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# A Study on the Relationship between Team Configuration and Schedule Deviation in Energy Engineering Projects

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***Abstract:*** *Energy engineering projects are typically long-term and complex, and team configuration structure has a significant impact on project schedule control. This study analyzes the mechanism of human resource input structure in relation to the relationship between project team configuration and schedule deviation. Data from 58 projects of an energy engineering company were selected, including project team member composition, professional division of labor ratios, and actual project duration records. Schedule deviation was measured as the difference between the actual and planned project duration. A quantile regression model was used to analyze the differences in the impact of different configuration structures under mild and severe delay scenarios. The results show that projects with a low proportion of technical personnel have a significant risk of delay in the later stages of the project, while a reasonable allocation of auxiliary positions helps to reduce extreme delays. This study provides quantitative support for human resource allocation decisions in engineering projects.*

***Keywords:*** *Energy engineering; Project management; Team configuration; Schedule deviation; Quantile regression*

## 1. Introduction:

Energy engineering projects are characterized by long implementation cycles, complex task interdependence, and intensive coordination across multiple technical disciplines. Under such conditions, schedule deviation remains a persistent managerial challenge and frequently results in cost escalation, contractual disputes, and delayed system commissioning. Empirical studies consistently report that time overruns are prevalent in large-scale energy and infrastructure projects and become increasingly difficult to mitigate once delays accumulate in later stages of execution [1]. At the same time, research on strategic human resource leadership and HR analytics highlights that organizational design and workforce configuration play a critical role in shaping operational performance in complex project-based environments [2]. These findings suggest that schedule outcomes cannot be explained solely by external disruptions but are also embedded in internal organizational structures. Consequently, schedule performance has become a central concern in project management research, with growing emphasis on data-driven monitoring and predictive analytics. A broad range of analytical approaches has been proposed to enhance schedule control. Digital progress tracking systems, real-time performance dashboards, and machine learning models have been developed to estimate completion time and delay probability with increasing accuracy [3,4]. Although these tools improve forecasting precision, most models concentrate on macro-level determinants such as supply chain interruptions, payment delays, design modifications, and contractual arrangements. Comparatively limited attention has been given to the internal organization of project teams, even though team members directly execute tasks, coordinate interfaces, and respond to schedule pressure on a daily basis [5]. Insights from human resource analytics further indicate that workforce structure influences coordination efficiency and decision speed, implying that team configuration may have measurable effects on time performance beyond traditional risk factors [6]. Parallel research in construction and engineering management has increasingly examined how team organization affects project outcomes. Evidence from large infrastructure programs shows that coordination quality and information exchange mechanisms shape the identification and mitigation of schedule risks [7,8]. Studies on multi-team systems demonstrate that performance depends not only on workforce size but also on the distribution of expertise across functional roles [9]. Organizational analyses reveal that clearer role allocation and complementary skill structures are associated with more stable delivery results [10]. Reviews of construction project performance also emphasize that the balance between technical specialists and supporting personnel becomes particularly important under complex execution conditions and tight deadlines [11]. Together, these findings imply that staffing composition is likely to influence schedule deviation through mechanisms such as communication efficiency, problem-solving capacity, and workload distribution. Despite these advances, quantitative evidence directly linking team configuration to schedule deviation remains limited. Many existing studies rely on perception-based surveys or aggregated labor indicators, which restrict the ability to evaluate how specific staffing ratios influence time performance at the project level [12,13]. Empirical models often estimate average effects and implicitly assume that the same determinants operate across all levels of delay. This assumption overlooks the possibility that factors driving minor schedule slippages may differ from those associated with severe overruns, as escalation dynamics and managerial responses vary substantially across delay magnitudes [14]. In addition, available datasets are frequently small in scale or heterogeneous in project type, which constrains the generalizability of conclusions to energy engineering enterprises that follow standardized delivery procedures [15,16]. These limitations indicate the need for analytical approaches capable of capturing heterogeneous effects across the full distribution of schedule outcomes. From a methodological perspective, quantile regression offers a suitable framework to address this challenge. Unlike mean-based models, quantile regression allows the estimated effects of explanatory variables to vary at different points of the outcome distribution. This property is particularly relevant in engineering project contexts, where a staffing structure may exert limited influence under normal operating conditions but may significantly affect outcomes when projects face high execution pressure or late-stage rework. Recent methodological research recommends quantile regression for analyzing asymmetric and heterogeneous effects in project performance data [17], and its application in construction-related studies has demonstrated its value in revealing differentiated schedule risk patterns [18]. By modeling multiple quantiles of schedule deviation, it becomes possible to distinguish factors associated with routine time variance from those linked to extreme overruns. Against this background, the present study investigates the relationship between project team configuration and schedule deviation using operational data from an energy engineering enterprise. The dataset comprises 58 completed projects with detailed records of team member composition, discipline allocation ratios, and planned versus actual project durations. Schedule deviation is defined as the difference between actual and planned completion time. Quantile regression is employed to evaluate how variations in staffing structure influence both moderate and severe delays. Particular attention is given to the proportion of technical staff and the allocation of support positions, as these dimensions reflect the balance between specialized expertise and coordination capacity within project teams. By integrating organizational staffing variables with distribution-sensitive statistical modeling, this study provides empirical evidence on how internal team configuration shapes schedule performance across different risk levels. The findings contribute to project management theory by extending schedule deviation analysis from macro-level risk factors to micro-level human resource structure, and they offer practical implications for human resource planning and schedule risk control in energy engineering enterprises operating under standardized yet high-pressure delivery environments.

## 1.Materials and Methods

### 2.1 Sample and Study Context

The analysis is based on project records from an energy engineering enterprise involved in power and energy infrastructure delivery. The sample consists of 58 completed projects with complete information on staffing and schedule performance. All projects were managed under the same internal procedures and organizational rules, which reduces variability related to management systems. The projects cover engineering and construction activities with planned durations ranging from several months to multiple years. For each project, data include team size, role composition, professional allocation, planned duration, and actual completion time. Projects with incomplete records or major scope revisions were excluded to ensure consistency across observations.

### 2.2 Study Design and Comparison Framework

The study follows a comparative observational design based on differences in team configuration. Projects were grouped according to staffing structure, with particular attention to the proportion of technical personnel and the distribution of support roles. Projects with higher technical staff proportions were treated as reference cases, while those with lower proportions formed comparison cases. This design is consistent with established project management principles, which emphasize the link between task complexity and skill composition. By examining projects executed within the same organizational environment, the analysis focuses on the relationship between team configuration and schedule deviation under comparable conditions.

### 2.3 Measurement and Quality Control

Schedule deviation was defined as the difference between actual project duration and planned duration, measured in calendar days. Staffing variables were calculated using final team rosters and verified against internal human resource records. All data entries were checked for completeness and internal consistency. Projects with missing values or conflicting records were removed prior to analysis. Basic descriptive checks were conducted to identify extreme values. Where appropriate, variables were standardized to improve comparability across projects with different scales.

### 2.4 Data Processing and Model Formulation

Data processing included the calculation of staffing ratios and inspection of variable distributions. To examine how team configuration affects different levels of schedule deviation, quantile regression was applied. The model is specified as

$$Q_\tau(D_i)=\beta_{0,\tau}+\beta_{1,\tau}T_i+\beta_{2,\tau}S_i+\varepsilon_{i,\tau},$$

where $D_i$ denotes schedule deviation for project i, $T_i$ represents the proportion of technical staff, and $S_i$ denotes the proportion of support roles. For comparison, a linear regression model was also estimated:

$$D_i=\alpha+\gamma_1 T_i+\gamma_2 S_i+u_i.$$

The two models allow assessment of differences between average effects and effects observed at different points of the distribution.

### 2.5 Statistical Analysis

Quantile levels were selected to represent projects with small, moderate, and large schedule deviations. Changes in coefficient values across quantiles were examined to identify variation in staffing effects under different delay conditions. Additional checks were performed by adjusting quantile ranges and excluding extreme observations. Correlation among explanatory variables was assessed to avoid unstable estimates. All analyses were conducted using standard statistical software, and statistical significance was evaluated using commonly accepted confidence levels.

## 3.Results and Discussion

### 3.1 Distribution of schedule deviation and staffing structure

The observed schedule deviation across the 58 projects shows an uneven distribution, with most projects experiencing limited delay and a smaller number exhibiting substantial overruns. This pattern reflects a common feature of engineering projects, where extreme delays account for a disproportionate share of schedule risk [19]. Projects with a lower share of technical staff display a wider spread of delay outcomes, indicating that insufficient technical coverage does not necessarily affect routine progress but becomes more relevant when execution difficulties increase. Similar delay accumulation patterns have been documented in industrial and infrastructure projects, where schedule pressure intensifies during later implementation stages rather than growing steadily from project start [20]. Fig.1. Research model for management-related drivers of project schedule delay.

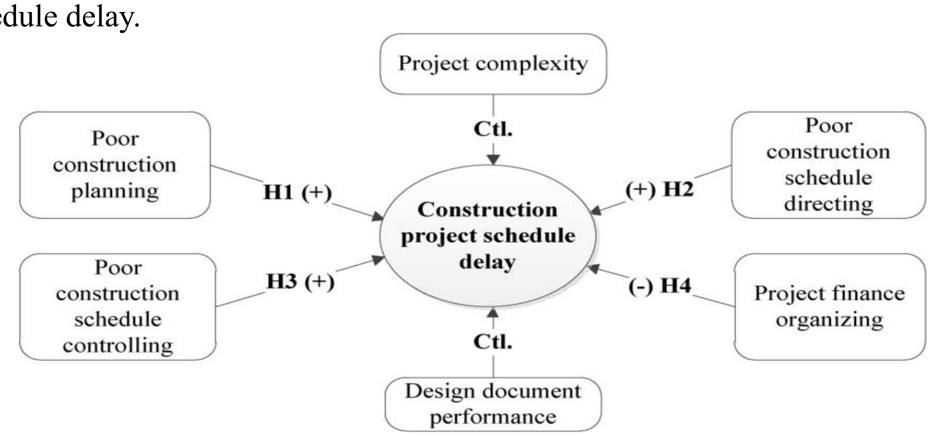


**Fig.1.**Schematic diagram showing the relationship between project team configuration and schedule deviation through coordination and management processes.

### 3.2 Effects of team configuration under different delay conditions

Results from the quantile regression analysis show that the influence of team configuration varies across delay levels. Around the median of the delay distribution, the proportion of technical staff exhibits a weak relationship with schedule deviation, suggesting that moderate delays are often influenced by short-term coordination issues or external disturbances rather than staffing structure alone. In contrast, at higher quantiles representing severe delay conditions, a lower technical-staff share is associated with noticeably larger overruns. This pattern implies that when projects encounter complex technical or interface problems, limited technical capacity slows issue resolution and prolongs recovery time [21]. The role of support positions differs from that of technical staff. Projects with a more balanced allocation of support roles tend to show lower delay values at the upper end of the distribution. This finding indicates that functions such as documentation control, coordination support, and follow-up activities help prevent local disruptions from escalating into major schedule failures [22]. Such effects are less visible under mild delay conditions but become important when task interdependence and uncertainty increase.

### 3.3 Comparison with existing studies and interpretation

Previous studies on energy and industrial construction delays have largely focused on planning quality, procurement constraints, and contractual arrangements, while the internal composition of project teams has received less quantitative attention. The present results are consistent with evidence showing that major delays often emerge during later project phases, when unresolved technical issues directly affect construction and commissioning activities. The observed sensitivity of severe delays to technical-staff proportion supports the view that technical capacity acts as a limiting factor once projects move beyond routine execution [23,24]. The stabilizing effect of support-role allocation also corresponds with earlier findings that many schedule failures stem from weaknesses in coordination, monitoring, and control rather than from isolated technical problems. Together, these results suggest that different staffing roles influence different parts of the delay distribution: technical staff primarily affect the ability to resolve high-impact issues, while support roles help maintain process continuity and information flow under stress.

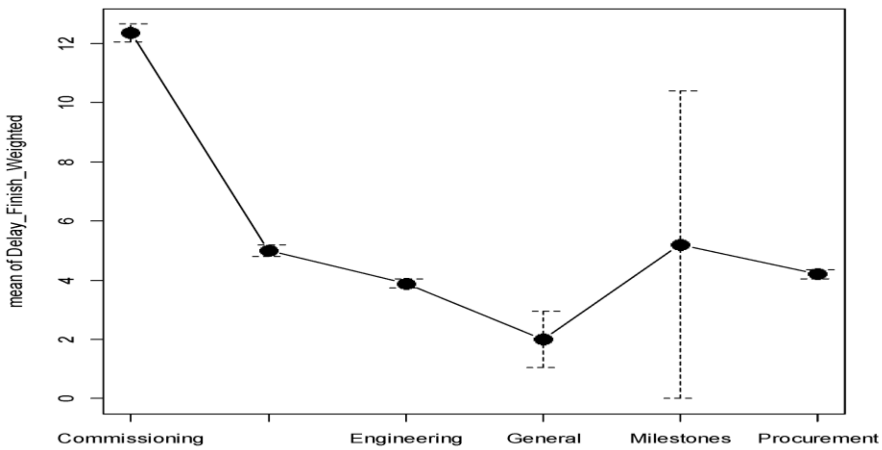


***Fig.2.****Schedule delay patterns across project phases, indicating larger delays in later stages of project execution.*

### 3.4 Managerial implications and study limitations

The findings provide practical guidance for staffing decisions in energy engineering projects. Maintaining adequate technical coverage appears essential for limiting severe schedule overruns, even if such coverage has limited influence on small delays. This suggests that staffing decisions should prioritize technical capacity during later project stages, when recovery options become constrained. In addition, support roles should be viewed as contributors to schedule stability rather than as auxiliary overhead, particularly in complex projects with tight coordination requirements. Several limitations should be noted. The analysis is based on projects from a single enterprise, which may limit the general applicability of the results. Factors such as project complexity, subcontracting arrangements, and procurement strategies were not explicitly modeled and may interact with staffing effects. Future research could extend the analysis using multi-company datasets and phase-level staffing information to further examine how team configuration affects schedule outcomes across different types of energy engineering projects.

## 4.Conclusion

This study analyzed the relationship between project team configuration and schedule deviation in energy engineering projects using project-level data and quantile regression. The results show that staffing structure influences schedule performance differently across delay levels. A low share of technical staff shows little association with small schedule delays but is closely linked to severe overruns, indicating that technical capacity becomes more important when projects face complex execution conditions and late-stage problem resolution. In contrast, a well-proportioned allocation of support roles helps limit extreme delays by strengthening coordination, tracking, and process continuity under high workload and uncertainty. The study advances existing research by moving beyond average-based analysis and examining how staffing effects vary across the distribution of schedule deviation. This distribution-focused approach provides clearer insight into the drivers of severe delays, which are often underrepresented in project management studies. From an application standpoint, the findings suggest that energy engineering projects should maintain sufficient technical coverage during later stages and treat support functions as integral to schedule control rather than as secondary overhead. Several limitations remain. The analysis relies on data from a single enterprise, and factors such as project complexity, subcontracting structure, and external disruptions were not fully modeled. Future work may expand the dataset across multiple organizations and incorporate phase-level staffing information to further test the stability and applicability of the observed relationships.

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