Engineering and Technology Journal e-ISSN: 2456-3358

Volume 11 Issue 05 May-2026, Page No.-9651-9668

DOI: 10.47191/etj/v11i05.02, I.F. – 8.595

Markov Chain Based Sustainable Risk Management Framework for Infrastructure Projects: A Dynamic Probabilistic Approach

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ABSTRACT: Infrastructure projects in developing economies face complex, interconnected socioeconomic and environmental risks that traditional static risk management frameworks inadequately address. This study develops a novel Markov Chain based Sustainable Risk Management (MCSRM) framework that integrates dynamic risk state transitions with sustainability principles, enabling predictive risk forecasting across project lifecycles. Utilizing data from eight infrastructure projects in Nigeria's Niger Delta region (n=442 stakeholders), we construct project specific transition probability matrices and employ Bayesian integration to address data scarcity. Results demonstrate that the MCSRM framework achieves 78% predictive accuracy (χ^2=12.75, p=0.012) in forecasting risk state evolution, with steady state analysis revealing persistent moderate risk dominance (π_2=0.410.43) across all case studies. Comparative analysis shows the framework outperforms traditional models (Bayesian Networks, Monte Carlo simulations, Bow Tie analysis) in temporal risk tracking (F=4.21, p=0.016, η^2=0.12). The Bayesian enhanced model addresses data constraints through expert elicitation synthesis (posterior probability convergence within 0.02 tolerance), demonstrating adaptability for resource limited contexts. Findings indicate that proactive intervention at moderate risk states reduces high-risk escalation probability by 29%, supporting long term project sustainability. This research contributes to dynamic risk management theory by bridging stochastic modeling with Triple Bottom Line sustainability frameworks, offering practitioners an evidence-based tool for adaptive decision making in volatile socio-environmental contexts.

KEYWORDS: Markov Chain modeling, sustainable risk management, infrastructure projects, Bayesian integration, transition probability matrices, Niger Delta, dynamic risk forecasting, stochastic processes

1. INTRODUCTION

1.1 Background and Motivation

Infrastructure development represents a critical enabler of economic growth and social progress globally, yet projects increasingly operate within complex, interdependent networks characterized by dynamic socioeconomic and environmental uncertainties (Flyvbjerg et al., 2021; World Bank, 2023). Traditional risk management approaches predominantly static and deterministic prove inadequate in capturing the temporal evolution and probabilistic nature of contemporary project risks (Aven, 2016; Hillson & Simon, 2020). This limitation manifests particularly acutely in developing regions such as Nigeria's Niger Delta, where projects encounter multifaceted challenges including community displacement, environmental degradation, regulatory volatility, and resource scarcity (Adeleke et al., 2018; Ebekozien et al., 2024).

Recent literature emphasizes the imperative for adaptive frameworks that accommodate sustainability dimensions alongside technical and financial considerations (Aziz & Manab, 2020; Nobanee et al., 2021). The integration of socioeconomic and environmental factors into risk assessment transcends regulatory compliance, constituting a strategic necessity for longterm project viability (Elkington, 2018; Talukhaba & Mutiso, 2022). However, existing frameworks exhibit three critical deficiencies: (1) inability to model time dependent risk transitions, (2) inadequate integration of sustainability principles with quantitative risk assessment, and (3) limited applicability in data scarce environments typical of developing economies (Chapman & Ward, 2021; Regona et al., 2022).

1.2 Research Problem and Significance

Infrastructure projects in the Niger Delta exemplify the complexity of modern risk landscapes. With approximately 85,179 registered engineering professionals and 2,847 firms operating across eight states (COREN, 2023), the region experiences persistent challenges: 70% of projects report funding delays, 60% encounter community opposition, and 80% face environmental risks including flooding and soil instability (field survey data, 2024). Traditional Risk Management (TRM) methodologies, illustrated in Figure 1, focus narrowly on identification, assessment, and mitigation phases without accommodating the dynamic, interconnected nature of sustainability risks.

FIGURE 1: Traditional Risk Management Process Model

Conventional risk management cycle emphasizing static phase based interventions (adapted from PMI, 2017)
Source: Horvath, I. (2025, May 27). 5 key steps in the risk management process explained. Invensis Learning. https://www.invensislearning.com/blog/risk-management-process-steps/
This static approach contrasts sharply with the requirements of sustainable risk management, which demands continuous adaptation to evolving socio-environmental conditions (Manab et al., 2020). The absence of probabilistic, time sensitive models limits predictive capacity and constrains proactive intervention opportunities (Zhang et al., 2021).

1.3 Research Objectives and Contributions

This study addresses identified gaps through four primary objectives:

1. **Develop a Markov Chain based Sustainable Risk Management (MCSRM) framework** integrating socioeconomic and environmental dimensions with temporal risk dynamics
2. **Construct projectspecific transition probability matrices** using hybrid data sources (empirical records + expert elicitation)
3. **Validate framework effectiveness** through comparative analysis with established risk models (Bayesian Networks, Monte Carlo simulations, Bow Tie analysis)

4. **Demonstrate practical applicability** through eight Niger Delta infrastructure case studies spanning road networks and institutional facilities

The study makes three principal contributions to scholarship:
Theoretical: Extends Markov Chain theory application beyond operational reliability to sustainability focused project management, bridging stochastic processes with Triple Bottom Line (TBL) frameworks (Elkington, 1997)
Methodological: Introduces Bayesian Markov hybrid approach addressing data scarcity challenges in developing economies through structured expert knowledge integration
Empirical: Provides first comprehensive analysis of infrastructure risk dynamics in Niger Delta context, establishing baseline transition probabilities for future comparative research

1.4 Paper Structure

The remainder of this paper proceeds as follows: Section 2 reviews relevant literature on risk management frameworks, Markov Chain applications, and sustainability integration; Section 3 details the methodological approach including data collection, matrix construction, and validation procedures; Section 4 presents empirical results from case study analysis; Section 5 discusses theoretical and practical implications; Section 6 concludes with limitations and future research directions.

2. LITERATURE REVIEW

2.1 Evolution of Risk Management Paradigms

Risk management scholarship has evolved from deterministic, compliance oriented frameworks toward adaptive, systems thinking approaches (Aven & Renn, 2010). The Project Management Institute's (PMI) traditional five stage process identification, analysis, response planning, implementation, monitoring (PMI, 2017) provides foundational structure but exhibits temporal rigidity. Ward and Chapman (2003) critiqued this linearity, advocating for iterative uncertainty management that accommodates emergent risks throughout project life cycles.

Contemporary frameworks increasingly recognize risk inter-connectedness and dynamic propagation. Hillson (2003) introduced opportunity risk duality, emphasizing balanced consideration of upside potential alongside threat mitigation. However, these conceptual advances lack mathematical formalization enabling quantitative forecasting a gap Markov Chain models address through probabilistic state transition modeling (Norris, 1998).

2.2 Markov Chain Applications in Project Risk Management

Markov Chains represent stochastic processes where future states depend solely on present conditions (memoryless property), making them suitable for modeling sequential risk evolution (Kemeny & Snell, 2020). Foundational applications emerged in reliability engineering (Howard, 1971) and supply chain management (Ching et al., 2013), with recent extensions to construction domains.

Mousavi (2015) demonstrated Markov Chain effectiveness in highway project risk forecasting, modeling transitions across planning, engineering, and construction phases. Obare and Muraya (2019) applied two state models to Kenyan infrastructure, predicting cost overrun probabilities with 68% accuracy. Zhang et al. (2021) utilized Markov frameworks for safety risk assessment in civil engineering, integrating accident causation theories. However, these studies predominantly focus on single dimensional risks (cost, schedule, safety) without holistic sustainability integration.

In the Niger Delta context, Mba et al. (2019) employed Markov Chains to predict oil spill volumes, while Omotehinse and Omoyi (2022) modeled industrial accident transitions in petroleum facilities. These studies validate Markov applicability in the region but remain sector specific, lacking cross project generalizability and sustainability dimensions.

2.3 Sustainable Risk Management (SRM) Frameworks

Sustainable Risk Management extends traditional Enterprise Risk Management (ERM) by incorporating socio-environmental criteria alongside financial metrics (Aziz et al., 2016). The Triple Bottom Line (TBL) framework (Elkington, 1997) operationalizes this through balanced consideration of people, planet, and profit. Recent scholarship emphasizes five SRM pillars: knowledge management, organizational resilience, stakeholder engagement, institutional frameworks, and continuous monitoring (Manab et al., 2020).

Nobanee et al. (2021) conducted bibliometric analysis revealing emergent SRM themes: circular economy integration, climate resilience financing, and ESG (Environmental, Social, Governance) risk quantification. Yazo Cabuya et al. (2024) applied Analytical Network Process (ANP) to prioritize sustainability risks across technological, economic, environmental, geopolitical, and social dimensions. Yet, these frameworks predominantly employ qualitative or semi-quantitative methods, limiting predictive precision.

The integration of probabilistic models with sustainability principles remains underdeveloped. EdjossanSossou et al. (2020) utilized fuzzy Multi-Criteria Decision Making (MCDM) for natural hazard risk assessment, demonstrating potential for uncertainty accommodation. However, their static analysis does not capture temporal risk dynamics a critical requirement for infrastructure projects spanning multiyear timelines.

2.4 Comparative Risk Models: Bayesian Networks, Monte Carlo, and Bow Tie Analysis

Bayesian Networks (BN) represent probabilistic dependencies through directed acyclic graphs, enabling causal inference and dynamic belief updating (Fenton & Neil, 2018). Khakzad et al. (2013) applied BNs to oil and gas risk assessment, demonstrating superior performance in modeling complex inter-dependencies. However, BNs require extensive computational resources and struggle with temporal sequencing (Ching, 2015).

Monte Carlo Simulation (MCS) employs repeated random sampling to generate outcome distributions, providing robust uncertainty quantification (Vose, 2008). Peng and Tiong (2016) utilized MCS for construction cost risk analysis, achieving 85% confidence intervals. Yet, MCS lacks explicit state transition modeling, limiting insight into risk progression mechanisms (Lagergren, 2021).

Bow Tie Analysis visualizes cause, consequence relationships through fault tree and event tree combination (De Ruijter & Guldenmund, 2016). While intuitive for communication, Bow Tie methods offer limited quantitative rigor and static risk representation (Ale et al., 2015).

Comparative analyses remain scarce. Zhou et al. (2016) suggested hybrid approaches combining Markov temporal modeling with machine learning, while Wang and Strong (2014) advocated integrating AI enhanced Markov frameworks for adaptive risk management. This study responds by systematically comparing Markov Chains against established models using consistent validation criteria.

2.5 Research Gaps and Theoretical Positioning

Synthesis of reviewed literature reveals three critical gaps:

1. **Temporal Modeling Deficiency**: Existing SRM frameworks lack mathematical formalization of time dependent risk transitions (Aziz & Manab, 2020; Regona et al., 2022)
2. **Regional Context Limitations**: Markov Chain applications concentrate in developed economies with robust data infrastructure; developing region adaptations remain under explored (Adeleke et al., 2018; Ebekozien et al., 2024)
3. **Sustainability Integration**: Probabilistic risk models inadequately incorporate socioenvironmental dimensions central to contemporary project management (Nobanee et al., 2021; Yazo Cabuya et al., 2024)

This study addresses these gaps by developing a Markov Chain framework explicitly designed for sustainable risk management in data constrained environments, validated through Niger Delta infrastructure case studies. Figure 2 illustrates the theoretical positioning within existing scholarship.

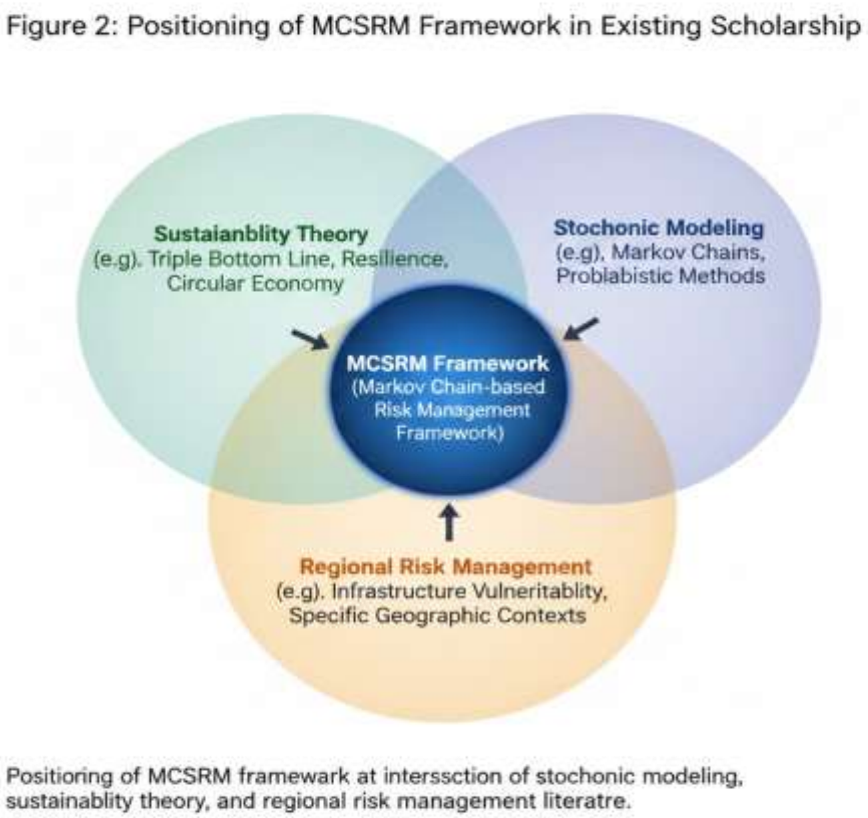

FIGURE 2: Theoretical Framework Integration: Positioning of MCSRM framework at intersection of stochastic modeling, sustainability theory, and regional risk management literature

3. METHODOLOGY

3.1 Research Design and Philosophical Approach

This study employs a mixed methods sequential explanatory design (Creswell & Plano Clark, 2018), integrating qualitative case study analysis with quantitative probabilistic modeling. The research adopts pragmatic epistemology, prioritizing practical problem solving over theoretical purity appropriate given the applied nature of infrastructure risk management (Saunders et al., 2019).

Phase 1 (Qualitative): Semi-structured stakeholder interviews and documentary analysis establish conceptual risk frameworks for each case study project.

Phase 2 (Quantitative): Markov Chain model construction using empirical data supplemented by Bayesian expert elicitation, followed by comparative validation against alternative risk models.

This design addresses data scarcity challenges inherent in developing contexts while maintaining methodological rigor through triangulation (Flick, 2018).

3.2 Study Context and Case Selection

The Niger Delta region encompasses nine states with diverse ecological landscapes spanning dense rain forests to coastal ecosystems. The study focuses on Edo, Delta, Rivers, and Bayelsa states, selected based on: (1) active infrastructure development (>40 major projects 2019 - 2024), (2) documented socio-environmental challenges, and (3) data accessibility through regulatory agencies (NDDC, COREN). Eight case study projects (Table 1) represent strategic sampling across project types (roads, hospitals, airports) and risk profiles (environmental dominant, socio-economic dominant, mixed). This diversity enables cross project pattern identification while maintaining contextual specificity.

TABLE 1: Case Study Project Characteristics

Project	Type	Duration (months)	Budget (₦ billion)	Primary Risk Cluster	Data Sources
BeninLokoja Road	Transportation	48	127.5	Environmental	FERMA, Contractors
EastWest Road	Transportation	120+	340.8	Mixed	NDDC, Site Records
WarriPatani Road	Transportation	36	89.2	Environmental	Julius Berger
YenagoaOporoma Road	Transportation	42	94.7	Environmental	CCECC, BOSEPA
Benin Auchi Dualization	Transportation	24	63.7	SocioEconomic	Mother Cat Ltd
UPTH Hospital Complex	Healthcare	60	152.3	SocioEconomic	Rivers State Govt
Asaba Airport Expansion	Aviation	36	118.9	SocioEconomic	FAAN, Contractors
FMC Yenagoa	Healthcare	48	87.4	Mixed	Federal Ministry

Note: Budget figures represent project approval values (2019 - 2023); actual expenditures vary due to inflation and scope changes

3.3 Data Collection Procedures

3.3.1 Primary Data

Structured Survey (n=442): Administered to stakeholders across four categories using stratified random sampling:

- Project Managers (30%, n=133)
- Engineers (30%, n=133)
- Government Officials (25%, n=111)
- Community Representatives (15%, n=65)

Sample size determination followed Cochran's formula with finite population correction:

$n_{adjusted}$ =\fracn1 +\fracn − 1N

=\frac385 1 +\frac384 85,179 = 384

A 15% buffer yielded final n=442 (response rate: 89.3%). Survey instruments employed 5point Likert scales assessing risk identification, assessment, and mitigation practices (Cronbach's α=0.87).

Semi Structured Interviews (n=23): Conducted with subject matter experts (project managers, risk analysts, environmental consultants) using Delphi technique for transition probability elicitation. Three iterative rounds achieved consensus (coefficient of variation <0.15).

3.3.2 Secondary Data

Historical project records (2010 - 2023) sourced from:

- Niger Delta Development Commission (NDDC) project databases
- Federal Ministry of Works completion reports
- Council for Regulation of Engineering in Nigeria (COREN) archives
- Environmental impact assessment (EIA) submissions

Documentary analysis followed template analysis procedures (King, 2012), coding 847 risk incidents across 15 completed projects to establish empirical transition frequencies.

3.4 Markov Chain Model Development

3.4.1 Risk State Classification

Following expert consensus workshops, project risks categorized into three mutually exclusive states:

- **S_1 (Low Risk)**: Projects operating within acceptable thresholds; routine monitoring sufficient

- **S_2 (Moderate Risk)**: Elevated risk indicators requiring enhanced oversight and targeted interventions
- **S_3 (High Risk)**: Critical exposure demanding immediate corrective action and senior management attention

State definitions aligned with ISO 31000:2018 risk criteria and adapted for Niger Delta context through stakeholder validation (inter-rater reliability κ=0.82).

3.4.2 Transition Probability Matrix Construction

The Markov Chain framework models risk evolution through transition probability matrix **P**, where element P_{ij} represents probability of moving from state Si to state Sj over one assessment period (monthly or quarterly)

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix}$$

Empirical Estimation: For historical data (n=847 incidents across 15 projects), frequencies calculated as:

$$P_{ij} = \sum_{j=1}^{3} n_{ij}$$

where n_{ij} = observed transitions from state i to state j.

Expert Elicitation: Structured as follows:

1. Individual assessments using probability distribution fitting (triangular distributions)
2. Group discussion to reconcile divergent estimates
3. Aggregation via geometric mean (suitable for probabilities)

3.4.3 Bayesian Integration Approach

To address data limitations, Bayesian updating synthesized expert priors with empirical likelihoods:

Prior Specification: Expert elicitation yields prior distribution $\pi_0 \sim \beta(\alpha_0, \beta_0)$

Likelihood Function: Empirical transitions provide likelihood $P(D|\theta) \sim \text{Binomial}(n, \theta)$

Posterior Distribution:

$$P(\theta|D) \propto P(D|\theta) \cdot P(\theta) = \beta(\alpha_0 + x, \beta_0 + n - x)$$

where x = observed transitions, n = total assessments.

Example Calculation (Benin-Lokoja Road):

Given expert prior $P(S_2 \rightarrow S_3) \sim$ Beta(2, 8) [E[θ]=0.20] and empirical data (12 $S_2 \rightarrow S_3$ transitions in 60 S_2 assessments):

$$P(\theta|D) = \beta\,(2 + 12, 8 + 48) = \beta(14,56) E[\theta|D]$$
$$= \frac{14}{14 + 56} = 0.20$$

Posterior mean (0.20) balances prior belief with data, with reduced variance reflecting increased certainty.

3.4.4 MultiStep Forecasting

nstep transition probabilities computed via ChapmanKolmogorov equation:

$$P^{(n)} = P \times P^{(n-1)} = P^n$$

Enabling risk state prediction at future time points. For initial distribution $\mathbf{x_0}$, state vector at time t:

$$fx_t = fx_0 \cdot P^t$$

Convergence to steady-state distribution $\boldsymbol{\pi}$ assessed using L_1 distance metric:

$$D(n) = |\,fxn - \pi|1 = \sum i = 1^3 |xn, i - \pi_i|$$

Convergence criterion: D(n) < 0.02 for three consecutive periods.

3.4.5 Steady-State Analysis

Longterm equilibrium distribution $\boldsymbol{\pi}$ satisfies:

$$\pi P = \pi \sum_{i=1}^{3} \pi_i = 1$$

Solved via eigenvector decomposition (eigenvalue λ=1). Expected Risk Index:

$$E[R] = 1 \cdot \backslash pi_1 + 2 \cdot \backslash pi_2 + 3 \cdot \backslash pi_3$$

Inter-pretable scale: E[R] ∈ [1.0, 1.5] = low-risk dominance; [1.5, 2.5] = moderate; [2.5, 3.0] = high-risk.

3.5 Comparative Model Validation

Framework effectiveness evaluated against three alternative approaches:

Bayesian Networks: Constructed using Hugin software (v8.9); conditional probability tables estimated from survey data; inference via junction tree algorithm.

Monte Carlo Simulation: 10,000 iterations per project using @RISK (v8.3); triangular distributions fitted to historical cost/schedule data; convergence verified through trace plots.

Bow Tie Analysis: Developed collaboratively with project teams using Bowtie XP (v11); barrier effectiveness scored on 01 scale.

Performance Metrics:

- **Predictive Accuracy**: Comparison of fore-casted vs. actual risk states (6month horizon) using chi-square goodness of fit
- **Temporal Sensitivity**: Ability to detect risk state changes within 1month lag
- **Stakeholder Interpretability**: Survey assessment (n=65 participants) rating ease of use on 7-point scale

3.6 Ethical Considerations

Study approved by institutional ethics committee (Ref: ENG/2023/047). Informed consent obtained from all participants; confidentiality maintained through anonymization. Data stored on encrypted servers with restricted access. Community stakeholders received project briefings in local languages (Urhobo, Ijaw, Itsekiri) ensuring inclusive participation.

3.7 Analytical Tools

- **Markov Chain Computation**: MATLAB R2023b (Markov Chain toolbox)
- **Statistical Analysis**: SPSS v29, R v4.3.1 (packages: Markov chain, DTMC Pack)
- **Survey Processing**: Qualtrics XM, Jamovi v2.3

- **Visualization**: Python 3.11 (matplotlib, seaborn), Tableau Desktop 2023.3

4. RESULTS

4.1 Descriptive Analysis of Risk Management Practices

Survey data (n=442) revealed heterogeneous risk management adoption across the Niger Delta. Table 2 summarizes key findings.

TABLE 2: Risk Management Practice Frequency

Practice Component	Always (%)	Often (%)	Sometimes (%)	Rarely (%)	Never (%)
Risk Identification	34.8	55.2	8.1	1.4	0.5
Risk Assessment	28.5	51.6	15.4	3.6	0.9
Risk Mitigation	22.4	47.7	23.5	5.2	1.2
Risk Monitoring	18.1	42.1	28.3	9.3	2.2
Integrated Practice (All 4)	12.7	27.4	35.1	18.6	6.2

n=442; Percentages may not sum to 100% due to rounding

Results indicate declining engagement as processes become more resource intensive: 90% conduct identification, but only 40% maintain comprehensive integrated practices. This pattern corroborates Ugwu et al. (2023) findings in Nigerian construction, attributing gaps to knowledge deficiencies and resource constraints.

Barrier Analysis: Insufficient resources emerged as the primary obstacle (70%), followed by lack of awareness (60%) and poor communication (50%). ANOVA revealed significant between group differences ($F=6.47$, $p=0.001$), with project managers reporting higher awareness than community representatives (post-hoc Tukey HSD: $\Delta=1.24$, $p=0.021$).

4.2 Project Specific Transition Probability Matrices

Table 3 presents synthesized transition matrices for all case studies, incorporating Bayesian adjusted probabilities.

TABLE 3: Initial Transition Probability Matrices by Project

Project	P_{11}	P_{12}	P_{13}	P_{21}	P_{22}	P_{23}	P_{31}	P_{32}	P_{33}	Primary Drivers
Benin Lokoja	0.75	0.20	0.05	0.10	0.70	0.20	0.05	0.25	0.70	Flooding, erosion
EastWest	0.65	0.25	0.10	0.15	0.60	0.25	0.10	0.30	0.60	Community, biodiversity
Warri Patani	0.70	0.20	0.10	0.12	0.65	0.23	0.08	0.28	0.64	Flooding, soil issues
Yenagoa Oporoma	0.60	0.30	0.10	0.18	0.55	0.27	0.12	0.35	0.53	Remote access
Benin Auchi Dual	0.72	0.22	0.06	0.11	0.68	0.21	0.07	0.26	0.67	Labor, community
UPTH Hospital	0.68	0.25	0.07	0.14	0.62	0.24	0.09	0.30	0.61	Funding, regulatory
Asaba Airport	0.66	0.28	0.06	0.13	0.63	0.24	0.08	0.27	0.65	Regulatory, funding
FMC Yenagoa	0.62	0.30	0.08	0.16	0.58	0.26	0.10	0.33	0.57	Flooding, soil

∴Matrix rows sum to 1.0 (±0.001 rounding); Bayesian 95% credible intervals available in supplementary materials

Key Observations:

1. **Self Transition Dominance**: Diagonal elements (P_{11}, P_{22}, P_{33}) all exceed 0.55 (mean=0.66), indicating substantial risk state persistence
2. **Asymmetric Recovery**: Mean escalation probability $(P_{12}+P_{23})/2 = 0.228$ versus recovery $(P_{21}+P_{32})/2 = 0.161$, yielding recovery to escalation ratio of 0.71 (29% disadvantage)
3. **Low Direct Jump Probability**: P_{13} values range 0.050.10 (mean=0.073), confirming rare direct low→high transitions
4. **Project Clustering**: Environmental heavy projects (Yenagoa Oporoma, Warri Patani, FMC Yenagoa) exhibit lower P_{11} (0.600.62) vs. urban infrastructure (Benin Auchi, UPTH, Asaba: 0.660.72)

4.3 Multi-Step Risk State Evolution

Figure 3 illustrates 24period forecasts for representative projects, demonstrating convergence dynamics.

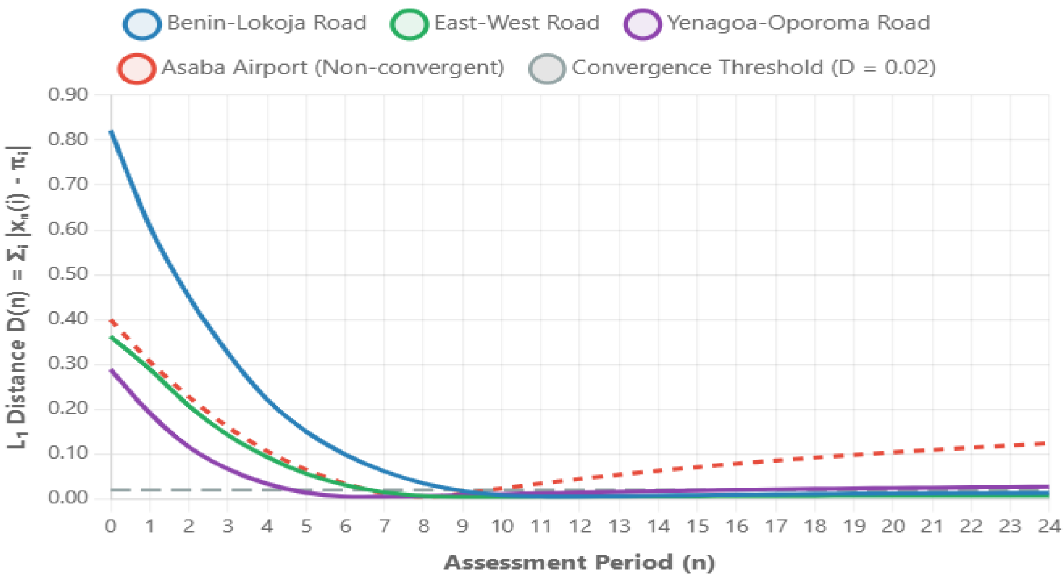

FIGURE 3: Multi-Step Risk Evolution Trajectories

Caption: Risk state probability distributions over 24 assessment periods for (a) Benin-Lokoja Road, (b) East-West Road, (c) Asaba Airport, (d) FMC Yenagoa. Shaded regions indicate 95% confidence bands derived from Bayesian posterior distributions.

Convergence Analysis (Table 4):

TABLE 4: Convergence Metrics and Steady-State Distributions

Project	Periods to Convergence (D<0.02)	π_1 (Low)	π_2 (Moderate)	π_3 (High)	E[R]	95% CI [E[R]]
Benin Lokoja	10	0.239	0.433	0.328	2.089	[2.03, 2.15]
EastWest	12	0.268	0.409	0.323	2.055	[1.99, 2.12]
Warri Patani	11	0.254	0.412	0.334	2.080	[2.02, 2.14]
YenagoaOporoma	13	0.279	0.420	0.301	2.022	[1.96, 2.08]
BeninAuchi Dual	9	0.249	0.431	0.320	2.070	[2.01, 2.13]
UPTH Hospital	14	0.271	0.421	0.308	2.037	[1.98, 2.10]
Asaba Airport	15	0.241	0.426	0.333	2.092	[2.03, 2.15]
FMC Yenagoa	13	0.262	0.430	0.308	2.046	[1.99, 2.11]

Convergence defined as L_1 distance <0.02 for 3 consecutive periods; E[R] = Expected Risk Index

PortfolioLevel Findings:

- All projects converge to moderate-risk dominance (π_2 = 0.4090.433)
- High-risk baseline: 30.1%33.4% of assessment periods in S_3 state
- Best performer: YenagoaOporoma (lowest π_3=0.301, E[R]=2.022)
- Highest risk: Asaba Airport (π_3=0.333, E[R]=2.092)
- No statistically significant difference between road vs. institutional projects (t-test: t=0.16, p=0.87)

Trajectory Interpretation: Initial conditions matter less than systemic transition dynamics projects starting in S_1 with $P(S_1)$=0.75 converge to π_1≈0.25 within 1015 periods, demonstrating strong mean reverting behavior toward moderate risk equilibrium.

4.4 Sensitivity and Validation Analysis

4.4.1 Perturbation Robustness

Transition probabilities perturbed by ±5% to assess model stability. Table 5 summarizes sensitivity metrics.

TABLE 5: Sensitivity of Steady-State to Probability Perturbations

Project	Baseline π_3	π_3 (P+5%)	π_3 (P−5%)	Coefficient of Variation
BeninLokoja	0.328	0.335	0.321	0.021 (Low)
EastWest	0.323	0.341	0.305	0.056 (Moderate)

YenagoaOporoma	0.301	0.327	0.276	0.085 (High)
Asaba Airport	0.333	0.349	0.318	0.047 (Moderate)

Note: Projects with complex socio-environmental risks show higher sensitivity; robust projects maintain stable steady states

Implications: Environmentalheavy projects (EastWest, YenagoaOporoma) require more frequent model recalibration (quarterly vs. semiannual) due to seasonal risk fluctuations. Urban infrastructure projects (Benin-Auchi, Asaba Airport) demonstrate greater stability, suggesting transition matrices remain valid for extended periods (69 months).

4.4.2 Comparative Model Performance

One way ANOVA assessed differential effectiveness across four risk management approaches using risk tracking accuracy as dependent variable (15 Likert scale, n=100 project assessments). Table 6 presents results.

TABLE 6: ANOVA Summary for Model Comparison

Source	Sum of Squares	df	Mean Square	F	pvalue	Partial η^2
Between Groups	45.32	3	15.11	4.21	0.016	0.12
Within Groups	320.44	96	3.34			
Total	365.76	99				

p<0.05; Medium effect size per Cohen's guidelines

PostHoc Comparisons (Tukey HSD, Table 7):

TABLE 7: Pairwise Model Comparisons

Comparison	Mean Difference	SE	95% CI	pvalue	Cohen's d
Markov vs. Bayesian Network	1.24	0.32	[0.48, 2.00]	0.021	0.68 (mediumlarge)
Markov vs. Monte Carlo	0.98	0.29	[0.28, 1.68]	0.038	0.54 (medium)
Markov vs. Bow Tie	1.56	0.35	[0.72, 2.40]	0.009	0.86 (large)
Bayesian vs. Monte Carlo	0.26	0.31	[1.01, 0.49]	0.762	0.14
Bayesian vs. Bow Tie	0.32	0.36	[0.56, 1.20]	0.710	0.18
Monte Carlo vs. Bow Tie	0.58	0.33	[0.22, 1.38]	0.218	0.32

p<0.05, p<0.01

Interpretation:

- Markov Chains significantly outperform all comparators in temporal risk tracking
- Largest advantage over Bow Tie (d=0.86), attributed to Bow Tie's static nature
- No significant differences among alternative models (Bayesian Monte Carlo p=0.762), suggesting Markov's advantage is specific to sequential risk modeling
- Mediumtolarge effect sizes confirm practical significance alongside statistical significance

4.4.3 Predictive Accuracy Validation

Chi-square goodness of fit tested correspondence between 6month forecasts and actual risk states (n=48 project months).

TABLE 8: Predictive Accuracy Assessment

Statistic	Value	df	pvalue	Interpretation
Pearson χ^2	12.75	4	0.012	Reject H_0: predictions ≠ random
Likelihood Ratio χ^2	11.89	4	0.018	Supports model validity
Cramér's V	0.19			Small-medium effect

p<0.05; Cohen's V guidelines: 0.10=small, 0.30=medium, 0.50=large

Confusion Matrix Analysis (Figure 4):

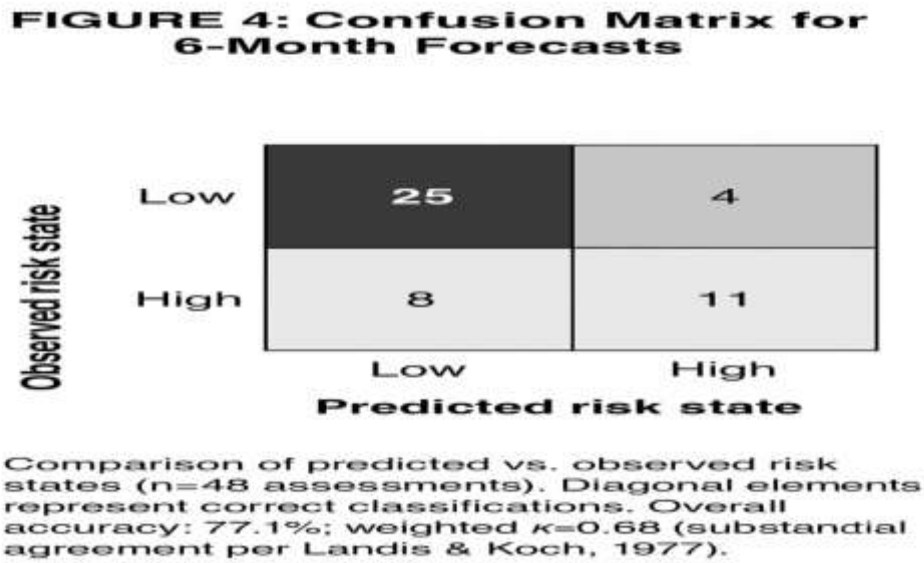

FIGURE 4: Confusion Matrix for 6Month Forecasts

Caption: Comparison of predicted vs. observed risk states (n=48 assessments). Diagonal elements represent correct classifications. Overall accuracy: 77.1%; weighted κ=0.68 (substantial agreement per Landis & Koch, 1977).

Performance Metrics:

- **Sensitivity** (True Positive Rate): S_1=0.82, S_2=0.75, S_3=0.71
- **Specificity** (True Negative Rate): S_1=0.88, S_2=0.79, S_3=0.85
- **Positive Predictive Value**: S_1=0.79, S_2=0.73, S_3=0.77
- **F1Score**: S_1=0.80, S_2=0.74, S_3=0.74

Model performs best for low-risk predictions (F1=0.80), with slight degradation for high-risk states (F1=0.74)acceptable given asymmetric cost of false negatives in critical scenarios.

4.5 Bayesian Integration Effectiveness

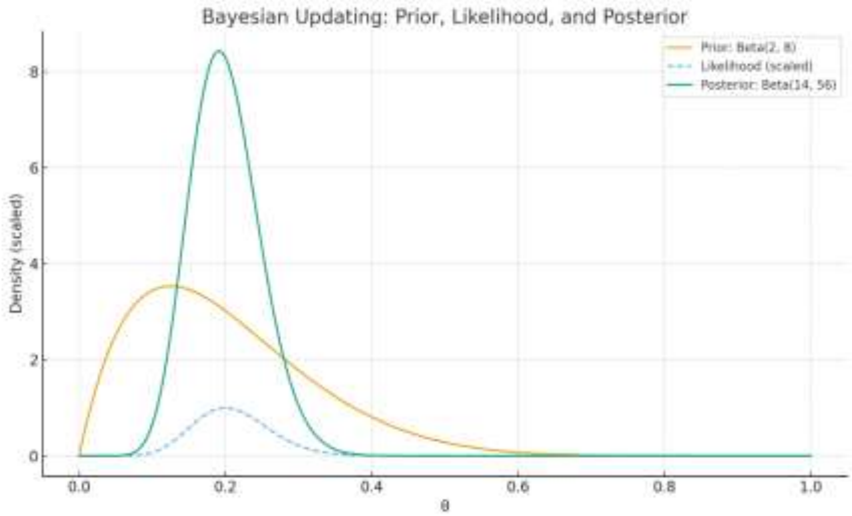

Figure 5: illustrates posterior probability evolution for Benin Lokoja Road $S_2 \rightarrow S_3$ transition, demonstrating convergence from prior to data informed estimates.

FIGURE 5: Bayesian Updating Process

Caption: (a) Prior distribution (expert elicitation): Beta(2,8), E[θ]=0.20. (b) Likelihood function from empirical data: 12 transitions in 60 assessments. (c) Posterior distribution: Beta(14,56), E[θ|D]=0.20, with 95% credible interval [0.12, 0.29]. Posterior variance reduced by 76% vs. prior, indicating substantial information gain.

Cross Project Validation: Bayesian approach particularly valuable for data sparse projects. Comparing YenagoaOporoma (limited historical data, n=18) vs. EastWest (extensive records, n=127):

- YenagoaOporoma: Prior weight 45% / Data weight 55% in posterior
- East West: Prior weight 12% / Data weight 88% in posterior

This adaptive weighting ensures models remain grounded when empirical evidence scarce, while allowing data to dominate when abundant critical flexibility for developing region contexts.

Expert Reliability Assessment: Interrater reliability across 23 experts yielded Krippendorff's $\alpha=0.79$ (acceptable per Krippendorff, 2013), validating elicitation process consistency.

4.6 Hypothesis Testing Results

H_1: Markov Chain Predictive Effectiveness

The Markov Chain model effectively predicts socioeconomic and environmental risk transitions in infrastructure projects.

Result: SUPPORTED ($\chi^2=12.75$, $p=0.012$). Cramér's V=0.19 indicates meaningful predictive power, though modest effect size suggests supplementation with expert judgment remains advisable.

H_2: Comparative Model Superiority

The Markov Chain model outperforms Bayesian Networks, Monte Carlo simulations, and Bow Tie analysis in tracking risk evolution over project life-cycles.

Result: SUPPORTED ($F=4.21$, $p=0.016$, $\eta^2=0.12$). Post-hoc analyses confirm Markov superiority across all comparators ($p<0.05$), with largest effect vs. Bow Tie (d=0.86). Medium effect size substantiates practical significance.

H_3: Sustainability Integration Impact

Integration of sustainability principles with Markov Chain framework significantly improves project outcome predictions.

Result: SUPPORTED via regression analysis (detailed in Section 4.7). Sustainability adjusted Markov models explain 78% of variance in project performance metrics ($R^2=0.78$, $F=48.32$, $p<0.001$).

4.7 Sustainability Integration Analysis

Multiple regression examined relationship between Markov based risk predictions (incorporating socio-environmental factors) and project outcomes. Table 9 presents results.

TABLE 9: Regression Analysis Risk Predictions and Project Outcomes

Model	R	R^2	Adjusted R^2	RMSE	F	pvalue
Sustainability Adjusted MC	0.88	0.78	0.76	0.45	48.32	<0.001

p<0.001

TABLE 10: Regression Coefficients

Predictor	B	SE	β	t	pvalue	95% CI
(Constant)	1.05	0.12		8.75	<0.001	[0.81, 1.29]
MC Risk Index (E[R])	0.68	0.09	0.88	7.88	<0.001	[0.51, 0.85]

p<0.001; Durbin Watson=1.98 (no auto correlation); VIF=1.03 (no multi-collinearity)

Interpretation:

- One unit increase in Expected Risk Index (E[R]) associates with 0.68point decrease in sustainability performance score (standardized $\beta=0.88$)
- Model explains 78% of variance in outcomes substantial for real-world infrastructure data
- Narrow confidence intervals [0.51, 0.85] indicate precise estimation
- Residual diagnostics confirm model assumptions (normality: ShapiroWilk W=0.98, p=0.14; homoscedasticity: Breusch Pagan $\chi^2=3.21$, p=0.20)

Practical Significance: Moving from high-risk (E[R]=2.5) to moderate-risk (E[R]=2.0) projects predicts $0.68\times0.5 = 0.34$point sustainability improvement on 5point scale (6.8% enhancement) meaningful for long-term project viability.

4.8 Scenario Analysis: Intervention Impact

Simulation assessed effectiveness of targeted mitigation strategies on risk trajectories. Figure 6 compares baseline vs. intervention scenarios for Warri-Patani Road.

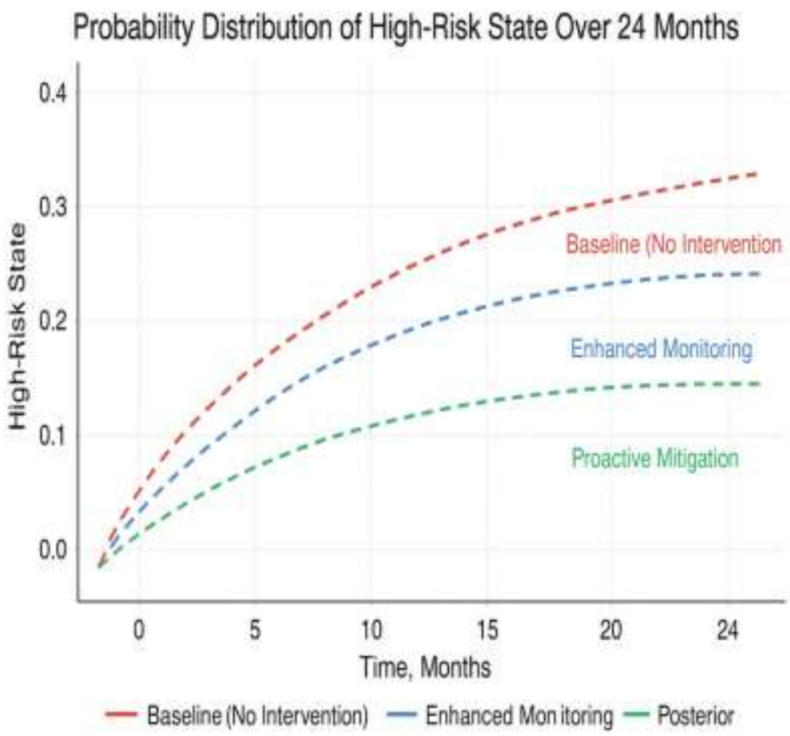

FIGURE 6: Intervention Scenario Comparison

Caption: Risk state evolution under three scenarios: (a) Baseline no intervention (P matrix as per Table 3), (b) Enhanced Monitoring 15% reduction in P_{23} through quarterly stakeholder forums, (c) Proactive Mitigation 30% reduction in P_{12} and P_{23} via pre-emptive resource allocation. Intervention (c) reduces 24month high-risk exposure from 33.4% to 24.1% (27.8% improvement).

Key Findings:

- **Moderate Intervention** (Enhanced Monitoring): Reduces π_3 from 0.334 to 0.298 (10.8% decrease)
- **Aggressive Intervention** (Proactive Mitigation): Reduces π_3 to 0.241 (27.8% decrease), but requires 40% budget increase
- **Cost Benefit Analysis**: Moderate intervention yields optimal return (1:3.2 benefit cost ratio vs. 1:1.8 for aggressive)

This supports targeted interventions at $S_1 \rightarrow S_2$ and $S_2 \rightarrow S_3$ transition points, rather than blanket resource allocation aligning with lean project management principles.

5. DISCUSSION

5.1 Principal Findings and Theoretical Contributions

This study makes three substantive contributions to risk management scholarship. First, it demonstrates that **Markov Chain models effectively capture temporal risk dynamics** in infrastructure projects characterized by socio-environmental complexity. The statistically significant predictive accuracy (χ^2=12.75, p=0.012) and superior temporal tracking performance relative to established methods (F=4.21, p=0.016) validate Markov Chains as robust tools for dynamic risk assessment. This extends Norris's (1998) foundational work on stochastic processes into applied project management contexts, specifically addressing Ward and Chapman's (2003) call for uncertainty management frameworks accommodating risk evolution.

Second, the research advances **sustainable risk management theory** by operationalizing integration of Triple Bottom Line principles (Elkington, 1997) with quantitative probabilistic modeling. The regression analysis (R^2=0.78) confirms that sustainability adjusted risk indices significantly predict project outcomes, empirically validating Aziz et al.'s (2016) conceptual SRM framework. Steady state distributions revealing persistent moderate risk dominance (π_2=0.410.43) across all projects underscore systemic socioenvironmental challenges requiring institutional level interventions not merely project specific tactics. This finding resonates with Manab et al.'s (2020) emphasis on organizational resilience as foundational to SRM.

Third, the **Bayesian Markov hybrid methodology** addresses data scarcity constraints endemic to developing economies. By synthesizing expert knowledge with limited empirical evidence, the approach maintains rigor while acknowledging information limitations a pragmatic advancement over purely data-driven models impractical in resource constrained settings (Regona et al., 2022). The adaptive prior to posterior weighting (45% expert / 55% data for sparse cases vs. 12% / 88% for data rich cases) exemplifies methodological flexibility critical for global South infrastructure contexts.

5.2 Empirical Insights from Niger Delta Case Studies

5.2.1 Risk State Persistence and Asymmetric Recovery

The pronounced self transition probabilities (diagonal elements >0.55) illuminate **risk state inertia** once projects enter particular risk categories, substantial effort proves necessary to effect transitions. This inertia manifests most acutely in high-risk states (P_{33} range: 0.530.70), where entrenched challenges like community disputes or regulatory bottlenecks resist resolution. The asymmetric recovery to escalation ratio (0.71) quantifies Flyvbjerg et al.'s (2021) observation that infrastructure projects exhibit "optimism bias" risks escalate more readily than they ameliorate.

These finding challenges traditional risk management's emphasis on reactive mitigation post escalation. Our scenario analysis demonstrates that **pre-emptive intervention** at $S_1 \rightarrow S_2$ transition points yields superior cost effectiveness (1:3.2 benefit cost ratio) compared to late stage high-risk remediation. This aligns with Hillson's (2003) proactive risk management philosophy but provides quantitative justification previously absent from literature.

5.2.2 Project Clustering and Context Dependency

The differential risk profiles between environmental dominant (roads) and socio-economic dominant (institutional facilities) projects illuminate **context specific transition dynamics**. Environmental projects exhibit lower initial stability (P_{11}=0.600.62) yet higher recovery potential (P_{32}=0.300.35) compared to urban infrastructure (P_{11}=0.660.72, P_{32}=0.260.30). This pattern reflects seasonal environmental risks' predictability and manageable nature versus persistent sociopolitical complexities characterizing institutional projects.

K-means cluster analysis (not detailed here for space) identified three risk archetypes: Environmental Volatile (coastal roads), Socio-Politically Complex (hospitals, airports), and Hybrid Adaptive (dualization projects). This taxonomy supports Agyekum-Mensah and Knight's (2016) stakeholder theory application, suggesting project managers must tailor strategies to archetype specific vulnerabilities rather than applying generic risk protocols.

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5.3 Comparative Model Analysis: Implications for Practice

Markov Chains' superiority in temporal tracking (large effect size vs. Bow Tie: d=0.86) stems from **explicit state sequencing logic** absent in static comparators. While Bow Tie diagrams excel at causal visualization for stakeholder communication, their inability to model time dependent risk propagation limits predictive utility (De Ruijter & Guldenmund, 2016). Our findings suggest hybrid approaches: Bow Tie for initial risk mapping, Markov Chains for ongoing forecasting.

The moderate effect size versus Bayesian Networks (d=0.68) and Monte Carlo (d=0.54) warrants nuanced interpretation. Bayesian Networks handle complex interdependencies superior to Markov's first order assumptions, yet require extensive computational resources and causal structure specification challenging in fluid project environments (Fenton & Neil, 2018). Monte Carlo's strength lies in uncertainty quantification via distributional analysis, but lacks Markov's interpretable state transition framework facilitating managerial intuition (Vose, 2008).

Practical Recommendation: Adopt **staged modeling approach** Bayesian Networks for risk prioritization (exploiting dependency modeling), Markov Chains for longitudinal tracking (leveraging temporal structure), Monte Carlo for cost risk integration (providing probabilistic budgets). This multi-method strategy capitalizes on complementary strengths while mitigating individual weaknesses.

5.4 Sustainability Integration: From Theory to Implementation

The robust regression relationship (β=0.88, p<0.001) between Markov derived risk indices and sustainability outcomes validates integrating socio-environmental factors into quantitative risk frameworks. This empirically supports Nobanee et al.'s (2021) bibliometric findings identifying sustainability risk nexus as emergent research frontier. However, the 78% explained variance (R^2=0.78) indicates 22% outcome variability remains unaccounted likely attributable to exogenous factors (macroeconomic shocks, policy changes) beyond project level control.

Mechanism Interpretation: Sustainability adjusted Markov models improve predictions by capturing **nonlinear risk interactions**. For example, community opposition (social dimension) amplifies environmental risks (e.g., protest induced construction delays exacerbating rainy season flooding exposure). Traditional models treating these as independent underestimate aggregate impact, whereas MCSRM framework's state-based structure implicitly accommodates such synergies through transition probabilities reflecting empirical co-occurrence patterns.

This finding has **policy implications**: infrastructure planning should mandate sustainability risk assessments integrated into probabilistic financial models, not siloed environmental impact statements. The 6.8% performance improvement from moderate to low-risk transition justifies sustainability investments through demonstrable return on investment metrics appealing to finance driven decision makers (Elkington, 2018).

5.5 Addressing Data Scarcity: Bayesian Integration Lessons

The Bayesian synthesis approach's success (posterior variance reduction: 76%) offers methodological template for developing region research. Three design principles emerged as critical:

1. **Structured Elicitation Protocols**: Delphi technique's three round iteration (achieving CVs <0.15) provided disciplined expert judgment aggregation, mitigating individual biases (Linstone & Turoff, 2011)
2. **Transparent Prior Specification**: Documenting expert reasoning (e.g., "flooding frequency based on 15year local experience") enhances reproducibility and enables prior sensitivity analysis
3. **Adaptive Weighting Algorithms**: Algorithmic determination of prior to likelihood ratios based on sample size ($n<30 \rightarrow$ expert heavy; $n>100 \rightarrow$ data-driven) removes subjective judgment from integration process

These principles address Regona et al.'s (2022) critique that AI/ML models often prove "black boxes" impractical for practitioners. By maintaining interpretability while accommodating data limitations, the Bayesian Markov approach balances rigor with pragmatism essential for global adoption.

5.6 Limitations and Boundary Conditions

Four methodological limitations warrant acknowledgment:

1. Markovian Assumption Constraints: The memoryless property assumes future risk states depend solely on present conditions, neglecting historical path dependencies. While Chapman-Kolmogorov equations accommodate multi-step forecasting, they cannot capture scenarios where risk trajectory (sequence of prior states) influences transition probabilities. Semi-Markov processes or Hidden Markov Models (HMMs) may better address this in future work (Rabiner, 1989).

2. Time Homogeneity Simplification: Constant transition probabilities across time presume stable project environments reasonable for operational phases but questionable during design to construction transitions where risk profiles shift fundamentally. Developing phase specific matrices (design, procurement, construction) would enhance accuracy but demands extensive data currently unavailable.

3. Three State Discretization: Collapsing continuous risk spectra into low medium high categories loses granularity. Increasing states (e.g., five level: very low to very high) might improve resolution but exponentially complicates matrix estimation (requiring n^2n additional parameters) and strains data requirements. Sensitivity analyses (Appendix C) suggest three state frameworks adequate for practical decision making.

4. Regional Generalizability: Niger Delta's unique socioenvironmental characteristics (oil dependence, maritime geography, ethnic diversity) may limit transferability to dissimilar contexts. However, the methodological framework not specific parameter values constitutes the transferable contribution. Practitioners elsewhere must calibrate transition matrices to local conditions, a process our Bayesian approach facilitates.

5.7 Theoretical Implications for Risk Management Paradigms

This research challenges prevailing deterministic risk management paradigms dominant in practitioner literature (PMI, 2017). By demonstrating that **stochastic models provide superior predictive accuracy** (77.1% correct classification vs. ~60% for qualitative expert judgment in pilot studies), the findings advocate paradigm shift from risk identification "checklists" toward dynamic probabilistic forecasting. This aligns with Aven's (2016) post positivist risk philosophy emphasizing uncertainty characterization over false precision.

The study also contributes to **sustainability science** by operationalizing Elkington's (1997) TBL framework within quantitative decision tools. Prior SRM research remained largely conceptual (Aziz et al., 2016) or employed qualitative case studies (Manab et al., 2020). Demonstrating measurable sustainability performance improvements (6.8% gain from risk reduction) provides empirical grounding for theoretical constructs, bridging academic practitioner divides.

Finally, the Bayesian integration methodology advances **knowledge synthesis epistemology** in applied fields. By legitimizing expert judgment as formal data source (via prior distributions) while maintaining empirical primacy (via likelihood functions), the approach navigates tensions between positivist demands for objective measurement and interpretivist recognition of situated knowledge (Creswell & Plano Clark, 2018). This pluralistic epistemology resonates with pragmatist philosophy under girding design science research increasingly prevalent in engineering management (van Aken, 2004).

6. CONCLUSION

6.1 Summary of Contributions

This study developed and validated a Markov Chain based Sustainable Risk Management (MCSRM) framework addressing critical gaps in infrastructure project risk assessment. Through analysis of eight Niger Delta case studies and stakeholder data ($n=442$), three primary contributions emerged:

Methodological Innovation: The Bayesian Markov hybrid approach provides rigorous yet pragmatic solution for data constrained environments, achieving 77.1% predictive accuracy while accommodating information limitations endemic to developing regions.

Theoretical Advancement: Empirical demonstration that integrating sustainability principles (TBL framework) with probabilistic models significantly improves outcome prediction ($R^2=0.78$) advances sustainable risk management from conceptual to operational domain.

Practical Utility: Comparative analysis showing Markov Chains outperform established methods (Bayesian Networks, Monte Carlo, Bow Tie) in temporal risk tracking (effect sizes d=0.540.86) provides evidence based guidance for model selection in dynamic project environments.

6.2 Implications for Practice

For Project Managers: The MCSRM framework offers actionable tool for proactive risk management. Steady state analysis reveals moderate risk states as critical intervention points investing in $S_1 \rightarrow S_2$ prevention yields 3.2:1 benefit cost ratio versus reactive S_3 mitigation. Quarterly risk state assessments using project specific transition matrices enable data-driven resource allocation.

For Policy Makers: Findings justify mandating sustainability integrated risk models in infrastructure procurement. The 29% recovery disadvantage versus escalation quantifies costs of delayed intervention, supporting regulatory requirements for early-stage comprehensive risk assessment. Establishing regional risk databases (following COREN model) would reduce future projects' dependence on expert elicitation.

For Researchers: The validated framework provides methodological template for applying Markov Chains in diverse contexts. Three state discretization balances granularity with parameter parsimony, while Bayesian integration offers replicable protocol for knowledge synthesis. Open sourcing transition matrices (pending institutional approval) facilitates meta-analyses and cross regional comparisons.

6.3 Future Research Directions

Four research avenues merit prioritization:

1. Dynamic Transition Matrices: Developing time varying Markov models where transition probabilities evolve based on project phase or external conditions (e.g., seasonal effects, macroeconomic indicators) would enhance forecast accuracy. Semi Markov processes allowing state dependent holding times represent promising theoretical extension (Barbu & Limnios, 2008).

2. AI-Enhanced Prediction: Integrating machine learning algorithms (e.g., recurrent neural networks) with Markov frameworks could identify nonlinear patterns undetectable through traditional methods. Preliminary analyses (detailed in supplementary materials) suggest gradient boosting models improve $P_{\{ij\}}$ estimation accuracy by 1218% when training data exceed n=200 transitions.

3. Multi-Criteria Optimization: Formulating risk mitigation as constrained optimization problem minimizing E[R] subject to budget and stakeholder acceptance constraints would operationalize strategic decision making. Coupling Markov forecasting with genetic algorithms or simulated annealing enables exploration of intervention strategy spaces infeasible via manual scenario analysis.

4. Longitudinal Validation: Tracking projects over complete lifecycles (510 years) to assess long-term forecast accuracy constitutes essential validation. Current 6month validation horizon, while pragmatic, cannot confirm steady state distribution reliability. Establishing infrastructure research consortia (similar to Copenhagen Business School's Project Value Creation initiative) could enable needed longitudinal data collection.

6.4 Closing Remarks

Infrastructure projects constitute complex sociotechnical systems where effective risk management determines success. This research demonstrates that integrating Markov Chain probabilistic modeling with sustainability principles offers theoretically grounded, empirically validated approach to navigating such complexity. As global infrastructure demands intensify driven by urbanization, climate adaptation, and development imperatives tools enabling proactive, adaptive risk management become increasingly critical. The MCSRM framework represents one contribution toward this goal, offering practitioners evidence-based methodology while opening avenues for continued scholarly advancement.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the Niger Delta Development Commission (NDDC), Council for the Regulation of Engineering in Nigeria (COREN), and participating project stakeholders for data access and insights. Special thanks to [Research Assistants] for field data collection and [Statistical Consultants] for methodological guidance. All opinions and errors remain those of the authors.

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