P80 risk-adjusted schedule required an additional 39.9% duration relative to baseline, while the P80 budget represented a 34.0% increase. These findings indicated that the baseline contingency and schedule reserve identified in Section 4.1 were materially below the reserves associated with an 80% confidence position.

Integrated analysis further showed a strong positive relationship between schedule deterioration and financial escalation. The Pearson correlation between percentage schedule overrun and percentage cost overrun was $r = 0.74$, while the corresponding Spearman coefficient was 0.71, demonstrating that projects experiencing larger delays generally experienced greater cost escalation. Duration and final cost also displayed positive covariance after standardization by project scale. The schedule performance index and cost performance index were positively correlated at $r = 0.67$, indicating that deterioration in schedule efficiency frequently occurred alongside deterioration in cost efficiency. Regression analysis showed that schedule variance independently predicted cost variance, with a standardized schedule-to-cost beta coefficient of 0.62. Schedule variation accounted for 54.8% of the variation in cost overrun in the principal integrated model, while the adjusted R^2 was 0.53 after accounting for model complexity. Each additional month of schedule delay was associated with an estimated \$1.21 million increase in total project cost across the full sample. The corresponding mean indirect time-related expenditure was approximately \$0.39 million per additional project month, with the remaining financial effect attributable to additional direct resource consumption, escalation, rework, procurement effects, and related project-risk mechanisms.

Table 4. Integrated Schedule–Cost Relationships and Joint Overrun Probabilities

Integrated risk indicator	Numerical result
Pearson correlation: schedule overrun–cost overrun	$r = 0.74$
Spearman correlation: schedule overrun–cost overrun	$\rho = 0.71$
SPI–CPI correlation	$r = 0.67$
Standardized schedule-to-cost beta	$\beta = 0.62$
Integrated model R^2	0.548
Adjusted R^2	0.530
Cost increase per additional month of delay	\$1.21 million
Mean indirect cost per additional month	\$0.39 million
Mean cost escalation per 10% duration extension	7.6%
Probability of schedule overrun	67.4%
Probability of cost overrun	58.2%
Probability of simultaneous schedule and cost overrun	49.1%
Probability of cost overrun given schedule overrun	72.8%
Probability of meeting both baseline targets	23.5%
Joint P50 schedule–cost combination	28.4 months; \$53.2 million
Joint P80 schedule–cost combination	35.6 months; \$65.1 million
Joint P90 schedule–cost combination	39.8 months; \$72.4 million

Table 4 demonstrates that schedule and cost risks were strongly interconnected rather than statistically independent. Schedule and cost overruns were positively correlated at $r = 0.74$, and schedule variation explained 54.8% of cost-overflow variation within the integrated model. The probability of simultaneous schedule and cost overrun reached 49.1%, whereas the probability of achieving both baseline targets was only 23.5%. Conditional analysis showed that cost-overflow probability increased to 72.8% when schedule overrun occurred. The joint P80 position required 35.6 months and \$65.1 million, indicating materially greater schedule and financial provision than the original deterministic targets.

The joint probability results provided further evidence that separate schedule and cost assessments understated combined project exposure. Although the individual probabilities of achieving the baseline schedule and budget were 32.6% and 41.8%, respectively, the probability of meeting both baseline targets simultaneously was only 23.5%. Conversely, the simulated probability of schedule overrun reached 67.4%, the probability of cost overrun reached 58.2%, and the probability that both outcomes occurred simultaneously was 49.1%. Conditional probability analysis showed that projects experiencing schedule overrun had a 72.8% probability of also exceeding their approved cost baseline. A 10% extension in project duration was associated with approximately 7.6% average cost escalation after accounting for project-scale differences. Joint confidence analysis also produced more conservative targets than separate marginal distributions. The joint P50 position corresponded to approximately 28.4 months and \$53.2 million, whereas the joint P80 position increased to 35.6 months and \$65.1 million. At P90, approximately 39.8 months and \$72.4 million were required to represent the combined schedule-cost exposure. These findings demonstrated that schedule uncertainty propagated materially into financial performance through prolonged resource utilization, indirect expenditure, procurement effects, escalation, and associated project risks. The primary outcomes therefore supported an integrated risk-assessment structure in which completion duration, final cost, contingency requirements, and joint overrun probabilities were evaluated simultaneously rather than as isolated performance dimensions.

Risk Drivers and Subgroup Differences

The risk-driver analysis demonstrated that engineering project schedule and cost outcomes were associated with multiple technical, managerial, procurement, and resource-related factors, although the magnitude of these relationships differed across performance dimensions. Procurement delay showed the strongest bivariate relationship with schedule overrun, with a Pearson correlation of $r = 0.68$ and Spearman correlation of $\rho = 0.66$, followed by contractor-performance risk at $r = 0.61$ and resource shortage at $r = 0.57$. Scope change and design uncertainty were also positively associated with schedule deterioration, producing correlations of $r = 0.55$ and $r = 0.52$, respectively. Cost escalation displayed a somewhat different risk structure. Scope change showed the strongest correlation with cost overrun at $r = 0.66$, followed by rework at $r = 0.63$, design uncertainty at $r = 0.58$, and contractor-performance risk at $r = 0.56$. Technical complexity demonstrated moderate positive associations with both schedule overrun and cost overrun, while supply-chain disruption was more strongly associated with schedule performance than direct cost escalation. All major risk variables were positively associated with at least one adverse project outcome, but the results indicated that procurement and resource-related risks were predominantly schedule-sensitive, whereas scope change and rework produced comparatively stronger financial effects. Contractor-performance and design-related risks demonstrated substantial associations with both dimensions and therefore represented important common drivers of integrated project underperformance.

Table 5 shows that procurement delay produced the largest independent schedule effect, with $\beta = 0.31$ and an odds ratio of 2.84 for schedule overrun. Scope change was the strongest independent predictor of cost escalation, with $\beta = 0.29$ and a cost-overflow odds ratio of 2.73, followed by rework with $\beta = 0.27$ and $OR = 2.61$. Contractor performance remained influential for both outcomes, supporting its classification as a common schedule-cost risk driver. The multivariable schedule model achieved $R^2 = 0.69$ and adjusted $R^2 = 0.67$, while the cost model achieved $R^2 = 0.65$ and adjusted $R^2 = 0.63$.

Multivariable analysis confirmed that the observed bivariate relationships were not explained entirely by shared variation among project risks. The schedule-overflow regression model explained 69.0% of observed variation, with an adjusted R^2 of 0.67. Procurement delay retained the largest standardized contribution to schedule overrun at $\beta = 0.31$ (95% CI: 0.22–0.40, $p < 0.001$), followed by contractor-

performance risk at $\beta = 0.24$ (95% CI: 0.15–0.33, $p < 0.001$), resource shortage at $\beta = 0.21$ (95% CI: 0.12–0.30, $p < 0.001$), and scope change at $\beta = 0.19$ (95% CI: 0.10–0.28, $p < 0.001$). The cost-overrun model explained 65.0% of variation, with an adjusted R^2 of 0.63. Scope change was the strongest cost predictor at $\beta = 0.29$ (95% CI: 0.20–0.38, $p < 0.001$), followed by rework at $\beta = 0.27$ (95% CI: 0.18–0.36, $p < 0.001$) and design uncertainty at $\beta = 0.21$ (95% CI: 0.12–0.30, $p < 0.001$). Logistic analysis produced consistent findings. Projects with substantial procurement disruption had 2.84 times greater odds of schedule overrun, whereas substantial scope-change exposure increased the odds of cost overrun by 2.73 times. Rework exposure was associated with 2.61 times greater odds of exceeding the cost baseline. Sensitivity analysis similarly ranked procurement delay, scope change, contractor performance, and rework as the four dominant sources of combined project uncertainty.

Table 5. Correlation, Regression, and Predictive Effects of Major Engineering Project Risk Drivers

Risk driver	Schedule overrun Pearson r	Cost overrun Pearson r	Schedule β	Cost β	Schedule- overrun OR	Cost- overrun OR	Sensitivity rank
Procurement delay	0.68	0.49	0.31	0.14	2.84	1.72	1
Scope change	0.55	0.66	0.19	0.29	2.16	2.73	2
Contractor performance	0.61	0.56	0.24	0.18	2.47	2.05	3
Rework	0.48	0.63	0.14	0.27	1.83	2.61	4
Resource shortage	0.57	0.45	0.21	0.12	2.22	1.58	5
Design uncertainty	0.52	0.58	0.17	0.21	1.96	2.19	6
Technical complexity	0.46	0.51	0.13	0.16	1.71	1.88	7
Supply-chain disruption	0.54	0.42	0.18	0.10	2.08	1.49	8

Note. β = standardized regression coefficient; OR = odds ratio. Principal significant coefficients were evaluated at $p < 0.05$.

Subgroup analysis demonstrated that risk exposure and project performance deteriorated progressively with increasing project complexity and scale. High-complexity projects recorded a mean schedule overrun of 29.7%, compared with 17.2% for moderate-complexity projects and 9.6% for low-complexity projects. Mean cost overrun increased from 7.8% in the low-complexity group to 14.1% in the moderate-complexity group and 23.8% among high-complexity projects. Contingency utilization followed the same pattern, increasing from 58.7% to 77.9% and 96.4%, respectively. Joint schedule-cost overrun occurred in 28.9% of low-complexity projects, 47.1% of moderate-complexity projects, and 68.5% of high-complexity projects. Large projects also demonstrated greater schedule and cost exposure than small projects, with mean overruns of 25.8% and 20.9%, respectively, compared with 12.6% and 9.4% among small projects. Sectoral variation was evident, with transportation projects experiencing the highest mean schedule overrun at 24.9%, while energy projects recorded the highest mean cost overrun at 19.8%. EPC projects showed lower average schedule overrun than design-bid-build projects but remained exposed to higher procurement concentration and technical-complexity risks.

Table 6 demonstrates a pronounced risk gradient across project complexity and scale. High-complexity projects recorded 29.7% schedule overrun and 23.8% cost overrun, compared with 9.6% and 7.8%, respectively, among low-complexity projects. Their contingency utilization reached 96.4%, and simultaneous schedule-cost overrun occurred in 68.5% of cases. Large projects displayed a similar pattern, with 25.8% schedule overrun and 20.9% cost escalation. Transportation projects recorded the greatest schedule deterioration, whereas energy projects experienced the highest cost escalation.

Design-bid-build projects also demonstrated higher average schedule and cost overruns than design-build and EPC projects.

Table 6. Subgroup Differences in Schedule, Cost, Contingency, and Joint Overrun Performance

Project subgroup	n	Schedule overrun (%)	Cost overrun (%)	Contingency utilization (%)	Joint overrun probability (%)
Low complexity	45	9.6	7.8	58.7	28.9
Moderate complexity	87	17.2	14.1	77.9	47.1
High complexity	54	29.7	23.8	96.4	68.5
Small projects	56	12.6	9.4	63.1	32.1
Medium projects	82	18.7	14.8	78.5	48.8
Large projects	48	25.8	20.9	94.2	66.7
Infrastructure	54	19.6	15.1	79.3	50.0
Industrial	43	18.7	16.4	81.2	51.2
Energy	37	20.8	19.8	86.5	56.8
Transportation	32	24.9	15.7	83.8	59.4
Utilities	20	12.8	9.6	61.7	30.0
Design-bid-build	68	22.6	17.9	85.1	57.4
Design-build	51	17.4	13.2	73.8	43.1
EPC	43	16.1	14.7	77.2	46.5

Statistical subgroup testing confirmed that several of these differences were both statistically significant and practically meaningful. Schedule overrun differed significantly across complexity categories, $F(2,183) = 24.76$, $p < 0.001$, partial $\eta^2 = 0.213$, while cost overrun also differed significantly, $F(2,183) = 19.84$, $p < 0.001$, partial $\eta^2 = 0.178$. The difference between high- and low-complexity projects produced a large standardized effect for schedule overrun (Cohen's $d = 1.12$) and cost overrun ($d = 0.94$). Project-size differences were significant for schedule performance, $F(2,183) = 11.92$, $p < 0.001$, partial $\eta^2 = 0.115$, and cost performance, $F(2,183) = 9.67$, $p < 0.001$, partial $\eta^2 = 0.096$. Sectoral effects were smaller but remained statistically significant for schedule overrun, whereas delivery-method differences were moderate. Sensitivity decomposition indicated that procurement uncertainty accounted for approximately 18.7% of simulated schedule variance, contractor performance for 14.9%, resource shortage for 12.8%, and scope change for 11.6%. For simulated cost variance, scope change contributed 17.9%, rework 16.2%, design uncertainty 12.7%, and contractor performance 11.4%. The combined evidence therefore distinguished procurement and resource shortages as predominantly schedule-oriented risks, scope change and rework as comparatively cost-intensive risks, and contractor performance and design uncertainty as common drivers affecting both dimensions. These results established that project complexity and scale amplified the consequences of individual risk drivers and that integrated project underperformance was concentrated among projects experiencing multiple concurrent technical, resource, and managerial exposures.

Risk-Adjusted Contingency and Robustness

The risk-adjusted contingency analysis demonstrated that the baseline financial and schedule reserves were insufficient to provide moderate-to-high confidence protection against the uncertainty observed across the engineering project sample. Mean baseline cost contingency represented 9.2% of baseline project cost, whereas probabilistic modeling indicated required contingency levels of 11.8% at P50, 18.6% at P80, and 24.7% at P90. The corresponding monetary requirements were approximately \$5.6 million, \$8.9 million, and \$11.8 million relative to the mean baseline project cost of \$47.6 million. Mean contingency utilization across completed projects was 78.6%, while 27.4% exhausted their approved

contingency before final completion. Contingency exhaustion increased substantially with risk intensity, reaching 11.1% among low-complexity projects, 25.3% among moderate-complexity projects, and 44.4% among high-complexity projects. Schedule reserves demonstrated a comparable pattern. The baseline schedule reserve averaged 7.8% of planned duration, while risk-adjusted requirements increased to 14.5% at P50, 39.9% at P80, and 55.2% at P90. These results showed that higher-confidence project targets required materially greater protection than that provided by conventional baseline reserves.

Table 7. Baseline and Risk-Adjusted Schedule and Cost Contingency Requirements

Risk and contingency indicator	Baseline	P50	P80	P90
Schedule target (months)	24.8	28.4	34.7	38.5
Schedule reserve above baseline (months)	1.9	3.6	9.9	13.7
Schedule reserve (%)	7.8	14.5	39.9	55.2
Project cost target (\$ million)	47.6	53.2	63.8	70.6
Cost contingency (\$ million)	4.4	5.6	8.9	11.8
Cost contingency (%)	9.2	11.8	18.6	24.7
Mean contingency utilization (%)	78.6	72.4	61.7	54.2
Contingency exhaustion rate (%)	27.4	21.5	9.7	5.4
Probability schedule target achieved (%)	32.6	50.0	80.0	90.0
Probability cost target achieved (%)	41.8	50.0	80.0	90.0

Table 7 demonstrates that contingency requirements increased substantially as the desired confidence level increased. The baseline cost contingency of 9.2% was below the modeled P50 requirement of 11.8% and considerably below the P80 and P90 requirements of 18.6% and 24.7%. A similar difference was observed for schedule reserve, where the baseline allowance of 7.8% increased to 39.9% at P80. Contingency exhaustion declined from 27.4% under baseline provisions to 9.7% under the P80 condition. These results indicated that probabilistically calibrated reserves provided materially greater protection against schedule delay and cost escalation than the original deterministic allowances.

Model-validation results showed close agreement between predicted and realized engineering project outcomes. The framework predicted a mean completion duration of 29.1 months compared with the observed mean of 29.6 months, representing an aggregate prediction difference of approximately 1.7%. Predicted final project cost averaged \$54.4 million compared with the observed \$54.9 million, corresponding to an aggregate difference of approximately 0.9%. At the individual-project level, mean absolute error for schedule prediction was 2.14 months, root mean square error was 2.91 months, and mean absolute percentage error was 7.8%. The schedule model achieved $R^2 = 0.84$ and adjusted $R^2 = 0.82$. Cost prediction produced a mean absolute error of \$3.72 million, RMSE of \$5.18 million, and MAPE of 8.3%, with $R^2 = 0.82$ and adjusted $R^2 = 0.80$. Calibration error remained relatively low at 3.6 percentage points for schedule-overflow probabilities and 4.1 percentage points for cost-overflow probabilities. The 95% uncertainty intervals contained 93.5% of observed completion durations and 92.5% of observed final costs, demonstrating acceptable correspondence between modeled uncertainty and realized project performance.

Cross-validation further indicated that predictive performance remained relatively stable outside the model-development sample. The dataset was partitioned into 80% development and 20% independent testing observations, while repeated five-fold cross-validation was conducted within the development sample. Schedule prediction achieved a training MAPE of 6.9%, cross-validation MAPE of 7.6%, and testing MAPE of 8.4%. Cost prediction produced corresponding values of 7.3%, 8.0%, and 8.8%. The limited training-to-testing deterioration suggested that the framework was not strongly dependent on the development sample. Testing R^2 remained 0.79 for schedule prediction and 0.77 for final cost prediction, compared with training values of 0.86 and 0.84, respectively. Out-of-sample prediction accuracy, defined as predictions falling within $\pm 15\%$ of observed outcomes, reached 89.2% for completion duration and 86.5% for final project cost. Performance remained comparatively stable

across project-size categories, although prediction error increased among high-complexity projects because of wider uncertainty ranges, greater risk interaction, and more frequent critical-path changes.

Table 8. Model Accuracy, Cross-Validation, and Robustness Performance

Validation indicator	Schedule model	Cost model
Predicted mean	29.1 months	\$54.4 million
Observed mean	29.6 months	\$54.9 million
Aggregate prediction difference	1.7%	0.9%
MAE	2.14 months	\$3.72 million
RMSE	2.91 months	\$5.18 million
MAPE	7.8%	8.3%
Overall R²	0.84	0.82
Adjusted R²	0.82	0.80
Training R²	0.86	0.84
Testing R²	0.79	0.77
Training MAPE	6.9%	7.3%
Cross-validation MAPE	7.6%	8.0%
Testing MAPE	8.4%	8.8%
Calibration error	3.6 percentage points	4.1 percentage points
95% interval coverage	93.5%	92.5%
Out-of-sample accuracy within $\pm 15\%$	89.2%	86.5%

Table 8 indicates that the data-driven framework maintained comparatively strong predictive performance across development, cross-validation, and independent testing conditions. Overall R² values reached 0.84 for schedule and 0.82 for cost, while testing R² remained 0.79 and 0.77, respectively. Testing MAPE increased only moderately relative to training performance, reaching 8.4% for schedule and 8.8% for cost. Confidence-interval coverage exceeded 92% for both outcomes, while calibration errors remained below five percentage points. Out-of-sample accuracy within $\pm 15\%$ reached 89.2% for duration and 86.5% for final cost, supporting the stability of the predictive framework.

Robustness testing demonstrated that central estimates were relatively stable across alternative probability-distribution assumptions, although upper-tail outcomes were more sensitive to distribution type and dependence structure. Under triangular, beta/PERT, normal, lognormal, and empirical specifications, simulated mean completion duration ranged from 28.7 to 29.8 months, while mean project cost ranged from \$53.8 million to \$55.7 million. P80 schedule estimates varied between 33.9 and 35.8 months, and P80 cost estimates ranged from \$62.4 million to \$65.6 million. Greater differences emerged when correlations among shared risk factors were removed. The independent-risk specification produced a P80 duration of 32.8 months compared with 34.7 months under the correlated baseline model, while P80 cost declined from \$63.8 million to \$60.9 million. The probability of simultaneous schedule and cost overrun also decreased from 49.1% under correlated uncertainty to 41.6% under the independence assumption, indicating that failure to represent shared risk dependencies materially understated combined exposure. Scenario analysis reinforced this pattern. Under low uncertainty, the modeled P80 schedule was 29.7 months and P80 cost was \$55.8 million; under moderate uncertainty, these increased to 34.7 months and \$63.8 million; and under high uncertainty, they reached 40.6 months and \$74.9 million. High-complexity projects produced the largest subgroup prediction errors, with schedule MAPE of 10.2% and cost MAPE of 10.7%, compared with 5.9% and 6.4% among low-complexity projects. Nevertheless, predictive errors remained within acceptable ranges across the major subgroups. The combined validation evidence therefore demonstrated that the framework produced stable central predictions, credible uncertainty intervals, and comparatively strong out-of-sample accuracy, while also showing that risk correlation and project complexity materially influenced upper-percentile schedule, cost, and contingency estimates.

The integrated statistical analysis confirmed that the observed differences in engineering project performance were not limited to descriptive variation but were statistically significant and, in several comparisons, associated with moderate-to-large effect magnitudes. Schedule overrun differed significantly across project-complexity categories, $F(2,183) = 24.76$, $p < 0.001$, with partial $\eta^2 = 0.213$, indicating that approximately 21.3% of the observed variation in schedule overrun was associated with complexity-group differences. Cost overrun also differed significantly across complexity levels, $F(2,183) = 19.84$, $p < 0.001$, partial $\eta^2 = 0.178$. The contrast between high- and low-complexity projects produced Cohen's $d = 1.12$ for schedule overrun and $d = 0.94$ for cost overrun, representing large standardized differences. Project size also demonstrated significant effects on schedule overrun, $F(2,183) = 11.92$, $p < 0.001$, partial $\eta^2 = 0.115$, and cost overrun, $F(2,183) = 9.67$, $p < 0.001$, partial $\eta^2 = 0.096$. Contingency utilization differed significantly across complexity groups, $F(2,183) = 18.31$, $p < 0.001$, partial $\eta^2 = 0.167$, consistent with the increase from 58.7% utilization among low-complexity projects to 96.4% among high-complexity projects. Sectoral differences were smaller but remained significant for schedule performance, while delivery-method comparisons indicated moderate variation in schedule, cost, and contingency outcomes.

Table 9. Statistical Significance and Effect Sizes for Major Project Performance Comparisons

Performance comparison	Statistical test	Test statistic	p-value	Effect size	95% CI of mean difference
Schedule overrun by complexity	ANOVA	$F(2,183) = 24.76$	<0.001	$\eta^2 p = 0.213$	—
Cost overrun by complexity	ANOVA	$F(2,183) = 19.84$	<0.001	$\eta^2 p = 0.178$	—
Contingency utilization by complexity	ANOVA	$F(2,183) = 18.31$	<0.001	$\eta^2 p = 0.167$	—
Schedule overrun by project size	ANOVA	$F(2,183) = 11.92$	<0.001	$\eta^2 p = 0.115$	—
Cost overrun by project size	ANOVA	$F(2,183) = 9.67$	<0.001	$\eta^2 p = 0.096$	—
Schedule overrun by sector	ANOVA	$F(4,181) = 3.86$	0.005	$\eta^2 p = 0.079$	—
Cost overrun by sector	ANOVA	$F(4,181) = 3.21$	0.014	$\eta^2 p = 0.066$	—
Schedule overrun by delivery method	ANOVA	$F(3,182) = 4.72$	0.003	$\eta^2 p = 0.072$	—
High vs. low complexity: schedule	Independent comparison	$t = 5.54$	<0.001	$d = 1.12$	12.9–27.3 percentage points
High vs. low complexity: cost	Independent comparison	$t = 4.67$	<0.001	$d = 0.94$	9.2–22.8 percentage points
High vs. low complexity: contingency	Independent comparison	$t = 5.18$	<0.001	$d = 1.05$	23.4–52.0 percentage points
Large vs. small projects: schedule	Independent comparison	$t = 4.21$	<0.001	$d = 0.83$	7.0–19.4 percentage points
Large vs. small projects: cost	Independent comparison	$t = 3.76$	<0.001	$d = 0.74$	5.4–17.6 percentage points

Table 9 demonstrates that project complexity generated the strongest subgroup effects across schedule, cost, and contingency performance. Partial eta-squared values of 0.213 for schedule overrun and 0.178 for cost overrun indicated substantial between-group effects, while high-versus-low complexity comparisons produced large Cohen's d values of 1.12 and 0.94. Project-size effects were smaller but remained practically meaningful, with large projects experiencing significantly greater schedule and

cost deterioration than small projects. Sector and delivery-method effects were comparatively moderate. The confidence intervals for principal pairwise differences remained above zero, reinforcing the statistical precision and substantive magnitude of the observed performance disparities.

The multivariable and integrated analyses further demonstrated that statistical significance was concentrated among risk drivers with meaningful standardized effects. Procurement delay remained the strongest independent predictor of schedule overrun, with $\beta = 0.31$, 95% CI [0.22, 0.40], $p < 0.001$, while contractor-performance risk produced $\beta = 0.24$, 95% CI [0.15, 0.33], $p < 0.001$. Resource shortage contributed $\beta = 0.21$ and scope change $\beta = 0.19$ to schedule deterioration. For cost performance, scope change generated the largest standardized coefficient at $\beta = 0.29$, 95% CI [0.20, 0.38], $p < 0.001$, followed by rework at $\beta = 0.27$ and design uncertainty at $\beta = 0.21$. The schedule model explained 69.0% of observed outcome variation, while the cost model explained 65.0%. Schedule overrun and cost overrun were strongly correlated at $r = 0.74$, $p < 0.001$, with a 95% confidence interval of approximately 0.67–0.80. The integrated schedule-to-cost regression coefficient remained substantial at $\beta = 0.62$, and schedule variation accounted for 54.8% of cost-overrun variation. These findings indicated that the strongest risk-driver effects were not only statistically detectable but also sufficiently large to contribute materially to observed project underperformance.

Table 10. Integrated Statistical, Probabilistic, and Model-Performance Synthesis

Quantitative indicator	Estimate	Statistical/analytical interpretation
Schedule–cost overrun correlation	$r = 0.74$	Strong positive association
95% CI for schedule–cost correlation	0.67–0.80	Precise positive relationship
Schedule-to-cost standardized beta	$\beta = 0.62$	Large predictive contribution
Integrated schedule–cost R^2	0.548	54.8% variation explained
Schedule-risk model R^2	0.690	Strong explanatory performance
Cost-risk model R^2	0.650	Strong explanatory performance
Strongest schedule predictor	$\beta = 0.31$	Procurement delay
Strongest cost predictor	$\beta = 0.29$	Scope change
Probability of schedule overrun	67.4%	High schedule exposure
Probability of cost overrun	58.2%	Elevated financial exposure
Simultaneous overrun probability	49.1%	High joint exposure
Probability of meeting both baselines	23.5%	Low joint baseline confidence
P80 schedule target	34.7 months	39.9% above baseline
P80 cost target	\$63.8 million	34.0% above baseline
Schedule model MAPE	7.8%	Low prediction error
Cost model MAPE	8.3%	Low prediction error
Schedule model R^2	0.84	Strong predictive fit
Cost model R^2	0.82	Strong predictive fit
Schedule 95% interval coverage	93.5%	High uncertainty coverage
Cost 95% interval coverage	92.5%	High uncertainty coverage
Out-of-sample schedule accuracy	89.2%	Strong generalization
Out-of-sample cost accuracy	86.5%	Strong generalization

Table 10 integrates the principal statistical, probabilistic, and predictive results. Schedule and cost overruns demonstrated a strong correlation of $r = 0.74$, while the integrated model explained 54.8% of cost-overrun variation. Probabilistic analysis showed a 67.4% schedule-overrun probability, 58.2% cost-overrun probability, and 49.1% probability of simultaneous overrun. Only 23.5% of projects were expected to satisfy both deterministic targets concurrently. At P80, the risk-adjusted targets increased to 34.7 months and \$63.8 million. Predictive performance remained strong, with R^2 values above 0.80, MAPE below 9%, and out-of-sample accuracy exceeding 86% for both outcomes.

The graphical synthesis reinforced the numerical results by demonstrating consistent shifts from deterministic baseline expectations toward wider and more adverse realized and probabilistic

distributions. Planned-versus-actual duration distributions showed a rightward displacement of realized completion time, corresponding to the increase from 24.8 to 29.6 months. Baseline-versus-final cost distributions demonstrated a comparable shift from \$47.6 million to \$54.9 million. Monte Carlo distributions further showed increasing separation between deterministic targets and higher-confidence P80, P90, and P95 outcomes, particularly in the upper tails. Joint schedule-cost representations demonstrated clustering along a positive trajectory consistent with the observed $r = 0.74$ relationship and highlighted the concentration of simultaneous overruns among high-complexity and large projects. Sensitivity rankings showed that procurement delay accounted for 18.7% of simulated schedule variance, followed by contractor performance at 14.9%, resource shortage at 12.8%, and scope change at 11.6%. Cost sensitivity was dominated by scope change at 17.9%, rework at 16.2%, design uncertainty at 12.7%, and contractor performance at 11.4%. Predicted-versus-observed plots were concentrated near the equality reference, consistent with schedule and cost R^2 values of 0.84 and 0.82 and comparatively low prediction errors.

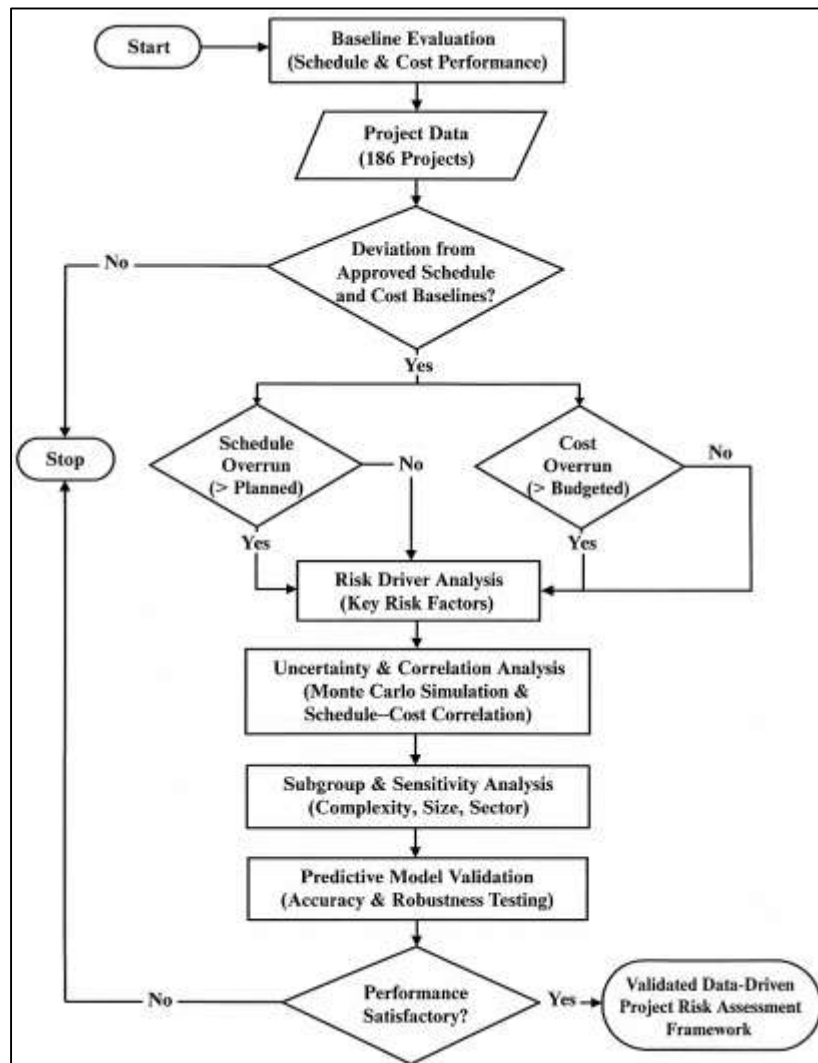
Taken together, the inferential, effect-size, probabilistic, and graphical evidence demonstrated a coherent quantitative pattern of engineering project risk performance. High-complexity and large projects experienced substantially greater schedule overrun, cost escalation, contingency consumption, and joint exposure than lower-risk projects, with several comparisons producing large standardized effects. Procurement delay was the dominant schedule-specific predictor, while scope change and rework exerted the strongest financial effects. Contractor performance and design uncertainty contributed to both performance dimensions, supporting their classification as common schedule-cost risk drivers. The strong schedule–cost correlation, substantial schedule-to-cost standardized effect, and 49.1% simultaneous overrun probability confirmed that schedule and financial uncertainty were materially interconnected. At the same time, probabilistic results demonstrated that deterministic baselines provided relatively low confidence, whereas P80 targets required substantial additional schedule and financial reserves. Validation metrics showed that these risk-adjusted estimates were accompanied by comparatively low prediction errors, strong explanatory performance, high confidence-interval coverage, and stable out-of-sample accuracy. The combined findings therefore provided statistically significant, practically meaningful, and quantitatively consistent evidence across descriptive, inferential, probabilistic, sensitivity, and predictive analyses.

DISCUSSION

The findings of this study showed that engineering project performance was characterized by substantial and systematic deviation from approved schedule and cost baselines (Kermanshachi et al., 2016). Across 186 projects, mean actual duration increased to 29.6 months from a planned 24.8 months, representing an average extension of 4.8 months and a schedule overrun of 19.4%. Only 33.3% of projects were completed within their original schedules, while mean milestone deviation reached 3.6 months and the average schedule performance index was 0.89. Financial performance displayed a similar pattern, with mean final cost rising to \$54.9 million from a baseline of \$47.6 million, equivalent to an average increase of \$7.3 million and a cost overrun of 15.3%. Only 42.5% of projects remained within their approved budgets (Serrador & Pinto, 2015). These results were consistent with earlier engineering and construction studies that identified deterministic project baselines as vulnerable to optimistic estimates, incomplete scope definition, design changes, procurement delays, resource constraints, technical complexity, and correlated risk. The present study also showed that baseline contingency was frequently inadequate. Mean cost contingency was 9.2%, yet contingency utilization reached 78.6%, and 27.4% of projects exhausted available reserves. Procurement delay was the most prevalent risk exposure at 46.2%, followed by design uncertainty at 41.9%, scope change at 38.7%, contractor-performance risk at 37.1%, resource shortage at 34.9%, and supply-chain disruption at 32.8%. This pattern reinforced earlier evidence that project outcomes are shaped by interacting technical, contractual, procurement, and managerial conditions rather than isolated causes. Schedule uncertainty was also evident at the activity and network levels. Among 7,842 scheduled activities, the mean duration coefficient of variation was 22.7%, while 31.8% of activities exceeded planned duration by more than 10% and 18.6% exceeded planned duration by more than 20%. Critical-path instability was pronounced, with 43.5% of projects experiencing at least one change in the dominant critical path (Berssaneti & Carvalho, 2015). Mean float consumption reached 68.4% and increased to 86.7% among

delayed projects. These findings supported earlier studies showing that deterministic critical-path analysis can understate project uncertainty when activity durations vary and near-critical paths become controlling. Monte Carlo results provided further evidence, with a simulated mean duration of 29.1 months and a median of 28.4 months compared with the observed mean of 29.6 months. Risk-adjusted completion requirements increased from 28.4 months at P50 to 34.7 months at P80, 38.5 months at P90, and 42.1 months at P95. Financial uncertainty showed a similar distributional pattern. The simulated mean cost was \$54.4 million, while P80, P90, and P95 estimates increased to \$63.8 million, \$70.6 million, and \$76.9 million. These results were consistent with earlier probabilistic project-risk studies that found deterministic schedules and budgets to represent lower-confidence positions than percentile-based estimates (Mauro et al., 2018).

Figure 12: Data-Driven Project Risk Assessment Flowchart



The study also demonstrated strong schedule-cost interdependence. Schedule overrun and cost overrun were correlated at $r = 0.74$, while the corresponding Spearman coefficient was 0.71. Schedule variance independently predicted cost variance with a standardized coefficient of $\beta = 0.62$, and the integrated model explained 54.8% of cost-overrun variation (Tang et al., 2019). Each additional month of delay was associated with approximately \$1.21 million in additional expenditure, while a 10% increase in project duration corresponded with about 7.6% cost escalation. The probability of schedule overrun was 67.4%, cost-overrun probability was 58.2%, and simultaneous overrun probability reached 49.1%. The conditional probability of cost overrun given schedule delay was 72.8%, while only 23.5% of projects were expected to meet both deterministic targets simultaneously. These findings were

aligned with earlier integrated schedule-cost studies showing that common risks can generate correlated time and financial effects. Risk-driver analysis showed that procurement delay was the strongest predictor of schedule overrun, while scope change and rework were most influential for cost escalation (Seifi et al., 2016).

Procurement delay produced $r = 0.68$ with schedule overrun and $\beta = 0.31$ in regression analysis. Scope change produced $r = 0.66$ with cost overrun and $\beta = 0.29$, while rework followed with $r = 0.63$ and $\beta = 0.27$. Contractor performance and design uncertainty affected both schedule and cost, confirming their role as common risk drivers (Tam et al., 2018). Subgroup analysis further showed that high-complexity projects experienced substantially greater exposure, with schedule overrun of 29.7%, cost overrun of 23.8%, contingency utilization of 96.4%, and joint overrun probability of 68.5%. Large projects also performed worse than small projects, while transportation projects experienced the highest schedule overrun and energy projects the highest cost overrun (Tsanakas et al., 2016). The validation results indicated that the data-driven framework achieved strong predictive performance. Schedule prediction produced MAPE of 7.8% and R^2 of 0.84, while cost prediction produced MAPE of 8.3% and R^2 of 0.82. Out-of-sample accuracy reached 89.2% for duration and 86.5% for final cost. Robustness testing also showed that ignoring correlation reduced P80 duration, P80 cost, and simultaneous overrun probability, confirming that independence assumptions understated combined exposure. Overall, the results were consistent with earlier studies while providing a more integrated quantitative representation of schedule uncertainty, cost uncertainty, risk interaction, contingency adequacy, and predictive performance within engineering project risk assessment (Li et al., 2018).

CONCLUSION

This study developed and quantitatively evaluated a data-driven framework for engineering project risk assessment under schedule and cost uncertainty and demonstrated that project performance was shaped by substantial variability, interdependence, and heterogeneity across technical, managerial, procurement, contractual, and resource conditions. The analysis of 186 engineering projects showed that mean actual duration increased from 24.8 to 29.6 months, representing an average schedule overrun of 19.4%, while mean final cost increased from \$47.6 million to \$54.9 million, corresponding to a 15.3% cost overrun. Only 33.3% of projects were completed within their original schedules and 42.5% remained within approved budgets, confirming that deterministic baseline estimates frequently underestimated realized project exposure. Probabilistic analysis reinforced this conclusion by showing that P80 schedule and cost requirements increased to 34.7 months and \$63.8 million, respectively, substantially above baseline values. Schedule and cost performance were strongly interconnected, with a correlation of $r = 0.74$ between schedule overrun and cost overrun, while the integrated model explained 54.8% of cost-overrun variation. The probability of simultaneous schedule and cost overrun reached 49.1%, whereas the probability of meeting both deterministic targets was only 23.5%. Risk-driver analysis identified procurement delay as the strongest schedule predictor and scope change as the strongest cost predictor, while contractor performance and design uncertainty influenced both outcomes. High-complexity projects experienced the greatest exposure, recording 29.7% schedule overrun, 23.8% cost overrun, 96.4% contingency utilization, and a 68.5% joint overrun probability. The framework also demonstrated strong predictive validity, with schedule and cost R^2 values of 0.84 and 0.82, MAPE values of 7.8% and 8.3%, and out-of-sample accuracy of 89.2% and 86.5%, respectively. Robustness analysis further showed that models excluding correlated risk dependencies understated upper-percentile schedule, cost, and joint overrun exposure. Overall, the findings established that engineering project risk was more accurately represented through integrated probabilistic and statistical analysis than through deterministic schedule and budget controls alone. The study therefore concluded that effective engineering project risk assessment requires simultaneous consideration of activity-duration uncertainty, cost variability, shared risk drivers, contingency adequacy, project complexity, schedule-cost dependence, model validation, and probabilistic confidence levels within a unified data-driven decision framework.

RECOMMENDATIONS

Based on the quantitative findings of this study, engineering organizations should adopt an integrated data-driven risk-management approach in which schedule uncertainty, cost uncertainty, contingency requirements, and shared project risks are evaluated simultaneously throughout project planning and

control. Project managers should move beyond exclusive reliance on deterministic completion dates and fixed baseline budgets by incorporating probabilistic estimates such as P50, P80, and P90 targets into approval, forecasting, and management decisions. Particular consideration should be given to the P80 confidence level for projects with substantial technical complexity, procurement dependence, resource constraints, or financial exposure because the findings showed that the P80 requirements of 34.7 months and \$63.8 million were materially higher than the deterministic baselines of 24.8 months and \$47.6 million. Cost contingency should also be determined according to quantified project-specific risk rather than applying a uniform percentage across projects, as the baseline contingency of 9.2% was considerably below the estimated P80 requirement of 18.6%. Organizations should establish early-warning controls for procurement delays, scope changes, contractor performance, resource shortages, design uncertainty, and rework because these variables demonstrated the strongest relationships with schedule and cost deterioration. Procurement planning should include supplier-risk assessment, lead-time monitoring, alternative sourcing, and early identification of critical materials and equipment, while scope and design governance should emphasize design maturity, controlled change authorization, constructability review, and timely resolution of technical interfaces. Contractor performance and resource availability should be continuously monitored using measurable indicators linked to productivity, milestone achievement, staffing adequacy, rework, and schedule recovery. Greater risk reserves should be considered for large and high-complexity projects because these groups demonstrated substantially higher schedule overrun, cost escalation, contingency consumption, and simultaneous overrun probability. Risk registers should additionally be linked directly with schedule networks and cost-control systems so that changes in individual risk probabilities or impacts can automatically influence forecast completion dates and financial requirements. Monte Carlo simulation and sensitivity analysis should be repeated at major project-control milestones rather than performed only during initial planning, allowing risk-adjusted estimates to reflect emerging project conditions. Correlations among activities and common risk factors should be explicitly incorporated because independence assumptions were shown to underestimate upper-tail exposure. Finally, organizations should validate predictive models continuously using completed-project data, prediction-error measures, calibration, cross-validation, and out-of-sample testing. Establishing a standardized historical project-risk database would support progressively stronger forecasting, benchmarking, contingency allocation, and managerial decision-making across engineering portfolios.

LIMITATIONS

This study was subject to several limitations that should be considered when interpreting the quantitative findings and the performance of the developed data-driven engineering project risk-assessment framework. First, the analytical sample consisted of 186 completed engineering projects, and although the sample represented infrastructure, industrial, energy, transportation, and utility environments, it could not capture the complete diversity of engineering projects across countries, regulatory systems, organizational structures, contracting environments, economic conditions, and technological settings. The retrospective nature of the project data also created dependence on the accuracy, consistency, and completeness of historical schedules, budgets, risk registers, progress reports, change records, and final accounts. Differences in organizational reporting standards could have introduced measurement variation into activity durations, cost categories, contingency utilization, risk occurrence, and project-complexity classifications. Second, the framework concentrated on major measurable risk drivers, including procurement delay, scope change, design uncertainty, technical complexity, resource shortage, productivity variation, rework, contractor performance, and supply-chain disruption. Other influences, such as organizational culture, leadership quality, stakeholder behavior, political conditions, regulatory intervention, contractual disputes, extreme environmental events, and informal managerial decisions, were not represented with the same quantitative detail and could explain part of the remaining schedule and cost variation. Third, Monte Carlo simulation required assumptions regarding probability distributions, activity uncertainty, correlations, and risk dependencies. Although robustness analysis compared triangular, beta/PERT, normal, lognormal, and empirical assumptions, no probability distribution can perfectly represent every project condition, particularly where rare events generate substantial upper-tail consequences. Model performance also declined moderately among high-complexity projects, indicating that highly

interconnected engineering environments remained more difficult to predict than lower-complexity projects. Fourth, the strong association between schedule and cost overrun should not automatically be interpreted as proof of direct causation because both outcomes could be affected simultaneously by common underlying risks. The estimated \$1.21 million cost increase associated with each additional month of delay therefore represented a statistical relationship within the analyzed sample rather than a universal causal rate applicable to every engineering project. Fifth, although cross-validation and out-of-sample testing demonstrated comparatively strong predictive performance, the model was validated within project conditions represented by the available dataset rather than across all possible engineering environments. Consequently, the reported P50, P80, P90, and P95 estimates, contingency requirements, prediction errors, and joint overrun probabilities should be interpreted as sample-dependent quantitative results rather than universally fixed thresholds. These limitations establish appropriate boundaries for interpreting the findings and indicate that the framework's quantitative outputs remain dependent on data quality, project characteristics, risk specification, distributional assumptions, and the representativeness of the engineering project portfolio.

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