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Multi-Criteria Decision Analysis of Procurement Delay Drivers in Subnational Road Infrastructure Projects: A Topsis-Based Approach

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ABSTRACT

Procurement delays pose a major constraint to the effective delivery of road infrastructure projects in developing economies. This study investigates the key causes, impacts, and relative importance of procurement delays in state-funded road projects in Rivers State, Nigeria. Adopting a quantitative, cross-sectional research approach, primary data were obtained through structured questionnaires and semi-structured interviews with procurement officers, engineers, consultants, and contractors. A Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) based multi-criteria decision-making model was employed to prioritize delay factors using frequency of occurrence (FOI), severity of impact (SoII), and the factor importance score (FIS). The results reveal that financial limitations, weak governance structures, macroeconomic instability, and security-related risks are the most influential contributors to procurement delays. Delayed release of project funds ($C_i = 0.88933$) ranked highest, followed by corruption and favoritism ($C_i = 0.74875$), inflation and fluctuating material costs ($C_i = 0.68924$), security challenges ($C_i = 0.57521$), and inadequate procurement planning ($C_i = 0.56707$). Robustness testing through sensitivity analysis confirmed the stability of the rankings, with strong correlation coefficients (Spearman's $\rho > 0.94$; Kendall's $\tau > 0.84$). The study concludes that meaningful improvements in project delivery performance can be achieved by integrating financial discipline, governance reforms, and risk management strategies with enhanced procurement processes. It recommends timely release of funds, strengthened anti-corruption frameworks, proactive risk mitigation, improved procurement planning, and increased adoption of digital procurement systems to reduce delays in road infrastructure projects.
Keywords: Multi-Criteria Decision Analysis, TOPSIS, Procurement Delay, Road Infrastructure Projects, Sensitivity, Robustness

1.0 INTRODUCTION

Infrastructure development, particularly road construction, is foundational to economic growth, social welfare, and regional integration in developing economies. Delivery of such projects on schedule is essential for maximizing socioeconomic benefits and avoiding wasteful cost escalation (Antoniou, 2021). However, a substantial body of research shows that project delays remain endemic in public infrastructure delivery, often beginning not in construction but well before through bottlenecks in procurement processes, including delayed planning approvals, extended tender evaluations, and slow contract awards (World Bank, 2024; Zagia, 2025). These delays, especially in road infrastructure, compromise the effectiveness of public spending and undermine public confidence in governance.

Procurement delays are distinct from general construction delays since they occur during the pre-execution phase, encompassing activities such as project planning, tendering, evaluation, and contract award. While construction delays are often associated with site-related issues (e.g., design changes, contractor inefficiencies, supply shortages), procurement delays stem mainly from institutional and administrative inefficiencies (World Bank, 2024). For example, delays in documentation approvals, protracted bid evaluations, and weak contract administration processes are frequently found to prolong the timeline before physical work even begins (World Bank, 2024; Zagia, 2025). Yet, current literature often aggregates delays into broad categories without isolating procurement-specific factors, particularly in subnational contexts where governance frameworks differ from federal or national project regimes.

A considerable number of studies have investigated causes of delays in infrastructure and construction projects, with researchers identifying large sets of potential delay factors. These factors typically include financial problems, lack of contractor experience, poor site management, design errors, and inadequate planning (Ayoush *et al.*, 2020). Other research highlights the prevalence of delays related to resource shortages, labor constraints, and decision-making inefficiencies that span client, contractor, and consultant actions (Zagia, 2025). While these studies provide valuable insights, they tend to focus on general project delay causes rather than separating procurement phase delays and quantifying their relative importance.

To rigorously examine complex decision problems like prioritizing delay causes, Multi-Criteria Decision Analysis (MCDA) methods have been increasingly adopted. MCDA enables researchers to evaluate alternatives against multiple, often conflicting criteria, a critical capability when dealing with procurement delay factors such as frequency, impact severity, and controllability. Among MCDA techniques, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has gained significant traction in construction and project management research due to its clear geometric interpretation of ideal and negative-ideal solutions (Hwang & Yoon, 1981/1993). TOPSIS ranks alternatives by computing each alternative's distance to the best and worst possible criterion outcomes, thus enabling a structured prioritization that aligns with decision-maker preferences and performance criteria.

TOPSIS has been applied in a range of construction decision contexts, from contractor selection and risk evaluation to prioritizing project performance factors, demonstrating its utility for domain problems requiring structured ranking under multiple criteria. For instance, hybrid approaches combining TOPSIS with fuzzy logic have been used to select contractors and prioritize risk factors in construction projects (Sabuncuoglu & Gorener, 2023). Additionally, research employing integrated TOPSIS approaches has shown how ranking of delay causes can be derived from quantitative criteria, offering improved decision clarity and practical guidance for stakeholders (Mansoorzadeh & Galankashi, 2024). However, there is a notable gap in applying TOPSIS specifically to procurement delay drivers in subnational road infrastructure projects, especially with added sensitivity and robustness analysis to ensure stable decision outcomes across varying criteria weights.

Robustness and sensitivity assessment are particularly important in MCDA since the choice of criteria weights can significantly influence rankings. Without such analysis, rankings may be methodologically plausible but practically unstable, potentially leading to conflicting policy recommendations when weights change even slightly (Zagia, 2025). Integrating sensitivity analysis within a TOPSIS framework provides a guardrail for interpreting rankings, ensuring that policy responses remain valid under plausible variations in decision emphasis.

Given these research gaps, this study quantifies procurement delay factors, applies TOPSIS to rank those factors in terms of frequency and significance, and conducts sensitivity analysis to evaluate robustness of priority rankings. Focusing on road infrastructure projects executed by the Rivers State Government, the study contributes to the literature by isolating procurement phase issues and providing subnational empirical insights that can inform targeted interventions for improving procurement performance.

2.0 LITERATURE REVIEW

2.1 Overview of Construction and Procurement Delays

Delays in construction and infrastructure projects are among the most studied issues in construction management due to their significant impacts on project cost, time, and quality (Sanni-Anibire *et al.*, 2020). A meta-analytical review by Sanni-Anibire *et al.* (2020) synthesized evidence from multiple global studies and found that common delay causes include contractor financial difficulties, slow material delivery, poor coordination among project parties, and inadequate planning and scheduling. These delays transcend contexts and sectors, affecting project outcomes universally.

In the specific case of road infrastructure, studies show that public road projects in developing countries experience significant delays due to financial constraints, planning issues, and coordination challenges (Mejía *et al.*, 2020). Road projects are critical for economic growth and public welfare, making timely delivery essential, yet they routinely exhibit delays caused by both technical and managerial shortcomings. Such delays not only affect delivered costs and time but also diminish expected socioeconomic benefits for local communities.

Despite the extensive literature on overall construction delays, procurement delays, the period encompassing planning, bidding, evaluation, and contract award, are less frequently explored as a distinct phase. This oversight weakens the ability of decision-makers to specifically target procurement inefficiencies that occur before physical construction begins, particularly in subnational road projects where governance and institutional capacity vary significantly compared to national or federal programs.

2.2 Theoretical and Conceptual Foundations

Understanding why construction and infrastructure projects experience delays requires theoretical lenses that capture the complexity, interaction, and strategic behavior inherent in project environments. Classical operational explanations are useful, but deeper analysis often invokes systemic and behavioral theories that highlight the structure and interdependencies within project processes.

Systems Theory and Complex Interdependencies; Systems theory conceptualizes projects as socio-technical systems characterized by multiple interacting components (stakeholders, processes, resources) that together determine performance outcomes (Prieto, 2015). In construction projects, delays emerge not simply from isolated issues but from interdependencies and feedback dynamics where disruption in one part of the system can cascade through others. For example, delays in procurement approvals can affect material delivery, labor deployment, and subsequent construction sequences, producing ripple effects throughout the project lifecycle. This theoretical orientation aligns with research showing complex networks and systemic fragility in engineering projects, where perturbations in critical activities propagate and enlarge downstream impacts (Santolini *et al.*, 2020). Similarly, construction delay studies underscore that project complexity, driven by stakeholder interactions, regulatory environments, and information flows, contributes to schedule uncertainty and timing risks (Omotayo, 2024). These insights position delays as emergent outcomes of structural complexity rather than discrete, independent events, justifying analytical frameworks that examine interactions, feedback loops, and systemic constraints.

Agency Theory and Strategic Behavior; Agency theory explains project delays through the lens of asymmetric information, divergent incentives, and strategic behavior among contract parties (Ceric, 2012; Gitahi, 2019). It posits that project owners (principals) and contractors (agents) may have conflicting priorities: agents seek to maximize their own benefits, such as profit or reduced risk, sometimes at the expense of project timelines or quality. This divergence can lead to opportunistic behaviors (e.g., delays in reporting problems, withholding information, or requesting cost adjustments) that contribute to project delays. Empirical research applying agency theory in construction contexts highlights how lack of aligned incentives and poor risk sharing increase the likelihood of opportunistic conduct by contractors and subcontractors, thereby undermining schedule adherence (Gitahi, 2019). Within complex infrastructure projects, contracting relationships often span multiple layers of stakeholders, making coordination of incentives and information sharing more difficult, a core prediction of agency frameworks.

Organizational and Principal-Agent Perspectives; In addition to classical agency theory, organizational theorists argue that institutional structures, governance norms, and procedural rigidity can delay decision making, particularly in public projects with multi-level approvals and hierarchical oversight. Organizational theory posits that delay causes are embedded in organizational behavior, rules, and routines, such as multi-stage reviews, bureaucratic bottlenecks, and risk-averse cultures, which slow down procurement and execution phases (Owusu, 2020). The principal-agent variant of agency theory further distinguishes between different types of information asymmetry (hidden characteristics, hidden actions, and hidden intentions) that emerge among clients, contractors, consultants, and regulators in construction projects (Ceric, 2012). Such asymmetries can lead to adverse selection and moral hazard, where incomplete or distorted information affects decision outcomes, causing delays in project approval and execution.

Complexity Theory and Project Management; Complexity theory extends systems thinking by emphasizing the non-linear, dynamic characteristics of project environments where small changes can produce disproportionate impacts on timelines and costs. Research applying complexity theory to construction project time management suggests delays often result from interactions among uncertain, interdependent factors including stakeholder behavior, regulatory requirements, and real-time resource constraints (Ahmadi & Golabchi, 2013). Rather than viewing delays as isolated events, complexity models treat them as emergent from high levels of structural and contextual uncertainty.

Organizational Structures and Systems Interplay; Studies adopting systems thinking in project management demonstrate the importance of understanding stakeholder engagement, project complexity, and information flows when explaining delays (Omotayo, 2024). This research shows that delays are not just process inefficiencies but reflections of broader systemic dynamics where misalignment among system components (e.g., procurement procedures, decision hierarchies, coordination practices) exacerbates schedule disruptions.

Together, these theoretical perspectives illustrate that project delays are multi-dimensional phenomena shaped by interdependencies, strategic behavior, organizational constraints, and complexity. Systems and complexity theories foreground structural interactions and feedback loops, while agency and organizational theories emphasize behavioral incentives and institutional factors. In procurement delays, which precede physical construction, institutional decision processes, governance structures, information asymmetry, and stakeholder interactions play critical roles, especially in public sector environments (Owusu, 2020). Recognizing these theoretical dimensions helps frame why traditional project management tools (e.g., critical path analysis) may be insufficient to fully capture delay causality without incorporating broader socio-technical and behavioral factors.

2.3 Procurement Delays and Their Impacts

While general construction delay literature is extensive, research that focuses specifically on procurement delays, distinct from delays during physical construction, remains limited but is gradually increasing in prominence. Procurement delays encompass delays occurring during stages such as contract preparation, tendering, bid evaluation, approval, and contract award, all of which can significantly extend project timelines and increase costs (World Bank, 2024; Israel, 2023).

The World Bank's analysis of infrastructure procurement delays highlights that inefficiencies in contract preparation, tendering, evaluation, and award processes are major contributors to extended project cycles and elevated costs. The study shows that procurement delays can sometimes exceed the duration of actual construction work, challenging the often-held assumption that construction execution is the primary source of project delay (World Bank, 2024). Procurement postponement, especially in large infrastructure projects, often stems from weak project and contract management, frequent scope or design changes, and funding constraints.

Empirical research further shows that procurement deficiencies contribute substantially to both time and cost overruns in developing contexts. For example, Baraka Israel's investigation into Tanzanian construction projects found that bureaucratic bidding processes, corruption, non-compliance with contractual terms, inappropriate procurement methods, and inexperienced contractors were significant contributors to procurement delays and corresponding cost and schedule overruns. The study reported that over half (52.2%) of surveyed projects experienced measurable cost and time overruns due to stakeholder procurement deficiencies (Israel, 2023). This aligns with broader evidence showing that procurement processes are not merely administrative procedures but strategic determinants of project performance.

Procurement delays often result from bureaucratic procedures, inadequate institutional capacity, and poor coordination among approval bodies. For instance, Mabilu's report on electrical infrastructure procurement in South Africa highlights how understaffed procurement units, unavailability of stakeholders for negotiation, and poor communication among departments extend pre-contract procurement timelines (Mabilu, 2021). Similarly, ineffective contract management and inadequate planning have been linked to procurement delays and cost escalation in Nigerian construction projects (Unegbu *et al.*, 2024).

From a practical standpoint, procurement delays have several downstream impacts on project execution. First, delays extend the period before contractors can mobilize resources and begin construction, sometimes leading to rushed contractor selection and insufficient vetting, which can compromise contractor performance and project quality. Second, extended procurement timeframes often lead to cost escalations, as inflationary pressures on materials, labor, and financing multiply the financial burden the longer procurement is delayed (Xegwana *et al.*, 2025). Third, delays in procurement decisions can disrupt cash flows for contractors and suppliers, leading to disputes, work stoppages, and higher risk premiums embedded into project costs.

Research also indicates that procurement delays are interwoven with other structural issues, like regulatory complexity and design changes. Studies show that delays in permitting, regulatory approvals, and scope adjustments, factors that often precede tender awards, contribute to overall procurement delays and associated schedule risk (Faku, 2025). In some contexts, weak procurement capacity and governance issues, such as corruption and non-transparent bidding, further aggravate delays, undermining stakeholder trust and institutional accountability (Israel, 2023).

Despite these documented impacts, most existing studies embed procurement delay causes within general construction delay frameworks without isolating pre-contract procurement phase delays. This limits the clarity needed for tailored interventions that explicitly target procurement inefficiencies as distinct from on-site execution problems. The current literature seldom disaggregates procurement from other delay phases, leaving nuanced drivers, like pre-award administrative bottlenecks, bid evaluation inefficiencies, and inter-agency coordination failures, insufficiently understood. Addressing this gap requires focused quantitative analyses that partition procurement delays from other delay categories and assess their specific effects on project outcomes.

In sum, while it is well established that delays negatively impact infrastructure project delivery, procurement delays have unique origins and impacts. They arise from institutional and procedural issues that extend project timelines long before physical construction begins, and they significantly contribute to cost overruns, reduced quality outcomes, and stakeholder dissatisfaction. Greater scholarly focus on this phase is imperative for advancing effective mitigation strategies and improving procurement performance in infrastructure projects.

2.4 Multi-Criteria Decision Analysis (MCDA) and TOPSIS Application

The multifaceted nature of procurement delay causes, involving time, cost, quality, institutional, and human factors, has led researchers to increasingly adopt Multi-Criteria Decision Analysis (MCDA) techniques to prioritize delay factors. MCDA provides a structured framework that enables decision makers to evaluate alternatives against multiple, often conflicting criteria simultaneously, which is especially crucial in complex infrastructure decision environments where trade-offs are inherent (Taylan *et al.*, 2014).

One of the most widely applied MCDA techniques in construction research is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS ranks alternatives based on their relative closeness to an ideal solution, the hypothetical best performance across all criteria, and their distance from a negative ideal solution, the worst performance across all criteria (Hwang & Yoon, 1981/1993). This conceptual basis allows MCDA users to capture multiple dimensions of performance and make informed decisions that reflect both quantitative and qualitative assessments.

In construction project management, TOPSIS has been effectively applied in a range of decision contexts. For instance, Banihashemi *et al.* (2021) employed a fuzzy SWARA-TOPSIS model to balance time–cost–quality trade-offs in project scheduling, demonstrating how structural evaluation of alternatives can help identify optimal scheduling trade-offs that meet diverse stakeholder requirements. Similarly, Gebrehiwet and Luo (2019) integrated fuzzy comprehensive evaluation with TOPSIS to assess schedule delay risk across construction project lifecycles, providing a mechanism to quantify phase-specific risk levels and guide mitigation strategies.

MCDA applications extend beyond risk and schedule evaluation. In infrastructure project performance assessment, MCDA methods, including TOPSIS, have been used to rank and compare project success across multiple indicators such as cost, time, quality, and management performance. For example, Yuan *et al.* (2022) applied TOPSIS and Simple Additive Weighting to evaluate success indices of road projects, illustrating the method's utility in synthesizing performance across diverse criteria into actionable rankings.

Hybrid MCDA models that combine TOPSIS with other decision techniques have gained traction due to their enhanced capability to handle uncertainty and subjective judgments. Sabuncuoğlu and Görener (2016) integrated Analytic Hierarchy Process (AHP) with fuzzy TOPSIS (FTOPSIS) for contractor selection, showing that combining weight derivation (AHP) with TOPSIS ranking provides more reliable results when dealing with qualitative and quantitative criteria. Further, hybrid models combining fuzzy TOPSIS with other tools such as Failure Mode and Effects Analysis (FMEA) have been used to rank safety risks in construction projects, showcasing the broader adaptability of MCDA frameworks (Emamgholizadeh & Hoseini, 2021).

Beyond construction, MCDA and TOPSIS have been successfully applied in related disciplines involving complex decision environments. For example, hybrid fuzzy AHP-TOPSIS has been used to support sustainable material selection in green building decision-making, highlighting how decision science tools assist with multi-objective prioritization beyond traditional engineering contexts. Despite the demonstrated utility of TOPSIS and hybrid MCDA models, several methodological challenges and research gaps remain. First, many applications focus on contractor selection, risk ranking, or general performance evaluation, with limited studies specifically targeting procurement delay factor prioritization in infrastructure projects. Second, while fuzzy extensions and hybrid models help address uncertainty and subjective judgments, few studies systematically incorporate robust sensitivity analysis into TOPSIS ranking to assess the stability of prioritized outputs under varying criteria weights. This limitation may lead to decision outputs that are overly sensitive to input weight assumptions. Third, the integration of institutional and governance factors, particularly those relevant to public sector procurement processes, is rarely embedded within MCDA frameworks, leaving context-specific drivers such as procedural bottlenecks and administrative inefficiencies insufficiently captured.

Addressing these gaps, recent research advocating integrated TOPSIS applications emphasizes the need for rigorous frameworks that combine quantitative prioritization with robustness checks and context-specific variables. Such advances would enhance the relevance and reliability of MCDA outputs for complex phenomena like procurement delays, where multiple interacting criteria and stakeholder perspectives must be reconciled for effective decision support

2.5Sensitivity and Robustness Analysis within MCDA

A core methodological challenge in Multi-Criteria Decision Analysis (MCDA) is the subjectivity and uncertainty associated with criteria weights, that is, how researchers or decision-makers assign relative importance to each criterion. Since MCDA outcomes (such as rankings from TOPSIS) depend heavily on the weights assigned to criteria, even small variations in criterion weights can cause significant changes in ranking outcomes. This is why sensitivity and robustness analysis has become a vital part of rigorous MCDA research (Demir, 2024; Więckowski & Sałabun, 2023).

Sensitivity analysis examines how changes in input elements, usually weights or scores, affect the final ranking of alternatives. In the context of TOPSIS, this typically involves testing a range of weight configurations to see whether the top-ranked alternative remains stable across plausible weight variations (World Bank, 2024; Więckowski & Sałabun, 2023). This helps researchers and practitioners understand whether decision outcomes are resilient or fragile to uncertainty in the judgment process and input assumptions.

Systematic reviews have found that sensitivity analysis is increasingly recognized as a fundamental component of MCDA for enhancing model credibility and reliability. Więckowski and Sałabun's (2023) review of sensitivity analysis approaches in MCDA highlights that sensitivity analysis frameworks reveal vulnerabilities in results due to input perturbations and help identify which criteria and weight changes exert the greatest influence on ranking outcomes.

Several methods and strategies have been proposed in the MCDA literature to assess robustness. One common strategy is the One-At-A-Time (OAT) approach, where one criterion's weight is altered while keeping others constant to examine how ranking positions change, a straightforward but limited approach that tests local sensitivity (Gaona *et al.*, 2025; Więckowski & Sałabun, 2023).

More advanced techniques systematically explore large portions of the criteria weight space. For example, Gaona *et al.* (2025) introduced a Full-Range Weight Sensitivity Analysis (FRWSA) integrated with TOPSIS that exhaustively evaluates all plausible combinations of criterion weights across a discretised weight space. This approach provides a quantitative measure of ranking robustness by calculating the proportion of weight space for which each alternative remains top-ranked, offering a deterministic and comprehensive robustness assessment.

In addition to exhaustive methods, comparative sensitivity strategies that combine interval TOPSIS with multi-sensitivity frameworks have been developed to handle uncertain data and detect thresholds at which alternatives change positions. These interval sensitivity strategies identify critical weight thresholds beyond which the ranking order is altered, supporting robust decision making in dynamic decision environments (Du *et al.*, 2023).

Beyond empirical examples, systematic literature reviews corroborate that sensitivity analysis frameworks help decision-makers understand robustness across MCDA methods, including TOPSIS. They reveal that TOPSIS is often sensitive to weights, especially when dealing with imprecise, conflicting, or uncertain data. Such research underscores that sensitivity analysis not only tests stability of rankings but also reveals which criteria drive the decision outcomes, empowering decision-makers to focus on the most influential factors (Demir, 2024; Więckowski & Sałabun, 2023).

The importance of sensitivity and robustness analysis in MCDA applies directly to procurement delay factor prioritization. In the context of infrastructure procurement, where expert judgments on weights may vary and criteria (e.g., frequency, impact severity, controllability) interact, sensitivity analysis ensures that findings are not overly dependent on subjective weight settings. Incorporating such analytical rigor leads to decision outputs that are more reliable and generalizable, and supports effective policy and operational recommendations for procurement performance improvements.

2.6 Research Gaps and Unresolved Issues

A careful review of the literature highlights several significant gaps that continue to constrain understanding of procurement delays in infrastructure projects. First, there is a limited focus on procurement-specific delays. While numerous studies investigate general causes of delays during construction, few isolate delays occurring in the procurement phase, despite evidence that these early-stage delays critically influence overall project performance and downstream outcomes (World Bank, 2024; Israel, 2023).

Second, the application of Multi-Criteria Decision Analysis (MCDA) methods, such as TOPSIS, remains scarce in the procurement context. Existing MCDA research largely addresses scheduling trade-offs, contractor selection, or risk prioritization (Banihashemi *et al.*, 2021; Taylan *et al.*, 2014), leaving the systematic prioritization of procurement delay factors underexplored. This gap limits the ability to identify the most critical drivers of delays where multiple interacting criteria are at play.

Third, robustness and sensitivity analyses are often insufficiently applied in MCDA studies. Many applications report priority rankings without testing how changes in criteria weights might alter the results (Demir, 2024; Gaona *et al.*, 2025; Więckowski & Sałabun, 2023). Consequently, there is limited assurance that the identified rankings of delay factors are stable or generalizable under plausible variations in expert judgment.

Fourth, the literature shows a scarcity of subnational and context-specific studies. Research focusing on state-level road infrastructure projects, particularly in developing country settings such as Rivers State, Nigeria, is largely absent. This limits the availability of contextually relevant insights that can inform local policy, planning, and governance interventions (Faku & Lukman, 2025; Xegwana *et al.*, 2025).

Finally, there is a need for greater integration of institutional and governance variables. While studies often acknowledge that governance practices, regulatory frameworks, and institutional capacity influence procurement delays, these factors are frequently treated qualitatively rather than quantitatively, and rarely incorporated into formal MCDA frameworks (Israel, 2023; Unegbu *et al.*, 2024).

Taken together, these gaps justify the present study, which aims to systematically quantify procurement delay factors, apply a robust TOPSIS methodology, and conduct sensitivity analysis to ensure the stability and reliability of decision outcomes. By doing so within the specific context of Rivers State Road projects, this research provides actionable, evidence-based insights for improving procurement efficiency and mitigating delay risks in subnational infrastructure delivery.

3.0 METHODOLOGY

3.1 Research Design

This paper adopted a quantitative, cross-sectional, and analytical research design to systematically investigate procurement delay factors in road infrastructure projects in Rivers State and to develop evidence-based strategies for improving procurement efficiency. The design applied multi-criteria decision-making (MCDA) techniques, with a specific focus on TOPSIS and sensitivity/robustness analysis, in line with the study objectives.

The study begins with the identification of procurement delay factors, derived from a focused review of empirical studies, audit reports, and procurement regulations, ensuring the factors are contextually relevant to state-funded road projects in Rivers State.

Primary data was collected using structured questionnaires administered to stakeholders directly involved in procurement processes, including procurement officers, project engineers, consultants, and contractors. The questionnaire is designed to quantify the frequency and perceived impact of procurement delays.

The data analysis proceeded in multiple stages:

i. Quantification of the factors contributing to procurement delays in road infrastructure projects in Rivers State
ii. A TOPSIS-based multi-criteria decision model was developed to rank procurement delay factors according to their relative significance.
iii. To ensure robustness, a sensitivity analysis was conducted by systematically varying criteria weights across alternative scenarios, evaluating the stability of priority rankings under uncertainty.

The findings from the decision-analytic stages was synthesized to produce data-driven recommendations for mitigating procurement delays and enhancing procurement efficiency in future subnational road infrastructure projects. This design ensures a rigorous, context-specific, and statistically grounded approach to understanding and prioritizing the determinants of procurement delays.

3.2 Data Collection

3.2.1 Research Instrument

Primary data were collected through structured questionnaires and key informant interviews involving stakeholders engaged in the procurement and execution of public road projects in Rivers State, including procurement officers, engineers, consultants, and contractors. The questionnaires used a Likert-scale to assess the frequency, severity, and impacts of procurement delays on project time, cost, and quality, and were distributed electronically with ethical safeguards. Semi-structured interviews with senior officials provided in-depth insights into procedural bottlenecks and institutional challenges, primarily to validate and contextualize quantitative findings and refine TOPSIS decision criteria.

3.2.2 Design and Validity of Questionnaires

The target population comprised stakeholders directly involved in the procurement and execution of state-funded road infrastructure projects in Rivers State between 2015 and 2024, including registered contractors, civil engineers, project managers, procurement officers, planning and budget officials, legal/compliance officers, and independent purchasing consultants. Official records from the Rivers State Ministry of Works, RSBPP, and key LGAs indicated a total population of 135 individuals. The sample size was determined using the Slovin's formula:

$$n = \frac{P}{1+P(e^2)} \qquad (1)$$

Where; n is the sample size,

P is the population size (135) and

e is the margin of error (0.05 for 95% confidence level).

Applying the formula yielded a sample size of 100, of which 84 questionnaires were successfully returned, representing a response rate of 84%. A standardized procurement delay questionnaire was administered to capture quantitative data on the frequency, severity, and perceived impact of procurement delays. Questionnaires were distributed electronically, with follow-up reminders sent to ensure high response rates.

The instrument's validity and reliability were tested using the test–retest method. A subset of 20 participants, including contractors, civil engineers/project managers, procurement officers, planning/budget officials, and legal/compliance officers, completed the questionnaire twice over a three-week interval. Comparison of first and second responses using the Pearson correlation coefficient yielded a reliability index of 0.981 (98.1%), indicating a high level of consistency and dependability for capturing procurement delay data in Rivers State Road projects

3.3 Data Analysis

3.3.1 Data Analysis Tools/Software

Data analyses were conducted using Microsoft Excel and MATLAB. Excel was used for preliminary tasks, including data cleaning, organization, descriptive statistics, and identification of prominent procurement delay factors. MATLAB facilitated the TOPSIS-based ranking of delay factors and sensitivity analysis to test the stability and robustness of rankings under varying criteria weights. This integrated approach ensured reliable, data-driven prioritization of procurement delays and supported evidence-based recommendations for mitigating delays in Rivers State Road projects.

3.3.2 Screening of Procurement Delay Factors

Descriptive statistics were used to analyze questionnaire responses and systematically identify key procurement delay factors. Three indices were applied: Frequency of Occurrence (FO), Severity of Impact (SoI), and Factor Importance Score (FIS). FO measures how often a delay factor occurs, while SoI captures its effect on time, cost, and quality. Both indices were rated on a five-point Likert scale (1 = very low, 5 = very high). The Frequency of Occurrence Index (FOI) and Severity of Impact Index (SoII) are weighted averages computed as:

$$FOI = \frac{\sum_{x=1}^{5} FOI_x \, N_x}{N} \tag{2}$$

$$SoII = \frac{\sum_{x=1}^{5} SoII_x \, N_x}{N} \tag{3}$$

where N_x = respondents selecting option x, and N= total respondents (84).

The Factor Importance Score (FIS) integrates FOI and SoII into a single measure:

$$FIS_x = w_F * FOI_x + w_S * SoII_x \tag{4}$$

Subject to the constraint that: $w_F + w_S = 1$

weights of 0.4 (frequency) and 0.6 (severity) were assigned to reflect the greater emphasis on impact severity in road infrastructure projects. This weighting strategy is proposed here as a context-specific decision rule rather than taken directly from prior literature.

3.3.3 TOPSIS Model

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to rank procurement delay factors based on frequency, severity, and factor importance score. TOPSIS identifies alternatives closest to the ideal solution and farthest from the negative ideal solution. The TOPSIS model involved the following steps:

i. ***Identification of Alternatives and Criteria:***

Alternatives: identified procurement delay factors from stakeholder surveys.

Criteria: frequency of occurrence, severity of impact (on time, cost, quality), and FIS. All were treated as benefit criteria

ii. ***Decision Matrix Construction:***

Matrix, $X = \left[x_{ij}\right]$, with rows as factors and columns as criteria.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix} \tag{5}$$

iii. ***Normalization of the Decision Matrix:***

To remove scale inconsistencies among the criteria, vector normalization was applied:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

Where; r_{ij} represents the normalized score of factor i under criterion j

iv. ***Weighted Normalized Decision Matrix:***

Criteria weights w_j applied (sum = 1).

$$v_{ij} = w_j \ x \ r_{ij} \tag{7}$$

v. ***Ideal Solutions:***

The positive ideal solution (A^+) and negative ideal solution (A^-) were determined as:

$$A^+ = \{\max(v_{ij})\} \quad \text{and} \quad A^- = \{\min(v_{ij})\} \tag{8}$$

vi. ***Separation Measures;***

The Euclidean distance of each procurement delay factor from the ideal and negative ideal solutions was calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{3}\left(v_{ij} - v_j^+\right)^2} \tag{9a}$$

$$S_i^- = \sqrt{\sum_{j=1}^{3}\left(v_{ij} - v_j^-\right)^2} \tag{9b}$$

Where: Si^+ is the distance of factor fi from the ideal solution, Si^- is the distance of factor fi from the negative ideal solution, v_{ij} is the weighted value of factor fi under criterion Cj, vj^+ and vj^- are the ideal and negative ideal values for criterion Cj, respectively.

vii. ***Relative Closeness Coefficient;***

This coefficient quantifies how close each factor is to the ideal solution relative to the negative ideal solution. The relative closeness coefficient (Ci∗) was computed using Equation (10).

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{10}$$

Where: Si^+ is the distance from the ideal solution (lower is better), Si^- is the distance from the negative ideal solution (higher is better), Ci* ranges between 0 and 1, where a higher value indicates a better alternative. After computing Ci* for each alternative, the alternatives are ranked in descending order based on their closeness coefficient.

viii. Ranking and Prioritization:

Factors ranked in descending order of C_i*; highest values indicate the most critical contributors to procurement delays.

This method provides a transparent, quantitative, and reproducible framework for identifying and prioritizing key procurement delay factors, supporting evidence-based decision-making in road infrastructure projects.

3.3.4 Sensitivity Analysis of TOPSIS Rankings

Sensitivity analysis was conducted to assess the robustness of TOPSIS-based rankings of procurement delay factors against variations in criterion weights;

Baseline Scenario: TOPSIS rankings were first generated using initially assigned, normalized weights for frequency, severity, and factor importance score as a reference.

One-Way Sensitivity: Each criterion weight was varied individually while adjusting the others proportionally: $w_S \in [0.2, 0.6]$;

$$w_F = w_I = \frac{1 - w_S}{2} \tag{11}$$

For each new weight combination, TOPSIS was recomputed and a new closeness coefficient obtained:

$$C_i^{(k)} = \frac{S_{i,k}^-}{S_{i,k}^+ + S_{i,k}^-} \tag{12}$$

The resulting rankings were compared with the baseline ranking.

Multi-Way Scenario Analysis: Alternative weighting scenarios reflected different stakeholder priorities:

Frequency-Dominant; $w_F = 0.5$, $w_S = 0.3$, $w_I = 0.2$

Severity-Dominant; $w_S = 0.5$, $w_F = 0.3$, $w_I = 0.2$

Importance-Dominant; $w_I = 0.5$, $w_F = 0.25$, $w_I = 0.25$

Each scenario produced a new ranking vector; $R^{(S)} = \left\{C_1^{(S)}, C_2^{(S)}, \ldots \ldots C_n^{(S)}\right\}$

Ranking Stability: Robustness was evaluated by comparing factor positions across scenarios using Spearman’s rank correlation with the baseline. Factors consistently top-ranked were considered stable, while those sensitive to weight changes highlighted areas for cautious interpretation. This analysis ensured reliable, credible prioritization of procurement delay factors under varying decision conditions.

4.0 Results

4.1 Major Procurement Delays Factors in Road Infrastructure Projects in Rivers State

Figure 1 displays the spider chart for the identification of the procurement delay factors, with procurement delay factors exceeding the FIS threshold of 3.0 highlighted in red. The FIS values were computed in accordance to Equation (4).

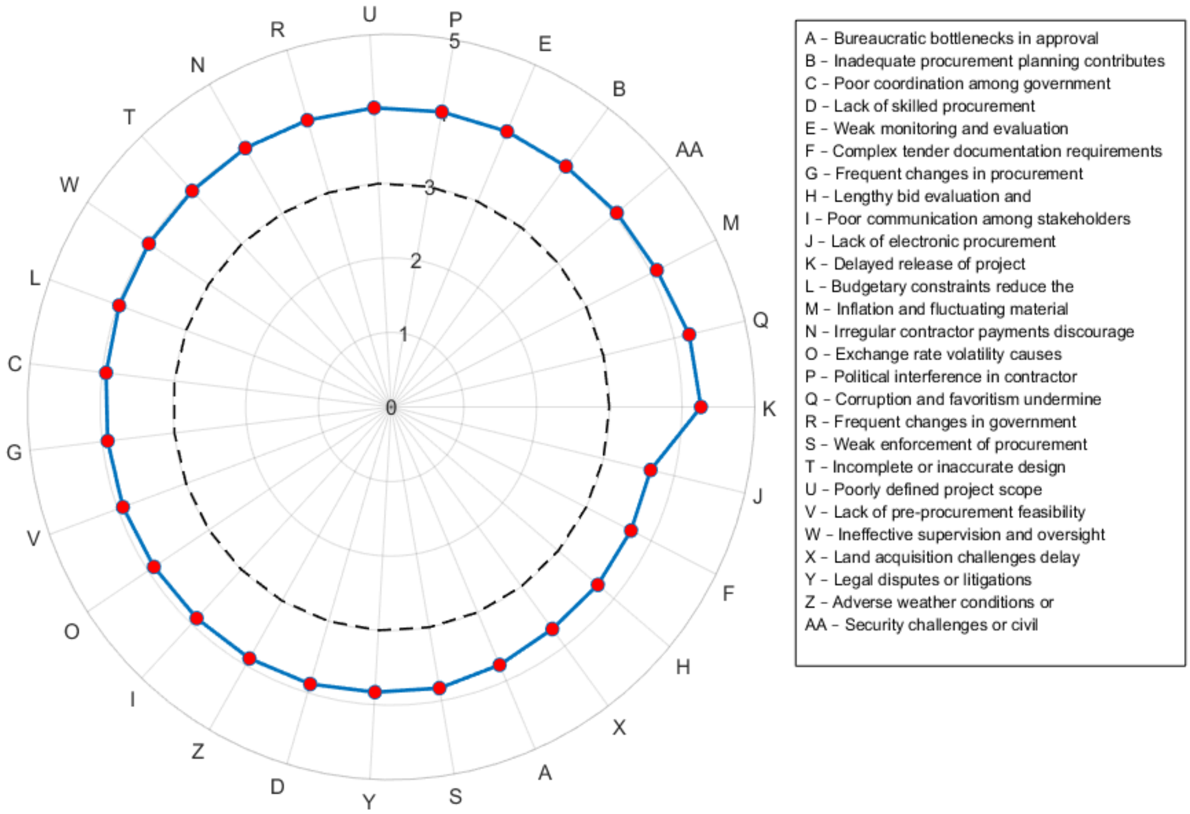

Figure 1. Spider Chart of Major Procurement Delay Factors in terms of FIS

4.2 TOPSIS for Ranking and Prioritizing Procurement Delays Factors Based on FOI, SoII and FIS

Appendix A presents the MATLAB code for ranking and prioritizing procurement delay factors using the TOPSIS technique in accordance to Section 3.3.3. The code was structured to display results for the decision matrix, normalized decision matrix, weighted normalized decision matrix, ideal and negative ideal solutions, separation measures, and relative closeness results.

Table 1 shows the Decision Matrix (X) for the 27 procurement delay factors. FOI represents the frequency of occurrence, SoII represents severity of impact, and FIS is the computed Factor Importance Score. Each factor is assigned a letter code (A, B, …, AA) for concise reference in subsequent analysis. Table 2 presents the normalized decision matrix (R). Normalization ensures comparability among criteria by scaling the data to unit length.

Table 3 shows the weighted normalized decision matrix (V), calculated using equal weights for FOI, SoII, and FIS. This matrix is used to determine the ideal solutions. Table 4 presents the positive and negative ideal solutions. The ideal solution represents the best performance across all factors, while the negative ideal represents the worst. Table 5 shows the separation measures, representing the Euclidean distance of each factor from the ideal (S^+) and negative-ideal (S^-) solutions. Table 6 presents the relative closeness (C_i*) of each factor to the ideal solution. Higher Ci* indicates higher priority or importance. Figure 2 summarizes the TOPSIS ranking of the 27 procurement delay factors. Rank 1 represents the most critical factor. The letter codes provide a concise reference, corresponding to all previous tables and figures.

Table 1. Decision Matrix (X)

Code	Factors	FOI	SoII	FIS
'A'	Bureaucratic bottlenecks in approval and tendering procedures cause procurement delays	3.9167	3.6667	3.7667
'B'	Inadequate procurement planning contributes to project delays	4.0952	3.9762	4.0238
'C'	Poor coordination among government agencies prolongs the procurement process	4.0952	3.8452	3.9452
'D'	Lack of skilled procurement personnel results in inefficient tender processing	3.8571	3.8929	3.8786
'E'	Weak monitoring and evaluation mechanisms delay procurement decisions	4.0595	4	4.0238
'F'	Complex tender documentation requirements slow down the procurement process	3.619	3.7381	3.6905
'G'	Frequent changes in procurement policies or guidelines cause confusion and delay	3.881	3.9524	3.9238
'H'	Lengthy bid evaluation and contract award procedures lead to time overruns	3.5952	3.7857	3.7095
'I'	Poor communication among stakeholders causes misinterpretation of procurement requirements	3.9881	3.8333	3.8952
'J'	Lack of electronic procurement systems contributes to process inefficiencies	3.7024	3.6429	3.6667

'K'	Delayed release of project funds leads to postponement of procurement activities	4.4881	4.1071	4.2595
'L'	Budgetary constraints reduce the pace of procurement execution	4.0357	3.9405	3.9786
'M'	Inflation and fluctuating material costs affect bid preparation and evaluation timelines	4.3452	3.9167	4.0881

Table 1. Decision Matrix (X) (Continued)

Code	Factors	FOI	SoII	FIS
'N'	Irregular contractor payments discourage participation in bidding processes	4.4524	3.7143	4.0095
'O'	Exchange rate volatility causes delays in procurement of imported materials and equipment	3.9524	3.869	3.9024
'P'	Political interference in contractor selection causes procurement delays	4.2262	3.881	4.019
'Q'	Corruption and favoritism undermine transparent procurement processes	4.1548	4.25	4.2119
'R'	Frequent changes in government or policy direction lead to project suspension	3.9643	4.0476	4.0143
'S'	Weak enforcement of procurement ethics prolongs decision-making	3.9643	3.7381	3.8286
'T'	Incomplete or inaccurate design documents delay procurement approval.	3.9286	4.0238	3.9857
'U'	Poorly defined project scope leads to repeated tender revisions	4.0119	4.0238	4.019
'V'	Lack of pre-procurement feasibility studies results in decision delays	3.9167	3.9286	3.9238

'W'	Ineffective supervision and oversight extend procurement timelines	4.1071	3.9048	3.9857
'X'	Land acquisition challenges delay project commencement	3.6548	3.75	3.7119
'Y'	Legal disputes or litigations arising from tendering halt procurement processes.	3.881	3.7976	3.831
'Z'	Adverse weather conditions or flooding affect procurement schedules	3.881	3.9048	3.8952
'AA'	Security challenges or civil unrest disrupt project procurement timelines	4.0357	4.0595	4.05

Table 2. Normalized Decision Matrix (R)

Coded Factors	FOI	SoII	FIS
A	0.18849	0.18101	0.18411
B	0.19709	0.19629	0.19668
C	0.19709	0.18982	0.19283
D	0.18563	0.19217	0.18958
E	0.19537	0.19746	0.19668
F	0.17417	0.18453	0.18038
G	0.18678	0.19511	0.19179
H	0.17303	0.18689	0.18131
I	0.19193	0.18924	0.19039
J	0.17818	0.17983	0.17922
K	0.216	0.20275	0.2082
L	0.19422	0.19452	0.19446
M	0.20912	0.19335	0.19982
N	0.21428	0.18336	0.19598
O	0.19021	0.191	0.19074
P	0.20339	0.19159	0.19644
Q	0.19995	0.2098	0.20587
R	0.19079	0.19981	0.19621
S	0.19079	0.18453	0.18713
T	0.18907	0.19864	0.19481
U	0.19308	0.19864	0.19644
V	0.18849	0.19394	0.19179
W	0.19766	0.19276	0.19481

X	0.17589	0.18512	0.18143
Y	0.18678	0.18747	0.18725
Z	0.18678	0.19276	0.19039
AA	0.19422	0.2004	0.19796

Table 3. Weighted Normalized Decision Matrix (V)

Coded Factors	FOI	SoII	FIS
A	0.062832	0.060336	0.061369
B	0.065696	0.065429	0.065558
C	0.065696	0.063274	0.064278
D	0.061877	0.064058	0.063192
E	0.065123	0.065821	0.065558
F	0.058057	0.061511	0.060127
G	0.062259	0.065038	0.063929
H	0.057675	0.062295	0.060438
I	0.063977	0.063079	0.063464
J	0.059394	0.059944	0.05974
K	0.071998	0.067584	0.069399
L	0.064741	0.064842	0.064821
M	0.069707	0.06445	0.066606
N	0.071426	0.06112	0.065326
O	0.063404	0.063666	0.06358
P	0.067797	0.063862	0.065481
Q	0.066651	0.069935	0.068623
R	0.063595	0.066605	0.065403
S	0.063595	0.061511	0.062377
T	0.063023	0.066213	0.064938
U	0.064359	0.066213	0.065481
V	0.062832	0.064646	0.063929
W	0.065887	0.064254	0.064938
X	0.05863	0.061707	0.060477
Y	0.062259	0.062491	0.062416
Z	0.062259	0.064254	0.063464
AA	0.064741	0.066801	0.065985

Table 4. Ideal and Negative-Ideal Solutions

Criterion	Positive Ideal (A^+)	Negative Ideal (A^-)
FOI	0.071998	0.057675
SoII	0.069935	0.059944

FIS	0.069399	0.05974

Table 5. Separation Measures (S^+ and S^-)

Coded Factors	S^+	S^-
'A'	0.015513	0.005422
'B'	0.008647	0.011326
'C'	0.010502	0.009799
'D'	0.013248	0.006819
'E'	0.008885	0.01113
'F'	0.018742	0.001659
'G'	0.012197	0.008031
'H'	0.018542	0.002452
'I'	0.012107	0.007963
'J'	0.018761	0.001719
'K'	0.002351	0.01889
'L'	0.009978	0.009987
'M'	0.006568	0.014567
'N'	0.009728	0.014888
'O'	0.012125	0.007838
'P'	0.00836	0.012279
'Q'	0.005403	0.016103
'R'	0.009883	0.010559
'S'	0.013815	0.006668
'T'	0.010692	0.009742
'U'	0.009357	0.010814
'V'	0.011913	0.008139
'W'	0.009462	0.010632
'X'	0.018056	0.002136
'Y'	0.014108	0.005887
'Z'	0.012742	0.007311
'AA'	0.008611	0.01166

Table 6. Relative Closeness (Ci*)

Code	Ci*
'A'	0.25899
'B'	0.56707
'C'	0.48269

'D'	0.3398
'E'	0.55608
'F'	0.08132
'G'	0.39703
'H'	0.1168
'I'	0.39677
'J'	0.083925
'K'	0.88933
'L'	0.50022
'M'	0.68924
'N'	0.60482
'O'	0.39262
'P'	0.59495
'Q'	0.74875
'R'	0.51654
'S'	0.32554
'T'	0.47676
'U'	0.5361
'V'	0.40589
'W'	0.52911
'X'	0.1058
'Y'	0.29443
'Z'	0.36458
'AA'	0.57521

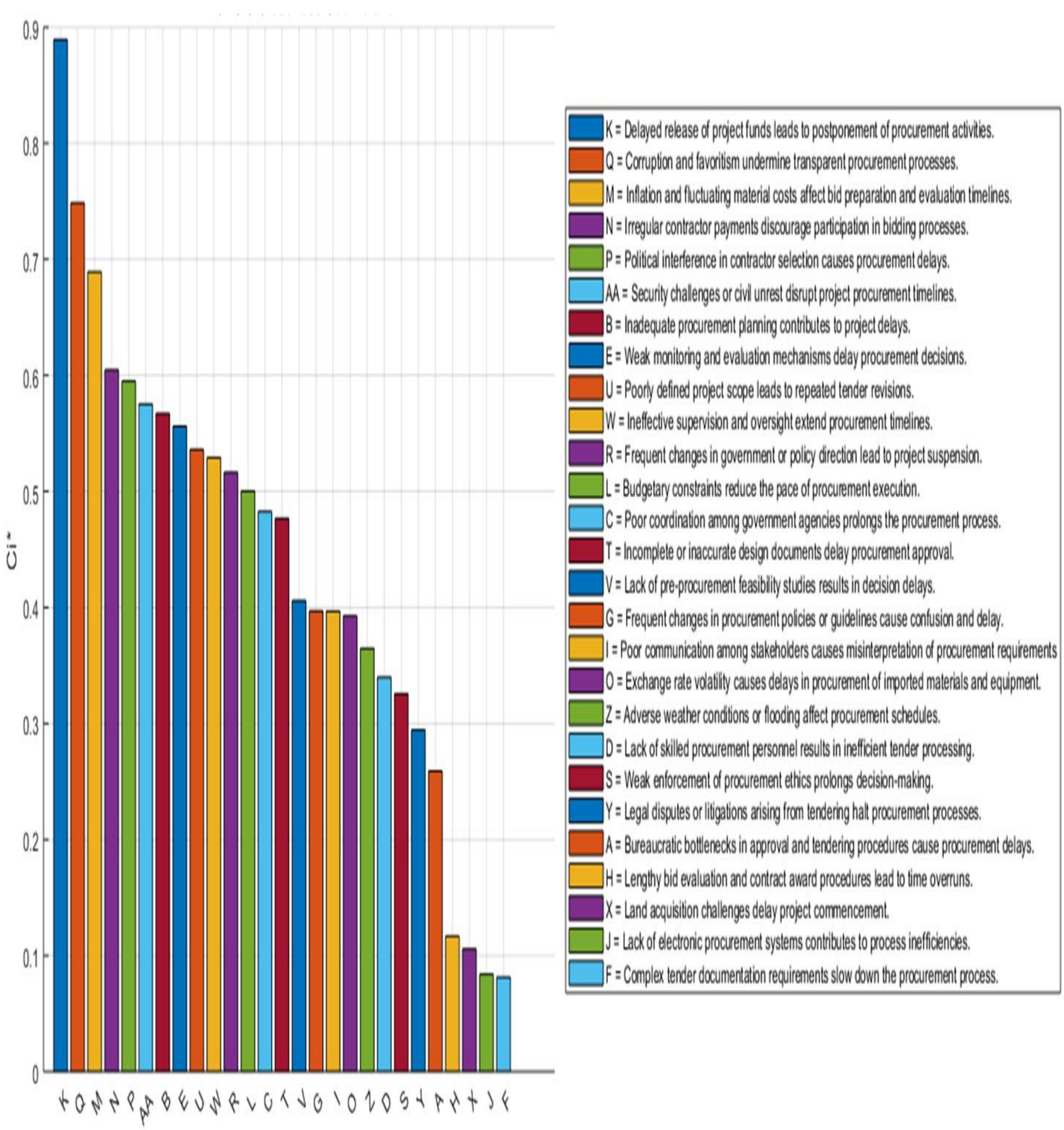

Figure 2. Bar Chart of TOPSIS Ranking of Procurement Factors Based on Relative Closeness

4.3 Sensitivity of the TOPSIS-based Rankings

Appendix B presents the MATLAB code for the sensitivity analysis of the TOPSIS-based rankings, in accordance to Section 3.3.4. The code was structured to display results for the one-way sensitivity analysis (through the severity weight variation), scenario-based (multi-way) sensitivity analysis, robustness and stability rankings, and and additional plots such as ranking stability, rank-switch heatmaps, and tornado plots. The results demonstrate how the

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prioritization of procurement delay factors varies with changes in criteria weights and scenario configurations.

One-way sensitivity analysis was performed by varying the weight of the severity criterion (ws) while proportionally adjusting the weights of the other criteria. The resulting Closeness Coefficients (Ci*) for each factor under different severity weights are presented visually in Figure 3. This analysis provides a visual and numerical representation of the effect of changing a single criterion weight on factor rankings.

The impact of varying stakeholder priorities on TOPSIS rankings was examined through three weighting scenarios: Frequency-Dominant, Severity-Dominant, and Importance-Dominant. The resulting Closeness Coefficients for each procurement delay factor under these scenarios are illustrated in Figure 4, providing a comparative view of factor prioritization across the different weighting configurations.

The robustness of the rankings was assessed using Spearman's rank correlation between the baseline TOPSIS ranking and each scenario-based ranking. Table 7 presents the correlation coefficients, providing a quantitative measure of ranking stability across different scenarios. A Ranking Stability Plot was used to compare the rankings of all factors under baseline and alternative scenarios. A Rank-Switch Heatmap highlighted changes in factor ranks relative to the baseline, where positive values indicated upward shifts and negative values indicated downward shifts. The Tornado Plot depicted the range of variation in the Closeness Coefficient for each factor across all scenarios, while Kendall's τ Robustness Test offered a non-parametric measure of the consistency of rankings between the baseline and scenario outcomes. The results of these analyses are presented in Figures 5, 6, 7, and Table 8.

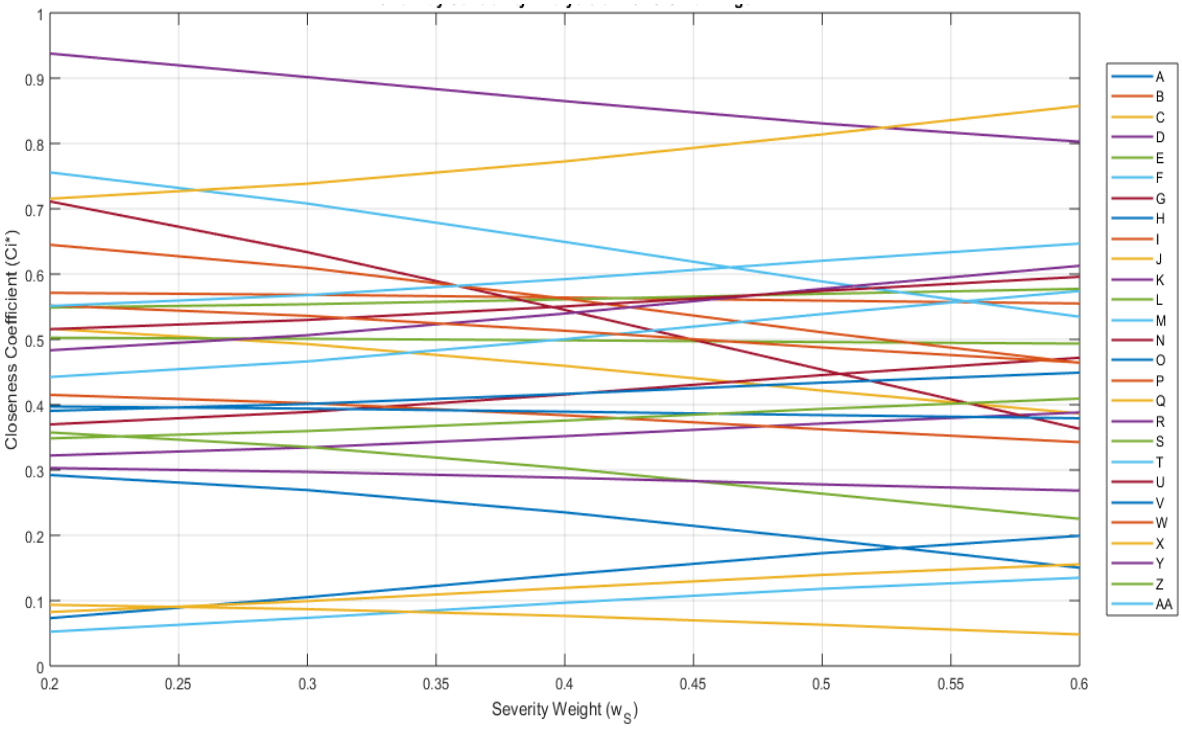

Figure 3. One-way Sensitivity Analysis of TOPSIS-based Rankings (Severity Weights Variation)

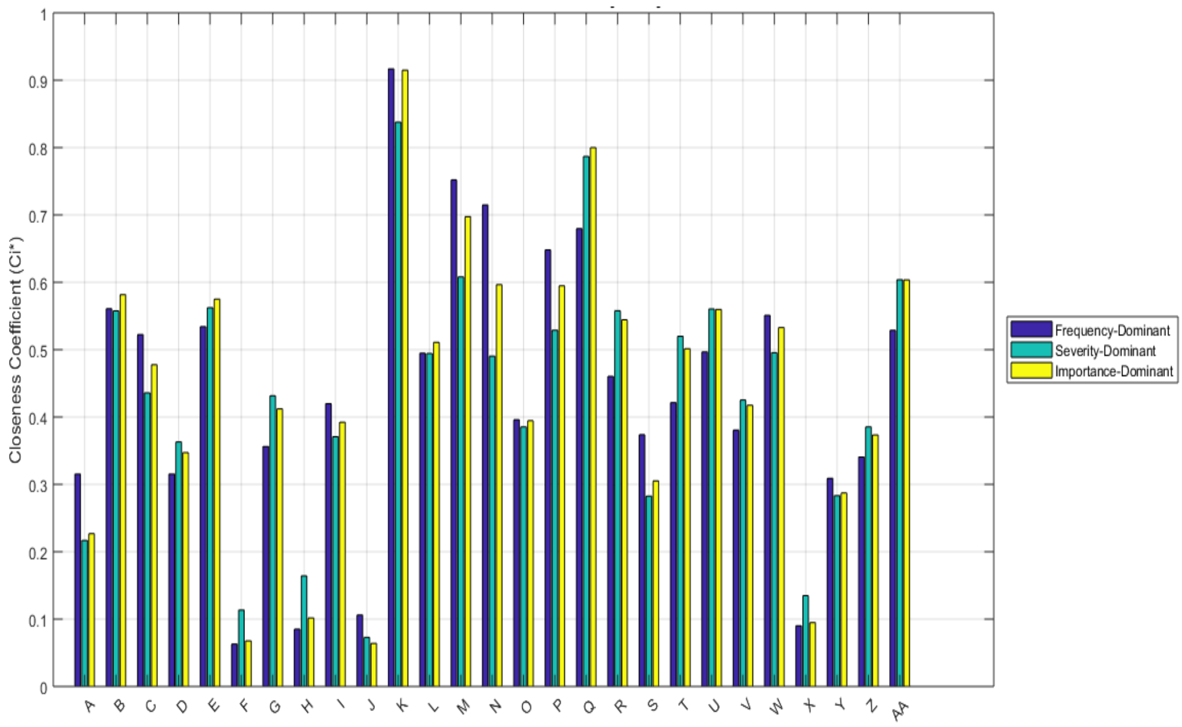

Figure 4. Scenario-Based TOPSIS Sensitivity Analysis

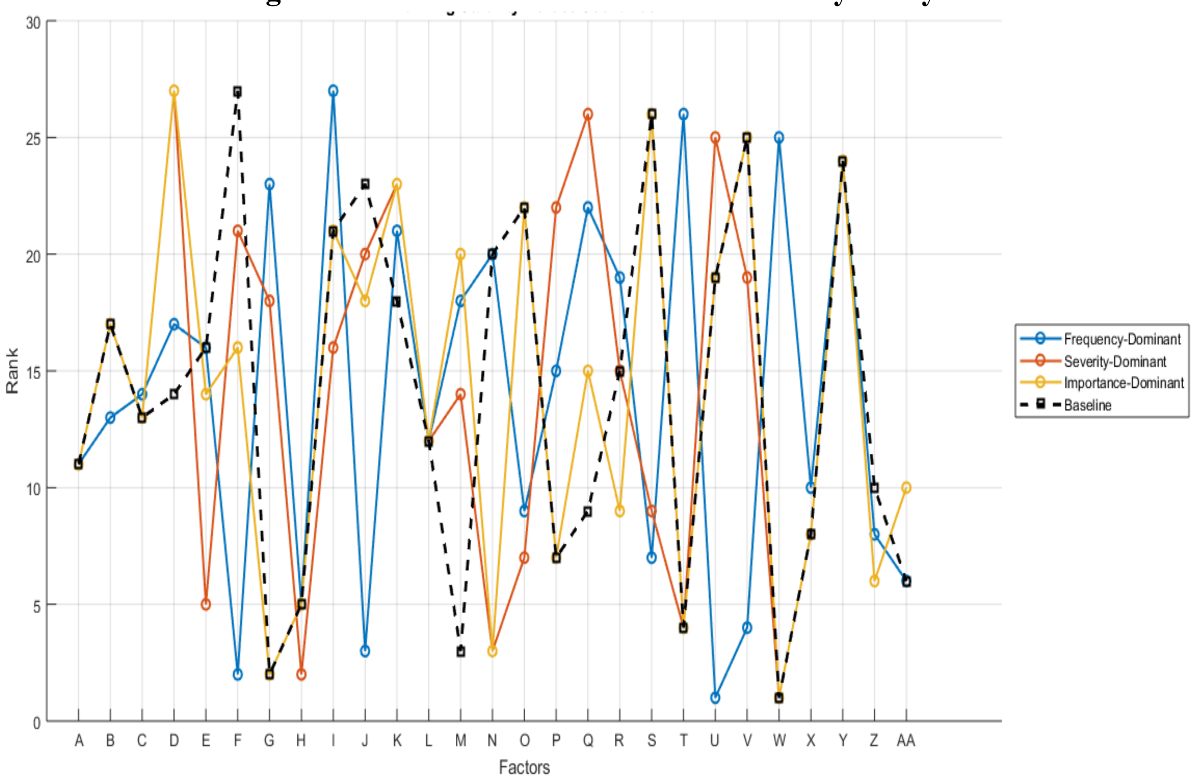

Figure 5. Ranking Stability Across Scenarios

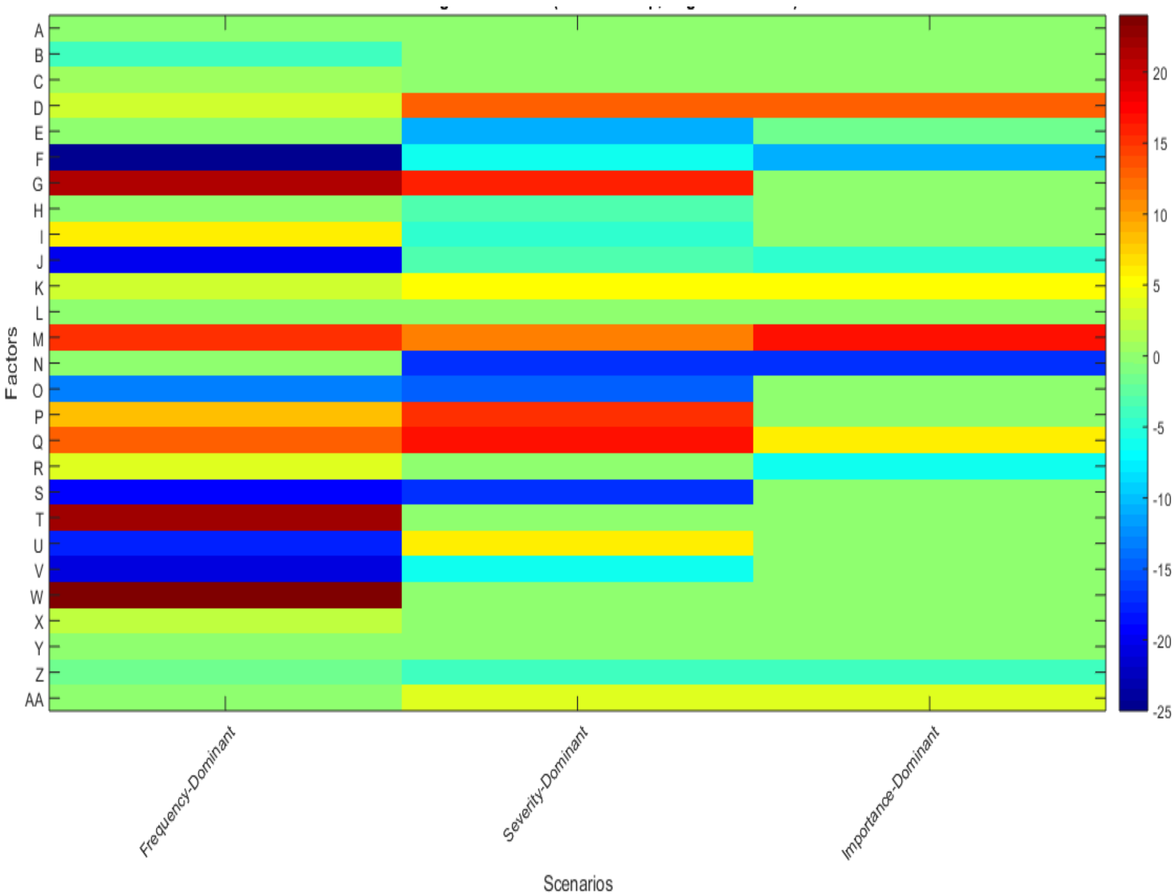

Figure 6. Rank-Switch Heat Map (Rank Change Vs Baseline (Positive = Up; Negative = Down)

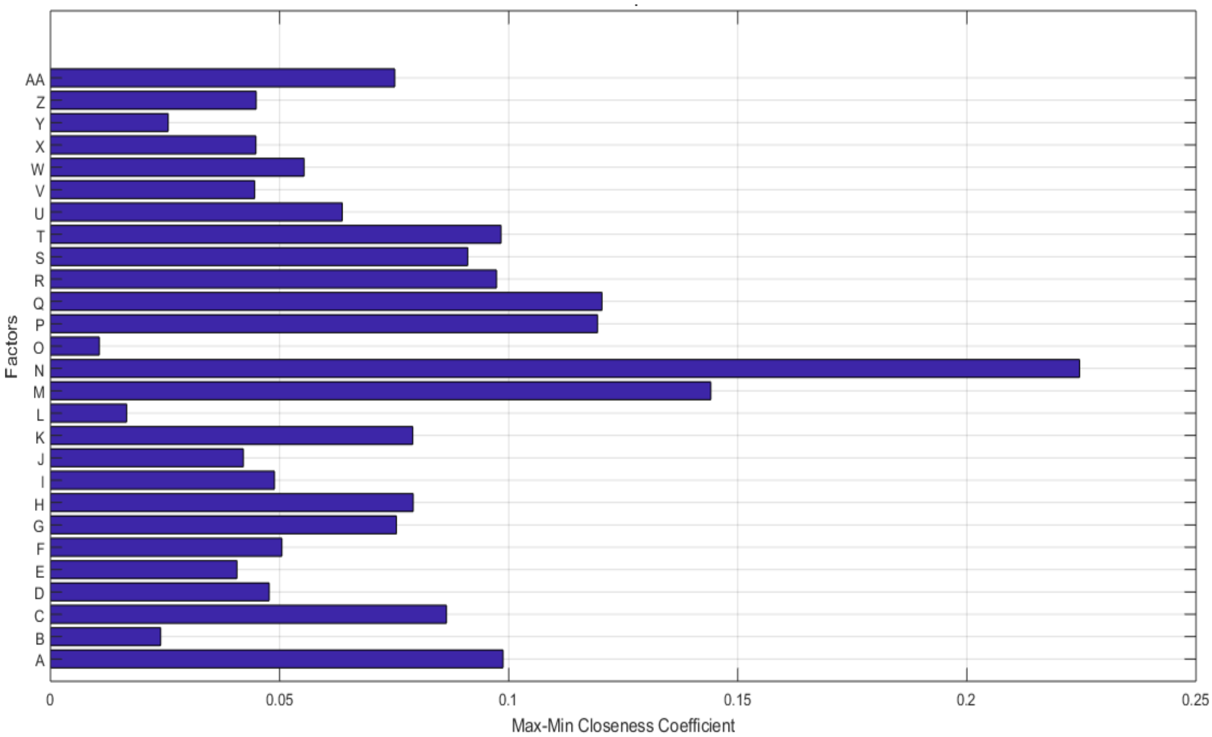

Figure 7. Tornado Plot of Factor Impact Across Scenarios

Table 7. Ranking Robustness (Spearman Correlation)

Scenario	Spearman_rho
'Frequency-Dominant'	0.97253
'Severity-Dominant'	0.94872
'Importance-Dominant'	0.99573

Table 8. Kendall Tau Robustness Test

Scenario	KendallTau
'Frequency-Dominant'	0.86895
'Severity-Dominant'	0.84615
'Importance-Dominant'	0.96581

5.0 Discussion

5.1. Major Procurement Delays Factors in Road Infrastructure Projects in Rivers State

From Figure 1, which presents the identified procurement delay factors in terms of Factor Importance Score (FIS), it is evident that all procurement delay factors have FIS values above the threshold of 3.0. This indicates that every factor is considered significant in contributing to project delays in road infrastructure projects in Rivers State. Similar observations that multiple delay factors simultaneously influence public infrastructure delivery have been widely reported in developing country contexts (Mohammed & Bello, 2022).

Among the most critical factors, delayed release of project funds (Factor K), corruption and favoritism in procurement (Factor Q), inflation and fluctuating material costs (Factor M), and security challenges (Factor AA) demonstrate the highest FIS values, exceeding 4.0. These results highlight that governance, financial, and security-related issues are the most influential in driving procurement delays. Comparable findings have been reported in studies on Nigerian and sub-Saharan African construction projects, where delayed payments, corruption, and macroeconomic instability were consistently ranked as dominant causes of project delays (Olaloku, 1994; Nundwe & Mulenga, 2021; Mohammed & Bello, 2022).

Factors with moderately high importance include inadequate procurement planning (Factor B), weak monitoring and evaluation (Factor E), frequent changes in procurement (Factor P), poorly defined project scope (Factor U), and frequent changes in government (Factor R), all registering FIS values close to 4.0. These factors underline the importance of planning, procedural consistency, and scope definition in mitigating procurement delays. Similar delay drivers, particularly poor planning, inadequate coordination, and procedural inefficiencies, have been extensively documented in the construction management literature (Mansfield *et al.*, 1994; Al-Saeedi & Karim, 2022; Mohammed & Bello, 2022).

While operational and administrative issues such as bureaucratic bottlenecks in approval (Factor A), lack of skilled procurement personnel (Factor D), and lack of electronic procurement (Factor J) are relatively less influential, with FIS values between 3.5 and 3.8, they still represent notable contributors to delays and cannot be ignored. Long-standing studies on construction performance in developing economies similarly emphasize that administrative capacity constraints and weak institutional systems, though sometimes secondary, continue to undermine project delivery efficiency (Mansfield *et al.*, 1994; Oyedele, 2024).

The quantification of procurement delay factors in road infrastructure projects in Rivers State underscores a systemic challenge within the procurement and project delivery environment. The observation that all 27 identified procurement delay factors exhibit high Frequency of Occurrence (FOI) values above the threshold of 3.0 highlights the pervasive nature of delays across multiple dimensions of the procurement process. This finding corroborates broader evidence from the construction management literature that public infrastructure projects in developing countries are routinely beset by delays arising from intertwined governance, financial, and administrative issues (Mohammed & Bello, 2022).

The Factor Importance Score (FIS), which integrates frequency and severity, further confirms that financial, governance, and security-related factors are the most influential drivers of procurement delays in the study context. Similar rankings of economic and governance determinants have been documented in Nigerian and sub-Saharan African construction studies, where financial constraints, corrupt practices, and policy instability frequently emerge as principal contributors to schedule disruptions and cost overruns (Olaloku, 1994; Nundwe & Mulenga, 2021).

Finally, although bureaucratic bottlenecks, limited procurement expertise, and weak adoption of electronic procurement systems recorded comparatively lower FIS values, they remain significant contributors to delays. Persistent institutional and administrative weaknesses have long been recognized as structural impediments to effective project delivery in Nigeria and other developing economies (Mansfield *et al.*, 1994; Oyedele, 2024), indicating that improvements in these areas can still yield meaningful gains in procurement performance.

5.2. TOPSIS-Based Ranking and Prioritization of Procurement Delays Factors

The prioritization and ranking of procurement delay factors in road infrastructure projects in Rivers State were performed using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), in accordance with the methodology outlined in Section 3.3.3. The MATLAB code developed for this analysis automated the entire process, including the construction of the decision matrix, normalization, application of weights, determination of positive and negative ideal solutions, computation of separation measures, and calculation of the relative closeness index (C_i*) for each factor.

The analysis began with the decision matrix (X), which included the 27 identified procurement delay factors and their corresponding values for Frequency of Occurrence (FOI), Severity of

Impact (SoII), and Factor Importance Score (FIS). For example, Factor 'K' (delayed release of project funds) recorded the highest FOI, SoII, and FIS values, indicating its critical role in procurement delays. Other high-ranking factors, such as corruption and favoritism ('Q') and inflation or fluctuating material costs ('M'), also exhibited high scores, signaling their relevance in delaying procurement processes.

To enable comparability across the three criteria, the values in the decision matrix were normalized to produce a unitless normalized decision matrix (R). Normalization ensured that differences in scales among FOI, SoII, and FIS did not bias the analysis. The normalized values were then weighted to produce the weighted normalized decision matrix (V), with equal weights applied to FOI, SoII, and FIS. This approach assumes that frequency, severity, and overall importance contribute equally to the impact of each factor on procurement delays.

The positive ideal solution (A^+) represents the best possible performance across all criteria, while the negative ideal solution (A^-) represents the worst-case scenario. These benchmarks enabled calculation of separation measures, representing Euclidean distances from the ideal and negative-ideal solutions. Factors with a small distance to the ideal and a large distance from the negative ideal score higher in closeness coefficients. The relative closeness index (C_i*) was then computed for each factor as the ratio of its distance from the negative ideal to the sum of distances from both ideal and negative-ideal solutions.

Results show that Factor 'K' (delayed release of project funds) had the highest C_i* value (0.88933), confirming it as the most significant contributor to procurement inefficiency. This finding is consistent with construction delay literature identifying financial constraints and payment delays as among the most common causes of project delays in developing contexts (Fashina *et al.*, 2021). Corruption and favoritism (Factor 'Q') and inflation and fluctuating material costs (Factor 'M') also ranked highly, reinforcing the prominence of governance and economic instability as delay drivers.

Procurement delays, including weak institutional capacity, are widely documented in World Bank analyses of infrastructure project procurement data, which report that weak procurement and contract management capacity, such as inadequate methods and poor contract administration, are significant contributors to delay (World Bank, 2024). The emphasis on external risks such as inflation reflects broader findings that macroeconomic variables interact with procurement processes to exacerbate project delays and cost escalation (World Bank, 2024).

Moderate-priority factors such as poorly defined project scope (Factor 'U') and ineffective supervision (Factor 'W') indicate that internal management and coordination challenges also contribute meaningfully to procurement delays, although their influence is less than the top-ranked financial and governance issues. Construction research similarly highlights that inadequate planning, weak coordination, and procedural inefficiencies are common delay causes (Fashina *et al.*, 2021). At the lower end, factors such as complex tender documentation (Factor 'F') and lack of electronic procurement systems (Factor 'J') had relatively low C_i* values, suggesting that while bureaucratic and technical processes may introduce procedural delays, they are less dominant than systemic financial and governance constraints.

The analysis demonstrates that financial bottlenecks, governance challenges, and external risk factors are the primary drivers of procurement delays, whereas procedural inefficiencies and administrative challenges are secondary. By systematically integrating frequency, severity, and overall importance, the TOPSIS approach delivers a clear and objective ranking of delay factors, offering actionable insights for project managers and policymakers. Prioritized interventions should focus on improving funding mechanisms, strengthening governance and anti-corruption practices, and managing economic risks to improve procurement efficiency and overall project performance in Rivers State's road infrastructure sector.

Overall, the TOPSIS analysis produced a robust prioritization of procurement delay factors, reflecting both the relative severity and practical implications of each factor on procurement performance. The highest-ranked factor, delayed release of project funds, underscores the centrality of reliable financing in infrastructure delivery, a finding supported by broader research on construction delays in developing countries. Additional research, including systematic frameworks that examine financial, governance, planning, and external risk factors across construction contexts, confirms that procurement and execution delays are complex and interdependent, requiring multifaceted mitigation strategies.

5.3. Sensitivity of the TOPSIS-based Rankings

The sensitivity analysis undertaken in this study constitutes a critical validation layer for the TOPSIS-based prioritization of procurement delay factors, ensuring that the resulting rankings are not artefacts of arbitrary or subjective weight assignments but are structurally stable under varying decision-maker preferences. In multi-criteria decision-making (MCDM) applications, particularly within complex construction and infrastructure environments, robustness and sensitivity testing are widely recognized as essential for enhancing analytical credibility, transparency, and policy relevance (Triantaphyllou & Sánchez, 1997; Kabir *et al.*, 2014).

To this end, MATLAB-based sensitivity analyses (Appendix B) was employed, incorporating one-way and multi-way weight perturbations, scenario-based evaluations, rank correlation tests, rank-switch analysis, and graphical diagnostics such as tornado plots. Collectively, these techniques provide a comprehensive assessment of how changes in criteria weights and stakeholder priorities influence the relative importance of procurement delay factors in road infrastructure projects in Rivers State.

The one-way sensitivity analysis focused on systematically varying the weight of the severity criterion (w_S) from 0.2 to 0.6 while proportionally adjusting the remaining criteria weights. This approach enabled an explicit examination of how increased or reduced emphasis on severity affects the relative closeness coefficients (C_i^*) and resulting rankings. The results demonstrate that the highest-ranked factors, most notably delayed release of project funds (Factor K) and corruption and favoritism (Factor Q), remain dominant across the entire range of severity weights. Although their C_i^* values declined as severity weight increased (for example, Factor K decreased from 0.93771 at w_S = 0.2 to 0.80275 at w_S = 0.6), their ordinal positions remained largely unchanged.

This finding has significant practical implications. It indicates that these factors are not only frequent but also sufficiently severe and important to retain their critical status regardless of stakeholder emphasis. Such robustness strongly supports their prioritization in policy formulation and procurement reform efforts. In contrast, moderate-ranked factors such as inflation and fluctuating material costs (Factor M) and irregular contractor payments (Factor N) exhibited greater sensitivity to changes in severity weighting, with noticeable declines in C_i* as severity emphasis increased. This behavior suggests that their relative importance is more contingent on how decision-makers balance severity against frequency and composite importance.

The observed pattern aligns closely with established TOPSIS theory, which suggests that alternatives demonstrating balanced performance across multiple criteria tend to exhibit greater ranking stability, whereas those dominated by a single criterion are more prone to rank shifts under weight variation (Behzadian *et al.*, 2012). Accordingly, while top-ranked factors warrant immediate and sustained attention, mid-ranked factors may justifiably shift in priority depending on stakeholder preferences, macroeconomic conditions, or project phase.

To further reflect real-world decision contexts, three stakeholder-driven weighting scenarios were evaluated: Frequency-Dominant, Severity-Dominant, and Importance-Dominant. The Importance-Dominant scenario produced rankings closely aligned with the baseline results, confirming that the Factor Importance Score (FIS) effectively captures the integrated influence of frequency and severity. Under the Frequency-Dominant scenario, recurrent procedural bottlenecks, such as inadequate procurement planning (Factor B) and inflation-related delays, gained prominence, reflecting their widespread occurrence across projects. Conversely, the Severity-Dominant scenario elevated governance-related and high-impact risks, particularly corruption and favoritism (Factor Q), while reducing the relative priority of low-severity but frequent issues.

These scenario-based outcomes demonstrate the flexibility of TOPSIS as a decision-support tool, capable of accommodating diverse stakeholder perspectives without fundamentally distorting the overall ranking structure. Importantly, this adaptability enhances the practical utility of the model for policymakers and project managers operating in heterogeneous institutional environments.

The robustness of the rankings across all scenarios was statistically confirmed using Spearman's rank correlation and Kendall's tau coefficients. Spearman's ρ values ranged from 0.94872 to 0.99573, while Kendall's tau values ranged from 0.84615 to 0.96581, indicating a very high degree of ordinal consistency between baseline and scenario-based rankings. These values exceed thresholds commonly reported in robust MCDM applications (Zavadskas *et al.*, 2010), providing strong evidence that the prioritization results are stable and reliable even under substantial variations in weighting assumptions.

Additional graphical diagnostics further enriched the robustness assessment. Ranking stability plots visually confirmed that top-ranked factors remained consistent across all scenarios, while rank-switch heatmaps revealed that only moderate- and low-priority factors experienced limited upward or downward movements. Tornado plots illustrated the range of variation in C_i* values across scenarios, clearly identifying which factors are most sensitive to weight changes and which remain largely invariant.

The overall robustness patterns observed in this study are strongly supported by existing literature. Triantaphyllou and Sánchez (1997) analytically demonstrated that TOPSIS rankings are generally stable for dominant alternatives, with rank reversals occurring mainly among mid-range options, an outcome directly reflected in the present findings. Behzadian *et al.* (2012), in their comprehensive review of TOPSIS applications, similarly reported that sensitivity analysis typically confirms the stability of top-ranked alternatives, particularly when composite or near-equal weights are employed. Kabir *et al.* (2014) further showed that while closeness coefficients may vary under different weighting schemes, the identity of top alternatives often remains unchanged, reinforcing the classification of such factors as systemic rather than situational issues. Zavadskas *et al.* (2010) emphasized that combining correlation analysis with sensitivity testing enhances interpretability and reduces the risk of misleading policy conclusions, an approach extended in this study through the use of rank-switch heatmaps and tornado plots.

Taken together, the sensitivity analysis validates the TOPSIS-based prioritization as both methodologically sound and decision-relevant. The persistent dominance of delayed fund release, corruption and favoritism, and inflation-related pressures underscores their strategic importance as core drivers of procurement delays. At the same time, the controlled variability observed among secondary factors reflects realistic stakeholder-driven trade-offs rather than methodological weakness. Consequently, interventions targeting the highest-ranked factors are likely to yield the greatest and most resilient improvements in procurement efficiency across road infrastructure projects in Rivers State. Meanwhile, the sensitivity of mid-ranked factors highlights the need for adaptive procurement strategies that can be recalibrated as institutional priorities, economic conditions, or policy objectives evolve. This balanced insight significantly strengthens the study's contribution to procurement management and infrastructure project decision-making in developing-economy contexts.

6.0 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

Based on the integrated analysis of procurement delays in road infrastructure projects in Rivers State, the following conclusions are drawn:

i. All 27 identified procurement delay factors exhibit high frequency, severity, and importance, confirming that delays are systemic rather than incidental. The most critical factors, delayed release of project funds, corruption and favoritism, and inflation/fluctuating material costs, highlight that financial bottlenecks, governance weaknesses, and macro-environmental instability are the primary drivers of procurement inefficiency

ii. TOPSIS-based multi-criteria analysis objectively ranks delay factors, with financial and governance-related issues consistently emerging as most critical. Delayed fund release, corruption and favoritism, inflation, security challenges, and inadequate procurement planning top the rankings, whereas procedural inefficiencies have comparatively limited impact, emphasizing the systemic nature of major procurement challenges.

iii. Sensitivity and robustness assessments demonstrate that the prioritization of procurement delay factors is highly stable across alternative weighting schemes and decision scenarios. Strong correlation coefficients (Spearman's $\rho = 0.9487$–0.9957; Kendall's $\tau = 0.8462$–0.9658) confirm that the identified top-ranked factors are structurally significant, ensuring confidence in targeted interventions based on these rankings.

6.2 Recommendations

Based on the integrated findings of this study, the following recommendations are proposed to mitigate procurement delays and enhance the performance of road infrastructure projects in Rivers State:

i. Address Systemic Procurement Delay Factors; Given that all 27 procurement delay factors are pervasive, with delayed fund release, corruption and favoritism, and inflation/fluctuating material costs being the most critical, project stakeholders should implement targeted strategies to tackle these systemic financial, governance, and macro-environmental constraints. Policies should prioritize structural reforms that strengthen institutional capacity and reduce vulnerabilities in project procurement systems.

ii. Prioritize Critical Delay Drivers for Focused Interventions; TOPSIS rankings indicate that delayed fund release, corruption/favoritism, inflation, security challenges, and inadequate procurement planning are the most influential factors. Procurement reforms should prioritize these factors over procedural or low-impact administrative issues, ensuring that resources and corrective actions are directed where they can achieve the greatest effect.

iii. Ensure Robustness and Consistency of Procurement Reforms; Given the demonstrated stability of TOPSIS rankings under varying scenarios and weighting schemes, interventions should be based on these empirically validated priorities. Stakeholders should adopt data-driven, evidence-based decision-making frameworks to ensure that reforms target structurally significant delay factors rather than artefacts of methodological assumptions.

iv. Implement Targeted, Data-Driven Interventions; To maximize procurement performance, strategies should focus on timely fund disbursement, strengthening governance mechanisms, managing inflation risks, improving security, and enhancing procurement planning. Complementary actions such as procedural streamlining, capacity building, and continuous monitoring should support these core interventions, ensuring sustained improvements in project schedule, cost, and overall procurement efficiency

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The authors declare no conflict of interest

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APPENDIX A
MATLAB CODE FOR TOPSIS-BASED RANKING AND PRIORITIZATION OF PROCUREMENT DELAY FACTORS

```
%% =========================================================
% TOPSIS-Based Ranking of Procurement Delay Factors
% MATLAB 2017a Compatible
% Separate figures and command window tables with letter codes
% =========================================================
clc; clear; close all;
%% ===================== INPUT FILES =====================
FOI_file = 'FOI_PROCUREMENT_OWO.xlsx';
SOI_file = 'SOI_PROCUREMENT_OWO.xlsx';
N_total = 84;
%% ===================== READ DATA =====================
[~,~,FOI_raw] = xlsread(FOI_file);
[~,~,SOI_raw] = xlsread(SOI_file);
Factors = FOI_raw(2:end,1);
FOI_counts = cell2mat(FOI_raw(2:end,2:6));
SoII_counts = cell2mat(SOI_raw(2:end,2:6));
m = length(Factors);
%% ===================== COMPUTE FOI, SoII, FIS =====================
Likert_weights = 1:5;
FOI = sum(FOI_counts .* Likert_weights,2)/N_total;
SoII = sum(SoII_counts .* Likert_weights,2)/N_total;
w_F = 0.4; w_S = 0.6;
FIS = w_F .* FOI + w_S .* SoII;
%% ===================== LETTER CODING =====================
LetterCode = cell(m,1);
for i=1:m
  n=i; code='';
  while n>0
    n=n-1;
    code=[char(mod(n,26)+65) code];
    n=floor(n/26);
  end
  LetterCode{i}=code;
```

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```
end
 %% ===================== DECISION MATRIX =====================
X = [FOI, SoII, FIS];
DecisionTable = table(LetterCode, FOI, SoII, FIS, ...
   'VariableNames', {'Code','FOI','SoII','FIS'});
disp('===== Decision Matrix (X) =====');
disp(DecisionTable);
 %% ===================== NORMALIZED DECISION MATRIX
=====================
R = X ./ sqrt(sum(X.^2));
NormTable = array2table(R, 'VariableNames', {'FOI','SoII','FIS'}, 'RowNames', LetterCode);
disp('===== Normalized Decision Matrix (R) =====');
```

APPENDIX A (Continued)

```
disp(NormTable);
 %% ===================== WEIGHTED NORMALIZED DECISION MATRIX
=====================
w = [1/3 1/3 1/3];
V = R .* w;
WeightedNormTable = array2table(V, 'VariableNames', {'FOI','SoII','FIS'}, 'RowNames',
LetterCode);
disp('===== Weighted Normalized Decision Matrix (V) =====');
disp(WeightedNormTable);
 %% ===================== IDEAL SOLUTIONS =====================
A_plus  = max(V);
A_minus = min(V);
IdealTable = table(A_plus', A_minus', 'VariableNames', {'A_plus','A_minus'}, 'RowNames',
{'FOI','SoII','FIS'});
disp('===== Positive and Negative Ideal Solutions =====');
disp(IdealTable);
 %% ===================== SEPARATION MEASURES
=====================
S_plus  = sqrt(sum((V - A_plus).^2,2));
S_minus = sqrt(sum((V - A_minus).^2,2));
SeparationTable = table(LetterCode, S_plus, S_minus, 'VariableNames',
{'Code','S_plus','S_minus'});
disp('===== Separation Measures (S+ and S-) =====');
disp(SeparationTable);
 %% ===================== RELATIVE CLOSENESS =====================
C = S_minus ./ (S_plus + S_minus);
CiTable = table(LetterCode, C, 'VariableNames', {'Code','Ci_star'});
disp('===== Relative Closeness (Ci*) =====');
```

```
disp(CiTable);
 %% ===================== RANKING =====================
[Closeness_Rank, idx] = sort(C,'descend');
RankedFactors = Factors(idx);
FOI_Ranked    = FOI(idx);
SoII_Ranked   = SoII(idx);
FIS_Ranked    = FIS(idx);
RankedLetters = LetterCode(idx);
 % Create a results table
TOPSIS_Table = table(RankedLetters, RankedFactors, FOI_Ranked, SoII_Ranked,
FIS_Ranked, Closeness_Rank, (1:m)', ...
   'VariableNames', {'Code','Factor','FOI','SoII','FIS','Ci_star','Rank'});
disp('===== TOPSIS Ranking =====');
disp(TOPSIS_Table);
 %% ===================== FIS SORTED FOR BAR CHART
=====================
[FIS_Sorted, idxFIS] = sort(FIS_Ranked,'descend');
RankedFactors_FIS = RankedFactors(idxFIS);
RankedLetters_FIS = RankedLetters(idxFIS);
```

APPENDIX A (Continued)

```
%% ===================== PLOTS =====================
 % 1. Decision Matrix
figure('Name','Decision Matrix','Color','w')
uitable('Data', X, 'ColumnName', {'FOI','SoII','FIS'}, 'RowName', LetterCode,...
   'Units','normalized','Position',[0 0 1 1])
title('Decision Matrix (X)')
 % 2. Normalized Matrix
figure('Name','Normalized Decision Matrix','Color','w')
uitable('Data', R, 'ColumnName', {'FOI','SoII','FIS'}, 'RowName', LetterCode,...
   'Units','normalized','Position',[0 0 1 1])
title('Normalized Decision Matrix (R)')
 % 3. Weighted Normalized Matrix
figure('Name','Weighted Normalized Decision Matrix','Color','w')
uitable('Data', V, 'ColumnName', {'FOI','SoII','FIS'}, 'RowName', LetterCode,...
   'Units','normalized','Position',[0 0 1 1])
title('Weighted Normalized Decision Matrix (V)')
 % 4. Ideal Solutions
figure('Name','Ideal Solutions','Color','w')
uitable('Data',[A_plus; A_minus], 'ColumnName', {'FOI','SoII','FIS'}, ...
   'RowName', {'A+','A-'}, 'Units','normalized','Position',[0 0 1 1])
```

```
title('Positive and Negative Ideal Solutions')
 % 5. Separation Measures
figure('Name','Separation Measures','Color','w')
uitable('Data',[S_plus S_minus], 'ColumnName', {'S+','S-'}, 'RowName', LetterCode,...
    'Units','normalized','Position',[0 0 1 1])
title('Separation Measures (S+ and S-)')
 % 6. TOPSIS Ci*
figure('Name','TOPSIS Ci*','Color','w')
hold on
colors = lines(m);
for i=1:m
    bar(i, Closeness_Rank(i),'FaceColor',colors(i,:),...
        'DisplayName',[RankedLetters{i} ' = ' RankedFactors{i}])
end
set(gca,'XTick',1:m,'XTickLabel',RankedLetters,'XTickLabelRotation',45)
ylabel('Ci*'); title('TOPSIS Closeness Coefficient')
grid on; legend('show','Location','eastoutside'); hold off

% 7. FIS Ranking
figure('Name','FIS Ranking','Color','w')
hold on
for i=1:m
    bar(i, FIS_Sorted(i),'FaceColor',colors(i,:),...
        'DisplayName',[RankedLetters_FIS{i} ' = ' RankedFactors_FIS{i}])
end
set(gca,'XTick',1:m,'XTickLabel',RankedLetters_FIS,'XTickLabelRotation',45)
ylabel('FIS'); title('Factor Importance Score (FIS)')
grid on; legend('show','Location','eastoutside'); hold off
```

APPENDIX A (Continued)

```
% 8. Factor Code Mapping
figure('Name','Factor Code Mapping','Color','w')
text(0.01,1,'Factor Code Mapping:','FontWeight','bold','FontSize',12)
for i=1:m
    text(0.01,1-i*0.03,[LetterCode{i} ' = ' Factors{i}],'FontSize',10)
end
axis off
```

APPENDIX B
MATLAB CODE FOR TOPSIS-BASED SENSITIVITY ANALYSIS

```
%% ================================================================
% TOPSIS Sensitivity Analysis Only
% Procurement Delay Factors
% MATLAB 2017a Compatible
% ================================================================
clc; clear; close all;
 %% ====================== INPUT FILES ======================
FOI_file  = 'FOI_PROCUREMENT_OWO.xlsx';
SOI_file  = 'SOI_PROCUREMENT_OWO.xlsx';
N_total = 84;
 %% ====================== READ DATA ======================
[~,~,FOI_raw] = xlsread(FOI_file);
[~,~,SOI_raw] = xlsread(SOI_file);
 Factors     = FOI_raw(2:end,1);
FOI_counts  = cell2mat(FOI_raw(2:end,2:6));
SoII_counts = cell2mat(SOI_raw(2:end,2:6));
m = length(Factors);
 %% ====================== COMPUTE FOI, SoII, FIS ======================
Likert_weights = 1:5;
FOI  = sum(FOI_counts  .* Likert_weights,2)/N_total;
SoII = sum(SoII_counts .* Likert_weights,2)/N_total;
 w_F = 0.4; w_S = 0.6;
FIS = w_F.*FOI + w_S.*SoII;
 %% ====================== LETTER CODES ======================
LetterCode = cell(m,1);
for i = 1:m
    n=i; code='';
    while n>0
        n=n-1;
        code=[char(mod(n,26)+65) code];
        n=floor(n/26);
    end
    LetterCode{i}=code;
end
 %% ====================== BASELINE TOPSIS (NO DISPLAY)
======================
X = [FOI SoII FIS];
 % Normalize
den = sqrt(sum(X.^2));
```

```
R = zeros(size(X));
for j = 1:3
   R(:,j) = X(:,j) ./ den(j);
end
 % Weighted normalized
w0 = [1/3 1/3 1/3];
V0 = zeros(size(R));
for j = 1:3
```

APPENDIX B (Continued)

```
V0(:,j) = R(:,j) * w0(j);
end
 A_plus  = max(V0);
A_minus = min(V0);

S_plus  = sqrt(sum((V0 - A_plus).^2,2));
S_minus = sqrt(sum((V0 - A_minus).^2,2));
Baseline_C = S_minus ./ (S_plus + S_minus);
 %% ============================================================
%%  ONE-WAY SENSITIVITY ANALYSIS (Severity Weight)
%% ============================================================
wS_range = 0.2:0.1:0.6;
OneWay_C = zeros(m,length(wS_range));
 for k = 1:length(wS_range)
   wS = wS_range(k);
   wF = (1-wS)/2;
   wI = (1-wS)/2;
    Vt = zeros(size(R));
   weights = [wF wS wI];
   for j = 1:3
       Vt(:,j) = R(:,j) * weights(j);
   end
    Ap = max(Vt); Am = min(Vt);
   Sp = sqrt(sum((Vt-Ap).^2,2));
   Sm = sqrt(sum((Vt-Am).^2,2));
    OneWay_C(:,k) = Sm ./ (Sp+Sm);
end
 %% ---- DISPLAY ONE-WAY RESULTS (TABLE) ----
% Create valid variable names for MATLAB 2017a
VarNames_OneWay = cell(1,length(wS_range));
for k = 1:length(wS_range)
   VarNames_OneWay{k} = ['wS_' strrep(num2str(wS_range(k),'%.1f'),'.','_')];
```

```
end
 T_oneway = array2table(OneWay_C,'RowNames',LetterCode);
T_oneway.Properties.VariableNames = VarNames_OneWay;
 disp('===== ONE-WAY SENSITIVITY ANALYSIS (Severity Weight Variation) =====');
disp(T_oneway);
 %% ---- PLOT ONE-WAY SENSITIVITY ----
figure('Name','One-Way Sensitivity Analysis','Color','w')
plot(wS_range, OneWay_C','LineWidth',1.5)
xlabel('Severity Weight (w_S)')
ylabel('Closeness Coefficient (Ci*)')
title('One-Way Sensitivity Analysis of TOPSIS Rankings')
legend(LetterCode,'Location','eastoutside')
grid on
```

APPENDIX B (Continued)

```
%% ============================================================
%%  MULTI-WAY SENSITIVITY (SCENARIO ANALYSIS)
%% ============================================================
ScenarioWeights = [
    0.5  0.3  0.2
    0.3  0.5  0.2
    0.25 0.25 0.5
];
ScenarioNames = {
    'Frequency-Dominant'
    'Severity-Dominant'
    'Importance-Dominant'
};
 Scenario_C = zeros(m,3);
 for s = 1:3
    Vt = zeros(size(R));
    for j = 1:3
        Vt(:,j) = R(:,j) * ScenarioWeights(s,j);
    end
     Ap = max(Vt); Am = min(Vt);
    Sp = sqrt(sum((Vt-Ap).^2,2));
    Sm = sqrt(sum((Vt-Am).^2,2));
     Scenario_C(:,s) = Sm ./ (Sp+Sm);
end
 %% ---- DISPLAY SCENARIO RESULTS (TABLE) ----
% Make valid variable names
```

```
VarNames_Scenario = cell(1,length(ScenarioNames));
for k = 1:length(ScenarioNames)
   VarNames_Scenario{k} = strrep(ScenarioNames{k},'-','_');
   VarNames_Scenario{k} = strrep(VarNames_Scenario{k},' ','_');
end
 T_scenario = array2table(Scenario_C,'RowNames',LetterCode);
T_scenario.Properties.VariableNames = VarNames_Scenario;
 disp('===== MULTI-WAY (SCENARIO-BASED) SENSITIVITY ANALYSIS =====');
disp(T_scenario);
 %% ---- PLOT SCENARIO ANALYSIS ----
figure('Name','Scenario-Based Sensitivity Analysis','Color','w')
bar(Scenario_C)
set(gca,'XTick',1:m,'XTickLabel',LetterCode,'XTickLabelRotation',45)
ylabel('Closeness Coefficient (Ci*)')
title('Scenario-Based TOPSIS Sensitivity Analysis')
legend(ScenarioNames,'Location','eastoutside')
grid on
 %% ============================================================
%%  RANKING ROBUSTNESS (SPEARMAN CORRELATION)
%% ============================================================
Spearman_rho = zeros(3,1);
for s = 1:3
```

APPENDIX B (Continued)

```
Spearman_rho(s) = corr(Baseline_C, Scenario_C(:,s), ...
        'type','Spearman','rows','complete');
end
 disp('===== RANKING ROBUSTNESS (SPEARMAN CORRELATION) =====');
disp(table(ScenarioNames, Spearman_rho,...
   'VariableNames',{'Scenario','Spearman_rho'}));
 %% ============================================================
%%  ADDITIONAL ANALYSIS PLOTS
%% ============================================================
 % 1. Ranking stability plot (baseline vs scenario)
[~,baseline_rank] = sort(Baseline_C,'descend');
figure('Name','Ranking Stability Plot','Color','w')
hold on
for s = 1:3
   [~,scenario_rank] = sort(Scenario_C(:,s),'descend');
   plot(1:m, scenario_rank, '-o','LineWidth',1.5,'DisplayName',ScenarioNames{s})
end
plot(1:m, baseline_rank, '--ks','LineWidth',2,'DisplayName','Baseline')
```

```
set(gca,'XTick',1:m,'XTickLabel',LetterCode)
xlabel('Factors'); ylabel('Rank')
title('Ranking Stability Across Scenarios')
legend('Location','eastoutside'); grid on; hold off
 % 2. Rank-switch heatmap
RankSwitch = zeros(m,3);
for s = 1:3
   [~,scenario_rank] = sort(Scenario_C(:,s),'descend');
   RankSwitch(:,s) = scenario_rank - baseline_rank;
end
figure('Name','Rank Switch Heatmap','Color','w')
imagesc(RankSwitch)
colormap(jet); colorbar
set(gca,'XTick',1:3,'XTickLabel',ScenarioNames,'XTickLabelRotation',45)
set(gca,'YTick',1:m,'YTickLabel',LetterCode)
xlabel('Scenarios'); ylabel('Factors')
title('Rank Change vs Baseline (Positive = Up, Negative = Down)')
 % 3. Tornado plot (max-min impact of each factor)
FactorImpact = max(Scenario_C,[],2) - min(Scenario_C,[],2);
figure('Name','Tornado Plot','Color','w')
barh(FactorImpact)
set(gca,'YTick',1:m,'YTickLabel',LetterCode)
xlabel('Max-Min Closeness Coefficient'); ylabel('Factors')
title('Tornado Plot of Factor Impact Across Scenarios')
grid on
 % 4. Kendall tau rank correlation
KendallTau = zeros(3,1);
for s = 1:3
   [KendallTau(s),~] = corr(Baseline_C, Scenario_C(:,s), 'type','Kendall');
end
```

APPENDIX B (Continued)

```
disp('===== KENDALL TAU ROBUSTNESS TEST =====');
disp(table(ScenarioNames,KendallTau,'VariableNames',{'Scenario','KendallTau'}));
 %% ============================================================
%%  FACTOR CODE MAPPING (REFERENCE ONLY)
%% ============================================================
figure('Name','Factor Code Mapping','Color','w')
text(0.01,1,'Factor Code Mapping','FontWeight','bold','FontSize',12)
for i = 1:m
   text(0.01,1-i*0.035,[LetterCode{i} ' = ' Factors{i}],'FontSize',10)
end
```

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axis off