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Article

QUANTITATIVE RISK ASSESSMENT OF MEGA REAL ESTATE PROJECTS: A MONTE CARLO SIMULATION APPROACH

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ABSTRACT

This systematic literature review synthesizes how Monte Carlo simulation is designed, implemented, and interpreted for quantitative risk assessment in mega real estate projects. Following a PRISMA-aligned protocol, we searched Scopus, Web of Science, ASCE Library, ScienceDirect, IEEE Xplore, and Emerald Insight, complemented by Taylor & Francis Online and snowballing, screened records in two stages, and extracted standardized methodological variables. The final sample comprises 115 studies, analyzed across four decision-shaping themes: input distributions, dependence modeling, sampling discipline, and integration of cost, schedule, and finance. Most studies adopt triangular or PERT-style inputs, with lognormal alternatives common, while heavy-tailed forms remain underused despite escalation and long-lead exposures. Explicit dependence is unevenly treated, many models assume independence, whereas rank correlation, common drivers, or copulas reveal wider tails. Latin hypercube sampling dominates, quasi Monte Carlo appears in a minority, and only a subset justifies run size against precision targets. Where models link schedule to cost and propagate into cash flow and financing metrics such as debt service coverage ratio, credible bands widen and breach probabilities rise, improving alignment with lender and board thresholds. Sensitivity analysis is frequent yet mixed in rigor, with global and tail-focused measures offering clearer mitigation leverage than tornado charts, and validation by hindcasting or exceedance tests remains rare but decisive for credibility. We conclude that governance-ready practice requires tail-aware input fitting, co-movement, variance-efficient designs with accuracy goals, integrated cost, schedule, and finance modeling, and transparent sensitivity and validation protocols that yield auditable percentile contingencies and covenant risk statements for stage-gate decisions.

KEYWORDS
Monte Carlo simulation; Quantitative risk assessment; Mega real estate projects; PRISMA; Cost contingency; Schedule risk; Dependence modeling;

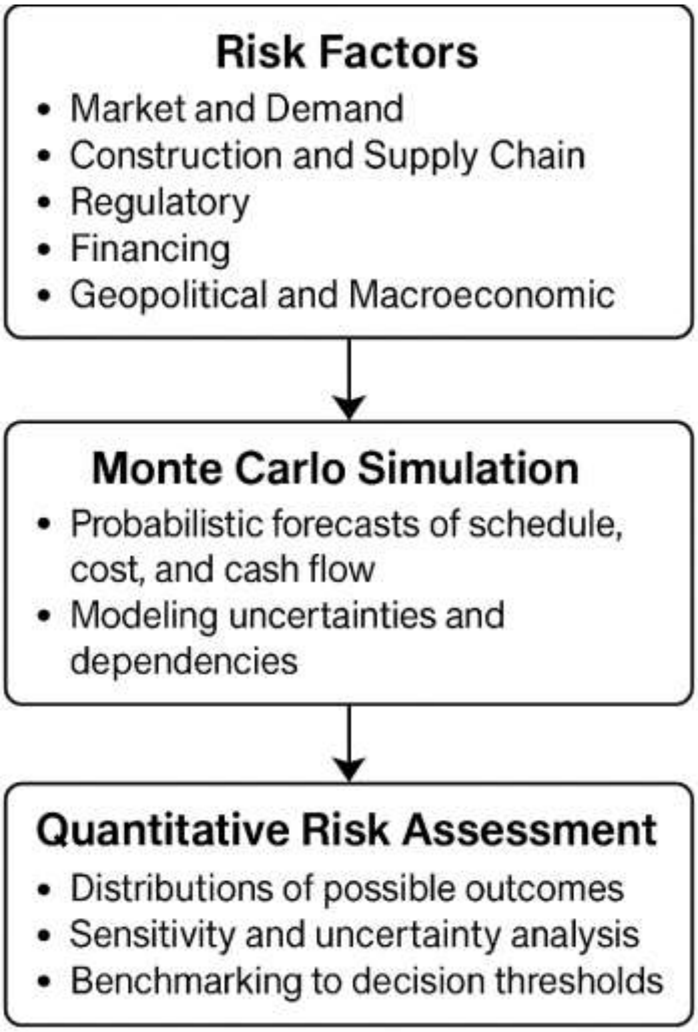
INTRODUCTION

Mega real estate projects are capital-intensive, multi-stakeholder property developments that typically span multiple asset classes (e.g., mixed-use commercial districts, new townships, large housing estates, megatall towers, and integrated resort-retail complexes) and budgets in the billions of dollars, executed over long horizons and embedded within complex institutional and financial ecosystems. In the megaprojects literature, such undertakings are widely characterized by high complexity, long supply chains, and intense interfaces with public policy, land-use regulation, and urban infrastructure features that amplify exposure to schedule slippage, cost growth, demand variability, and financing risks (Cantarelli et al., 2010; Flyvbjerg, 2014). International evidence continually documents systematic challenges managing outcomes at this scale cost overruns, benefit shortfalls, and delivery uncertainty have been reported across regions and sectors, including urban development, energy, and transport (Ansar et al., 2014; Love et al., 2016; Odeck, 2004). Within property markets specifically, the multi-cycle nature of real estate demand, exogenous macro shocks, and jurisdiction-specific planning and entitlement processes add layers of uncertainty to absorption, rent trajectories, cap rates, and exit timing factors that materially affect feasibility and funding structures (Capozza & Li, 2002; Gimpelevich, 2011; Loizou & French, 2012). Quantitative risk assessment (QRA) for these projects therefore begins by formalizing "risk" as the distribution of possible outcomes for key objectives (time, cost, revenue, and value) rather than point predictions, and by modeling how underlying drivers construction productivity, input prices, credit conditions, lease-up velocity propagate through financial and delivery models. This introduction positions Monte Carlo simulation (MCS) as a core engine for such QRA, because it converts uncertainties and dependencies into probabilistic forecasts of schedule, cost, and cash-flow results that decision-makers can interrogate with consistent metrics across international contexts (Touran, 1996; Touran & Wiser, 1992). Empirical foundations for these features have been documented extensively across countries and sectors, underscoring their global salience (Ansar et al., 2014; Jahid, 2022).

Monte Carlo simulation has a well-established theoretical lineage. Its statistical roots trace back to the Monte Carlo method introduced as repeated random sampling for solving numerical problems, with practical refinements that improve the efficiency and stability of simulation experiments. Latin hypercube sampling (LHS) is especially influential for project risk work because it stratifies the cumulative distribution of each input and samples in a way that achieves better space-filling with fewer trials (McKay et al., 1979), while rank-correlation induction methods allow analysts to impose realistic dependencies among inputs without requiring parametric joint distributions (Iman & Conover, 1982; Arifur & Noor, 2022). Sensitivity analysis techniques complement sampling: variance-based methods such as Sobol' indices decompose output variance to attribute influence to individual drivers and their interactions (Hasan & Uddin, 2022; Saltelli et al., 2008; Sobol', 2001), and broader simulation design guidance clarifies uncertainty propagation in complex systems and the handling of epistemic and aleatory components (Helton & Davis, 2003; Kleijnen, 1997). For risk measurement on financial outputs, coherent risk measures and tail-focused metrics advance beyond variance or standard deviation: Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) formalize loss quantiles and tail expectations, enabling governance-ready statements about potential shortfalls under uncertainty (Artzner et al., 1999; Rahaman, 2022). In real estate and construction settings, these elements cohere into a simulation framework that expresses time-cost-revenue uncertainty through distributions, preserves dependence structures among drivers (e.g., commodity prices and durations), and returns probabilistic outputs that can be benchmarked to decision thresholds (e.g., P50/P80 cost, schedule confidence, debt service coverage quantiles). These methodological building blocks collectively enable transparent, auditable QRA for mega real estate developments in varied international settings with heterogeneous data quality.

In the built-environment literature, identification and structuring of risk drivers is a prerequisite to credible quantification. Studies across multiple jurisdictions have established recurring categories market and demand risk, construction productivity and supply chain risk, regulatory and entitlement risk, procurement and contracting risk, financing and interest-rate risk, geopolitical and macroeconomic risk and have developed structured processes to elicit, assess, and allocate them (Caño & de la Cruz, 2002; Rahaman & Ashraf, 2022). For mega real estate efforts often involving phased delivery, complex public approvals, and layered capital stacks these categories are interactively coupled: entitlement timing affects land holding costs and cash-flow timing; contractor delivery strategies influence escalation exposure; leasing velocity interacts with draw schedules and covenant compliance. Simulation-based approaches naturally integrate such couplings: distributions are assigned to durations, costs, and market parameters; correlations are modeled when common drivers (inflation, supply bottlenecks) create co-movement; and mathematical transformations map input uncertainty into objective functions (e.g., total development cost, net present value). Within construction risk research, Monte Carlo studies highlight the importance of capturing interdependence among cost items and durations; failing to account for correlation understates tail risk and biases contingency (Barañano et al., 2020). Schedule-oriented risk analysis widely used to transform activity-level three-point estimates and risk registers into probabilistic milestone dates has matured into consistent practice guidance, with particular emphasis on model structure, uncertainty elicitation, and the distinction between inherent variability and discrete risk events (Islam, 2022). These structured processes enable analyses that connect risk identification to quantification in a manner that is reproducible across different national contexts and procurement regimes, which is essential for large cross-border capital allocations.

Figure 1: Monte Carlo Simulation Framework for Quantitative Risk Assessment



Real-estate-specific scholarship shows how simulation enriches valuation and feasibility under uncertainty. Within discounted cash-flow (DCF) models for income-producing property and development appraisals, parameter uncertainty appears in rents, vacancy, lease-up pace, operating expenses, cap-ex, exit yields, and residual values. Monte Carlo simulation treats these not as single-valued assumptions but as distributions derived from market data, expert judgment, or hybrid models, thereby producing distributions for value, internal rate of return, and debt service metrics (Gimpelevich, 2011; Hasan et al., 2022). When combined with tail-risk metrics (VaR/CVaR), the framework supports risk-informed capital structuring and covenant setting for lenders and

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investors (Redwanul & Zafor, 2022; Rockafellar & Uryasev, 2002). Studies modeling real-estate losses via Monte Carlo further illustrate how parametric assumptions for price dynamics translate into solvency capital requirements for institutions holding property risk, which is directly relevant to large, phased developments with staged funding (Barañano et al., 2020; Rezaul & Mesbaul, 2022). In parallel, the real options literature formalizes development timing and phasing decisions under uncertainty option value embedded in land banking, staged construction, or deferral interacts with Monte Carlo-generated distributions of market states and costs, providing a structured lens on irreversible commitments (Grenadier, 1996; Titman, 1985). For mega real estate projects where lease-up timing, absorption, and exit values are central this blend of simulation and option reasoning is internationally significant because it frames how different legal, financial, and market contexts alter risk-return profiles even when designs appear similar on paper. The literature thus supports probabilistic feasibility that speaks to both private capital allocation and public-interest scrutiny for large urban transformations.

On the delivery side, Monte Carlo Simulation (MCS) serves as a powerful framework for transforming schedule- and cost-risk data into integrated, decision-supporting outputs that offer clarity and rigor for project governance. In schedule risk analysis, activity durations are typically expressed as probability distributions often through three-point estimates or empirically calibrated models that capture the uncertainty inherent in project planning, while logical networks transmit these uncertainties to milestone forecasts, with dependencies or correlations represented through shared risk drivers or explicit assumption structures. The result is a set of confidence intervals around completion dates and buffers, providing stakeholders with probabilistic insights rather than deterministic deadlines (Hulett, 2009; Hasan, 2022). Parallel to this, cost-risk analysis employs stochastic sampling of uncertain parameters such as quantity-rate variability, inflationary escalation, and discrete risk events, yielding full distributions of anticipated development costs and enabling the allocation of contingency funds in alignment with confidence levels commonly set at benchmarks like P50 or P80 (Tarek, 2022; Touran, 1996). For mega-scale developments, where intricate procurement processes, extended material lead times, and volatile supply conditions prevail, faithfully modeling the interdependence of risk factors is essential, since shocks in labor markets, price inflation, and logistics frequently move in tandem and, if overlooked, can result in serious underestimations of variance and tail exposure. Methodological guidance underscores the necessity of rigorous input elicitation, transparent assumption documentation, and the application of global sensitivity analysis to spotlight the dominant drivers of schedule slippage and cost overrun, thereby directing managerial focus toward the risks with the greatest leverage for mitigation (Kamrul & Omar, 2022; Saltelli et al., 2008). Ultimately, such probabilistic outputs allow for seamless alignment with stakeholder-defined thresholds, whether they be lender-imposed covenants, sponsor-specific return requirements, or government-mandated service delivery targets, and they integrate smoothly into stage-gate governance structures that demand quantified confidence levels before approving advancement into subsequent project phases (Zhang & Zou, 2007; Zou et al., 2007).

Because mega real estate projects often intersect with public interests through mechanisms such as land assembly, infrastructure integration, government incentives, or public–private partnership frameworks, the international governance perspective on risk quantification has become a focal point of scholarly discourse. Empirical cross-country studies consistently reveal patterns of cost escalation and schedule slippage that undermine fiscal capacity and erode public trust, thus strengthening the case for ex-ante probabilistic appraisal methods and transparent disclosure of uncertainty throughout the project lifecycle (Kamrul & Tarek, 2022; Odeck, 2004). Governance literature on major engineering and urban development ventures underscores that decision-making under uncertainty, effective alignment of stakeholders, and robust institutional arrangements are critical factors influencing how risks are allocated, managed, and incentivized (Miller & Lessard, 2000; Mubashir & Abdul, 2022). Within this context, Monte Carlo Simulation-based Quantitative Risk Analysis (QRA) emerges as a shared analytical framework that allows sponsors, lenders, and public authorities to compare alternative procurement models, project phasing strategies, and entitlement pathways using standardized probability expressions for time, cost, and value outcomes. Particularly in property markets characterized by divergent transparency standards and inconsistent data availability across jurisdictions, simulation offers an invaluable bridge by systematically embedding expert judgment where empirical evidence is sparse, while simultaneously maintaining auditable protocols that allow updating as more reliable information becomes available (Caño & Cruz, 2002; Muhammad &

Kamrul, 2022). On an international scale, the adoption of such probabilistic tools reduces asymmetries in information distribution among diverse stakeholders, thereby facilitating structured negotiations over contingency reserves, performance guarantees, and contractual buffers. By anchoring these discussions in distributional evidence rather than deterministic projections, MCS-based QRA not only enhances the credibility of risk assessments but also strengthens the governance fabric of mega real estate undertakings, making the decision environment more transparent, accountable, and resilient to uncertainty.
The objective of this literature review is to produce a rigorous, practice-grounded synthesis of how Monte Carlo simulation is designed, implemented, and interpreted for quantitative risk assessment in mega real estate projects, culminating in a transparent set of standards that researchers and practitioners can apply consistently. First, it aims to delimit the domain by specifying what qualifies as a "mega" real estate project and by articulating the distinctive sources of uncertainty that arise from multi-phase delivery, layered capital structures, entitlement processes, and market absorption dynamics. Second, it seeks to organize a comprehensive risk taxonomy for such developments covering construction and productivity risk, supply-chain and escalation risk, land acquisition and permitting risk, financing and interest-rate risk, foreign-exchange and inflation exposure, demand and leasing risk, ESG and regulatory risk, and stakeholder/social-license risk so that subsequent modeling choices are anchored in a coherent structure. Third, it aims to document input-distribution modeling and parameterization practices, contrasting data-driven fitting with structured expert elicitation, and assessing how analysts represent time-varying processes such as inflation, credit spreads, and leasing velocity. Fourth, it evaluates how dependence is handled across inputs, including linear and rank correlation, common-cause risk drivers, and non-linear or tail-dependent structures, and it examines the quantitative consequences of alternative dependence assumptions for cost, schedule, and value outputs. Fifth, it appraises sampling strategies and computational efficiency including crude Monte Carlo, Latin hypercube, and quasi-Monte Carlo approaches with attention to convergence diagnostics, run-size justification, and reproducibility. Sixth, it assesses sensitivity and uncertainty analysis methods, prioritizing global techniques that attribute variance to inputs and interactions, and it clarifies how sensitivity results are used to target mitigation and refine data collection. Seventh, it examines output metrics and validation practices, including cost and schedule S-curves, percentile-based contingencies (e.g., P50/P80), tail-risk measures for cash-flow and financing outcomes, and empirical benchmarking through back-testing or hindcasting. Eighth, it compares integrated cost-schedule-finance modeling architectures that link risk registers, networks, escalation processes, and cash-flow models, and it codifies a reporting checklist that specifies minimum disclosures on inputs, dependence, sampling, sensitivity, convergence, validation, and governance-ready presentation. Collectively, these objectives ensure that the review not only maps the state of knowledge but also establishes a replicable analytic frame for evaluating, contrasting, and improving Monte Carlo–based risk assessments in mega real estate contexts across jurisdictions and delivery models.

LITERATURE REVIEW

The literature on quantitative risk assessment for mega real estate projects converges on a central premise: outcomes in time, cost, and value are best understood as probability distributions shaped by multiple, interacting sources of uncertainty rather than as single-point forecasts. Within this premise, scholarship spans several interconnected streams that collectively form the foundation for Monte Carlo–based appraisal. One stream characterizes megaproject specificity large scale, multi-phase delivery, complex approvals, and layered capital stacks showing how construction productivity, procurement structure, price escalation, and supply-chain dynamics intersect with market absorption, leasing velocity, and macro-financial conditions to shape project risk. A second stream addresses input modeling, documenting how analysts translate risk registers and empirical evidence into distributions for durations, quantities, unit rates, escalation processes, rents, operating costs, exit yields, and residual values, and how they calibrate parameters using historical data, structured expert judgment, or hybrid approaches. A third stream examines dependence, highlighting linear and rank correlations, common-cause risk drivers, and non-linear or tail-dependent structures that couple cost items, schedule paths, and financial variables, as well as the material impact of alternative dependence assumptions on variance and tail behavior. A fourth stream focuses on sampling and computational efficiency, comparing crude Monte Carlo with Latin hypercube and quasi–Monte Carlo methods, and establishing standards for convergence diagnostics, run-size justification, and reproducibility. A fifth stream details sensitivity and uncertainty analysis, advancing techniques that attribute output variance to inputs and interactions, thereby prioritizing mitigation levers and data-collection needs. A sixth stream integrates schedule and cost modeling with cash-flow and financing analytics, linking activity networks, escalation mechanisms, and leasing/price states to produce S-curves, percentile-based contingencies, and distributional metrics relevant to credit covenants and investment thresholds. A seventh stream evaluates validation and verification practices through back-testing, hindcasting, and calibration checks, situating model credibility alongside transparency of assumptions and documentation. Together, these streams provide a coherent scaffold for organizing the subsequent review: mapping how Monte Carlo simulation is operationalized, how modeling choices alter risk estimates, and how results are communicated for governance and decision-making in large, internationally significant real estate developments.

Megaproject Characteristics in Real Estate

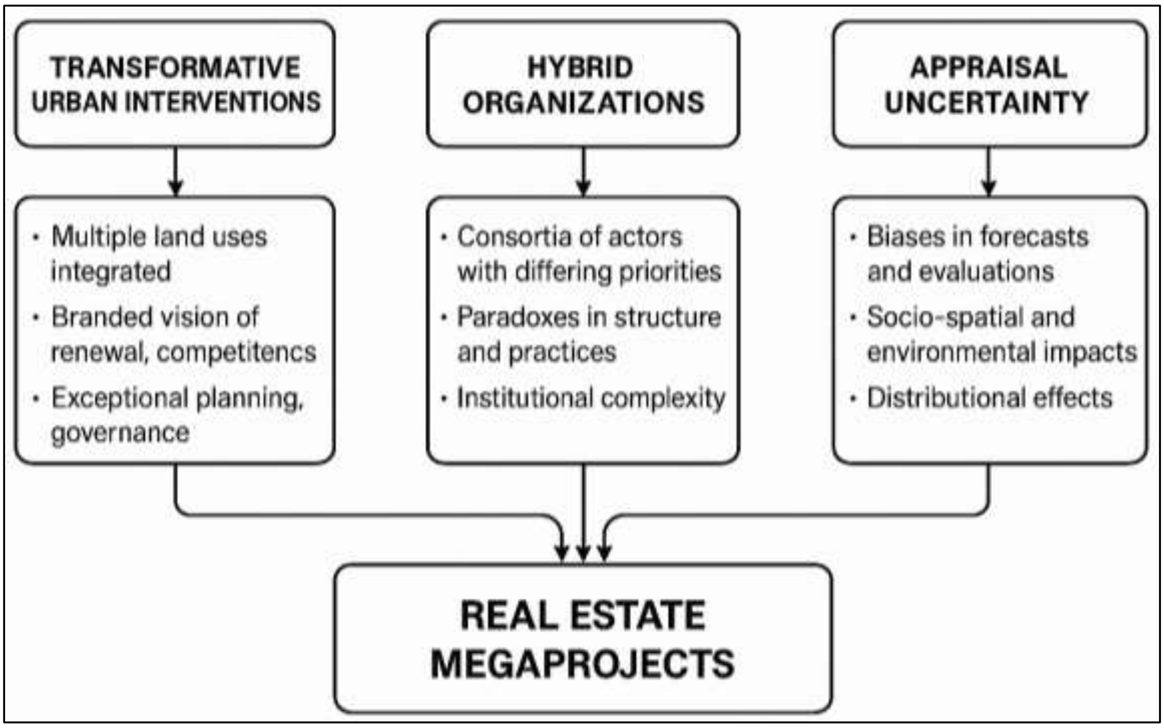
Real estate megaprojects (REMPs) are typically envisioned as transformative, large-scale urban interventions that integrate multiple land uses such as residential, commercial, retail, and leisure functions alongside significant public-realm investment, all unified under a branded vision of urban renewal and competitiveness. These undertakings are frequently advanced through exceptional planning mechanisms and innovative governance models, justified by narratives of global positioning and aspirations to elevate city status to "world-class." Within European and North American scholarship, large-scale urban projects have been interpreted as emblematic of a neoliberal "new urban policy," characterized by special purpose vehicles, accelerated approval processes, and public–private partnerships designed to redistribute risks while enabling rapid and expansive reconfiguration of urban landscapes (Reduanul & Shoeb, 2022; Swyngedouw et al., 2002). The contemporary manifestation of megaprojects diverges from the image of singular monumental schemes, instead emerging as diversified portfolios of parcels and functional components that are engineered to attract substantial flows of capital investment while projecting public benefits and catalytic spillover effects across metropolitan economies (Orueta & Fainstein, 2008; Kumar & Zobayer, 2022). Comparative inquiries into emblematic cases such as Atlantic Yards in New York, Stratford City in London, and Amsterdam's Zuidas/South Axis consistently reveal a convergence toward private-sector dominance in leadership, branding, and market-driven delivery strategies, albeit moderated in some contexts by locally negotiated inclusion mandates such as affordable housing obligations and commitments to public amenities (Fainstein, 2008; Sadia & Shaiful, 2022). Further examination of Toronto's waterfront redevelopment underscores how flexibility in phasing, the deployment of mixed-use programs, and appeals to "design excellence" are strategically mobilized to legitimate ambitious transformations of land–water interfaces, even as project rationales evolve in response to shifting political cycles and fluctuating market conditions, highlighting the dynamic and adaptive nature of governance frameworks that underpin these monumental ventures (Lehrer & Laidley, 2008; Noor & Momena, 2022).

The organizational DNA of real estate megaprojects (REMPs) is fundamentally hybrid, marked by paradoxes that permeate their structures and practices, since delivery is rarely entrusted to a single actor but instead depends on elaborate consortia of developers, financiers, municipal authorities, and state agencies whose priorities, accountability frameworks, and risk tolerances diverge significantly. Ethnographic and organizational analyses highlight that public–private megaprojects are intrinsically shaped by conflicting logics, role ambiguities, and "both–and" tensions such as balancing control with flexibility or reconciling pressures for innovation with the need for standardization that influence decision-making and day-to-day operations (Marrewijk et al., 2008). In contexts where projects must unfold under volatile market conditions, promoters attempt to tame uncertainty through phased delivery strategies, option-like land release mechanisms, and modular contractual structures; however, this pursuit of simplification often comes at the cost of robustness, obscuring critical interdependencies and introducing fragility at key interfaces that later manifest as vulnerabilities (Giezen, 2012). When REMPs extend across national boundaries or involve international partnerships, yet another layer of complexity emerges through institutional diversity, as variations in planning law, property rights regimes, land assembly procedures, and financial conventions introduce structural frictions that complicate dispute resolution, renegotiation, and the long-term coordination of stakeholders (Mahalingam & Levitt, 2007). These organizational attributes hybridity in composition, paradox in operational logics, and multiplicity in institutional embedding are not

Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421

marginal complications but essential features of REMPs that fundamentally condition how risks are distributed, how information is shared, and how adaptive adjustments can be pursued as political coalitions shift and markets evolve, making them core determinants of both project resilience and vulnerability over extended time horizons.

Figure 2: Core Characteristics of Real Estate Megaprojects



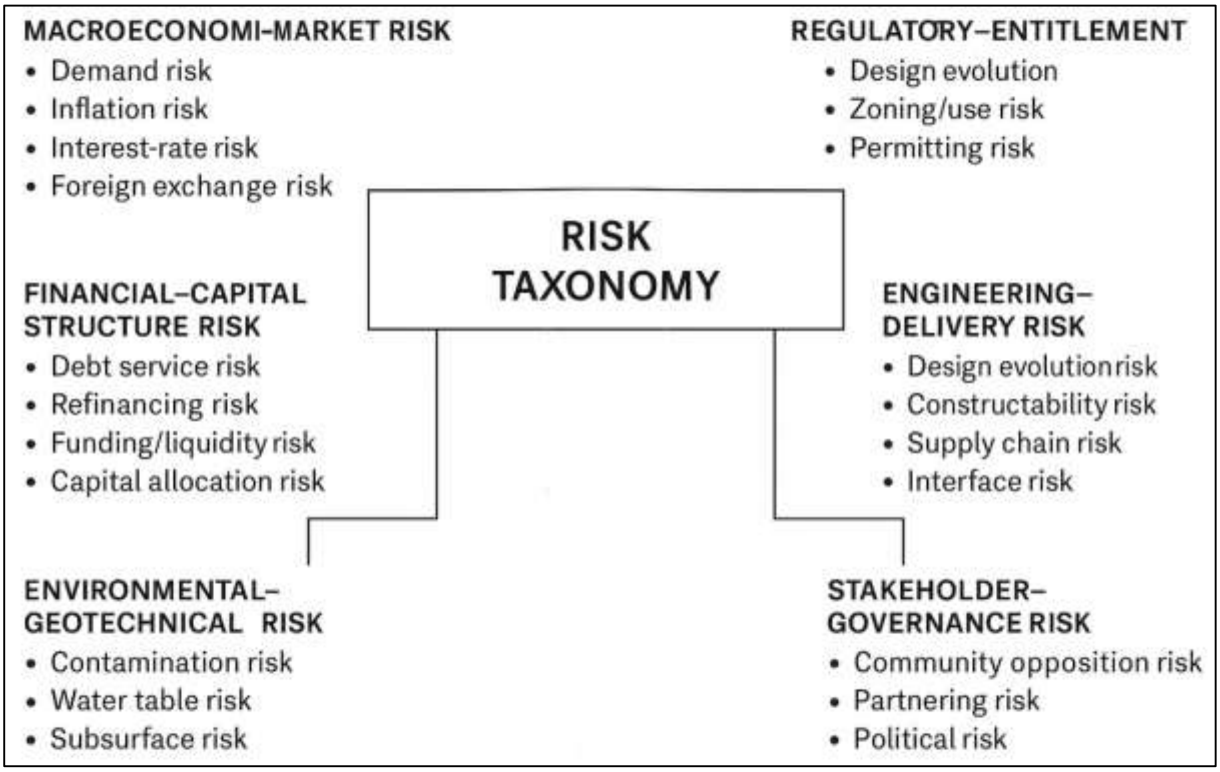
A defining hallmark of real estate megaprojects (REMPs) lies in their persistent appraisal uncertainty combined with the distributional externalities they generate, since decades of infrastructure research have consistently shown that ex-ante forecasts are systematically biased capital expenditures trend higher than expected while demand projections and benefit realization habitually fall short an asymmetry of outcomes that directly affects the staged land value capture, absorption rates, and amenity premiums upon which mixed-use urban ventures rely for financial sustainability (Flyvbjerg et al., 2004). Critical reviews of appraisal methodologies reveal that such distortions are rarely accidental but stem from a convergence of biases embedded at multiple levels of the evaluation process, including the initial framing of problems, the specification and exclusion of project options, the structural assumptions of forecasting models, the selection of parameters, and the prevailing valuation conventions, all of which predispose decision frameworks toward approvals while systematically downplaying the low-probability yet high-impact risks inherent in protracted urban schemes (Mackie & Preston, 1998). Importantly, these projects not only carry financial uncertainty but also impose significant socio-spatial and environmental consequences, as redevelopment interventions often displace communities, reconfigure existing social fabrics, and disrupt ecological systems, thereby redistributing risks and benefits across present residents, future users, local workers, and natural habitats in ways that provoke contestation and amplify governance challenges (Gellert & Lynch, 2003). Together, the intertwined phenomena of forecast error, appraisal bias, and displacement are not peripheral concerns but constitutive elements of REMPs that demand explicit recognition within quantitative risk assessment frameworks, since ignoring them inflates confidence in base-case scenarios. By calibrating Monte Carlo simulations with empirically grounded distributions for costs, schedules, absorption dynamics, and price trajectories, analysts can more faithfully reflect the uncertainty structures documented in both theory and practice, thereby creating risk models that are not only technically robust but also socially attuned to the broader redistributional effects that accompany large-scale urban transformation.

Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421

Risk Taxonomy and Sources of Uncertainty in Mega Real Estate Projects

A risk taxonomy for mega real estate projects (REMPs) must begin by distinguishing risk from uncertainty and by recognizing how scale multiplies the number and interaction of risk drivers. Within construction and development, industry evidence shows practitioners repeatedly grapple with clusters of contractual, financial, environmental, and market exposures, yet often rely on fragmented procedures (Akintoye & MacLeod, 1997). A taxonomy is not merely a list; it organizes hazards by origins, propagation paths, and couplings so analysis techniques can be aligned to the nature of the unknowns. Building on this premise, the project-management literature urges a shift from a narrow "risk register" mindset to broader uncertainty management, in which variability, ambiguity, and lack of knowledge are handled explicitly across the life cycle (Ward & Chapman, 2003). This reframing is critical for REMPs because feasibility rests on assumptions about absorption rates, debt costs, productivity, and permissions that evolve over long horizons. Under high novelty and information gaps, managerial strategies must match the type of uncertainty ranging from well-characterized variation to deep ambiguity rather than defaulting to deterministic plans (Pich et al., 2002). Equally important is the overlay of project complexity: the number of differentiated elements (e.g., towers, parcels, financing tranches) and the density of interdependencies among them (Baccarini, 1996). In REMPs, complexity amplifies exposure and the pathways through which disruptions cascade, turning minor delays in site access or utilities into budgetary and timing shocks. Accordingly, the proposed taxonomy groups risks into macroeconomic–market, financial–capital structure, regulatory–entitlement, engineering–delivery, environmental–geotechnical, and stakeholder–governance families, while tagging interfaces where interactions are most consequential. This structure provides the backbone for the paper's Monte Carlo–oriented synthesis, enabling consistent parameterization of distributions and dependencies when modeling adverse states. It also differentiates exogenous shocks from endogenous process risks to avoid conflating exposure with controllability and to target mitigation where it is most effective.

Figure 3: Risk Taxonomy and Sources of Uncertainty in Mega Real Estate Projects



At the operational core of REMPs, delivery risks arise from design development, procurement strategy, site logistics, and interface management across interdependent packages. Complexity elevates the likelihood that small coordination errors propagate into costly rework and schedule slippage, because multiple trades, temporary works, and supply nodes must be synchronized under

uncertain conditions (Gidado, 1996). To make the taxonomy actionable, the engineering–delivery family is decomposed into design evolution risk (scope growth and late design freeze), constructability and productivity risk (learning curves, labor availability, weather), supply chain risk (lead times, single-source components), and interface risk (clashes among structural, MEP, façade, and public-realm systems). Each subfamily contains hazards that are partially knowable ex ante yet difficult to quantify without probabilistic tools; for instance, productivity drift often exhibits autocorrelation and path dependence, which matters for Monte Carlo parameterization. Stakeholder–governance risks cut across these categories. Opposition by affected communities, shifts in municipal priorities, or contested land assembly can re-order phasing or increase compliance obligations, reconfiguring the project's feasible set even when engineering plans remain intact (Olander & Landin, 2005). Because REMPs frequently urbanize or renew large districts, the risk taxonomy must therefore encode not only who has power and interest but also how those attributes change over time as benefits and burdens become salient. Finally, domain-specific risk libraries are needed for certain asset types embedded in REMPs, such as underground transit connectors or podium-anchored retail. Underground works introduce distinctive uncertainty drivers geology, groundwater, and settlement that are difficult to observe before excavation and whose tail events can compromise adjacent assets, utilities, and reputation (Ghosh & Jintanapakanont, 2004).
Beyond construction, REMPs carry material exposure in market, finance, and regulatory domains, where risk allocation and incentives shape behavior. In mixed-use precincts, demand risk reflects volatility in take-up rates, rental growth, and buyer financing, while capital-structure risk captures debt service sensitivity to interest-rate shifts and covenant constraints; both interact with delivery timing and pre-sales strategies. Public–private interface risk is especially salient where enabling infrastructure, air rights, or land contributions are governed by concessions or development agreements. Evidence from UK PPP/PFI schemes shows that optimal allocation varies by risk class construction and availability risks can be transferred subject to performance regimes, whereas macroeconomic and political risks should be retained or shared with the public sponsor (Bing et al., 2005). Delphi studies in China suggest that expropriation, extraordinary policy change, and force majeure remain public risks, while revenue, demand, and operation risks are more efficiently borne by private partners controlling asset delivery and life-cycle performance (Ke et al., 2010). Where REMPs involve joint ventures with host-market partners, the taxonomy must extend to partner selection, governance capability, and cultural–legal fit, because misalignment here magnifies contractual and operational hazards across the portfolio (Shen et al., 2001). Regulatory–entitlement risks planning approvals, zoning compliance, environmental permitting, and development charges are a separate family to prevent their systemic effects from being buried within project controls. These permissions define the option to build, and their timing and conditions dominate stochastic cash-flow structure by gating land drawdowns and debt availability. Accordingly, the taxonomy tags regulatory milestones as risk nodes that interact with market cycles and financing windows, enabling analysts to map how delays change option value and risk-adjusted returns. Taken together, the taxonomy's macro-market, finance, regulatory, engineering, environmental, and stakeholder families provide a common language that supports scenario design and Monte Carlo modeling without losing granularity of REMPs.

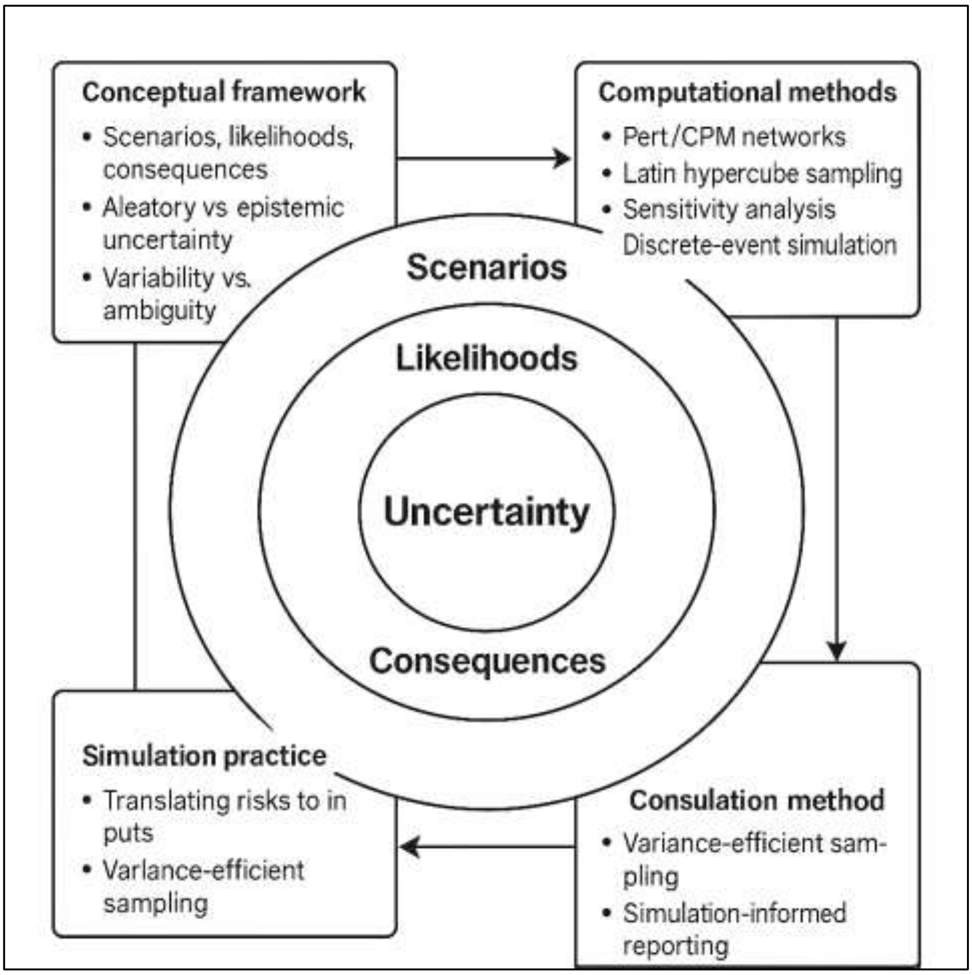
Monte Carlo Simulation for Quantitative Risk Assessment

A coherent foundation for Monte Carlo–based risk assessment begins with a precise conceptualization of "risk," which in quantitative terms can be represented as a triplet of scenarios, likelihoods, and consequences, thereby offering both a linguistic and mathematical framework for structuring uncertainty in large and complex undertakings (Kaplan & Garrick, 1981). Within engineering-oriented risk scholarship, this framing has been elaborated through distinctions among analytic modes, as deterministic methods treat uncertainty through fixed assumptions while probabilistic methods embed variability directly into model structures, requiring careful calibration of inputs to ensure alignment with data quality and decision context (Paté-Cornell, 1996). A further conceptual refinement separates aleatory variability, which reflects the irreducible randomness of natural or market-driven processes, from epistemic uncertainty, which arises from gaps in knowledge that can be reduced through additional data collection or improved modeling; the way analysts demarcate this boundary has profound implications for simulation design, the interpretation of outputs, and the communication of results to decision-makers (Der Kiureghian & Ditlevsen, 2009). Another critical distinction lies between propagating variability, which probability theory is well suited to quantify, and representing ignorance, which is better captured by intervals and other non-probabilistic approaches, since conflating the two sources of uncertainty risks generating distributions that falsely convey precision in project outcomes (Ferson & Ginzburg, 1996). Taken together, these theoretical insights establish the conceptual substrate upon which Monte Carlo methods operate in the context of real estate megaprojects (REMPs), where the simulation serves not merely as a computational technique but as the quantitative medium through which both reducible and irreducible uncertainties are integrated into the interlinked cost, schedule, and financing system. By embedding this layered understanding of uncertainty into simulation practice, REMPs can be appraised in a manner that is both technically rigorous and epistemologically transparent, thus avoiding the pitfalls of overconfidence and enabling more defensible decision-making under deep uncertainty.

The computational lineage of project simulation underscores why Monte Carlo remains central to risk assessment, since early applications to PERT/CPM networks demonstrated its capacity to relax restrictive assumptions about path independence and fixed structures, thereby generating empirically grounded distributions of completion times and criticality indices that continue to anchor contemporary schedule-risk analysis. Subsequent methodological refinements enhanced efficiency and reliability, most notably through Latin hypercube sampling (LHS), which achieves asymptotic variance reduction compared to simple random sampling while permitting practical constructions under dependence an essential capability for high-dimensional project models where correlated drivers such as cost escalation, labor productivity, and absorption rates interact in complex ways. Given that real estate megaprojects (REMPs) often involve numerous candidate inputs, global sensitivity screening techniques such as the Morris method offer cost-effective strategies for identifying the most influential factors and their interactions before investing in computationally intensive full variance-based sensitivity studies (Morris, 1991). Within construction engineering, complementary advances in discrete-event simulation have also proven indispensable, providing dynamic representations of queues, resource conflicts, and learning curves; beyond productivity forecasting, these models establish the scaffolding that links operational process representations to probabilistic risk assessment, enabling integrated experiments across alternative designs, sequencing strategies, and control mechanisms (AbouRizk, 2010). Collectively, these computational advances underpin standard practice in REMPs by justifying a disciplined methodology: first, translating qualitative risk registers into parameterized input distributions; second, preserving empirically observed or elicited dependence structures; third, employing variance-efficient sampling strategies with defensible convergence diagnostics and appropriate run sizes; and fourth, allocating modeling effort strategically through principled screening procedures that prioritize high-leverage uncertainties. This layered computational toolkit ensures that Monte Carlo simulation functions not merely as a numerical exercise but as a robust, theory-informed instrument for capturing the intricacies of risk in mega-scale urban development.

Methodological advances in contingency estimation, project control, and transparent reporting round out the foundation of Monte Carlo–based risk assessment by operationalizing simulation outputs into actionable governance tools. For cost risk, empirical research demonstrates that substituting arbitrary percentage add-ons with simulation-derived contingencies yields allowances that are both defensible and explicitly tied to recognized uncertainties; in practice, this involves parameterizing distributions for quantities, unit rates, and escalation factors to construct a probabilistic baseline, then reporting contingency levels such as P50 or P80 with traceability back to their underlying drivers (Mak & Picken, 2000). On the schedule-control side, contemporary performance frameworks separate time-based measures from cost signals and facilitate probabilistic forecasting of completion trajectories, enabling earned-value metrics to be integrated with Monte Carlo analysis for stress-testing recovery strategies and assessing the credibility of interim predictions (Khamooshi & Golafshani, 2014). When systematically implemented, these practices establish a robust feedback loop between modeling and governance: S-curves for cost and time provide a visual anchor for communicating both central tendencies and tail risks; sensitivity and screening analyses highlight the risk factors and interactions most deserving of mitigation effort; and transparent disclosure of modeling assumptions including input distributions, dependence specifications, sampling strategies, and validation checks supports comparability, reproducibility, and informed scrutiny across projects and jurisdictions. For real estate megaprojects (REMPs), where financing thresholds, phasing strategies, and entitlement negotiations intersect in non-linear ways, such simulation-informed methodologies are essential for moving beyond deterministic narratives to probabilistic evidence about both likelihoods and consequences. By clarifying which uncertainties are reducible and which reflect inherent variability, this approach enables stakeholders to align expectations, allocate responsibilities, and manage risks in ways that enhance credibility, accountability, and resilience in the delivery of large-scale urban transformation.

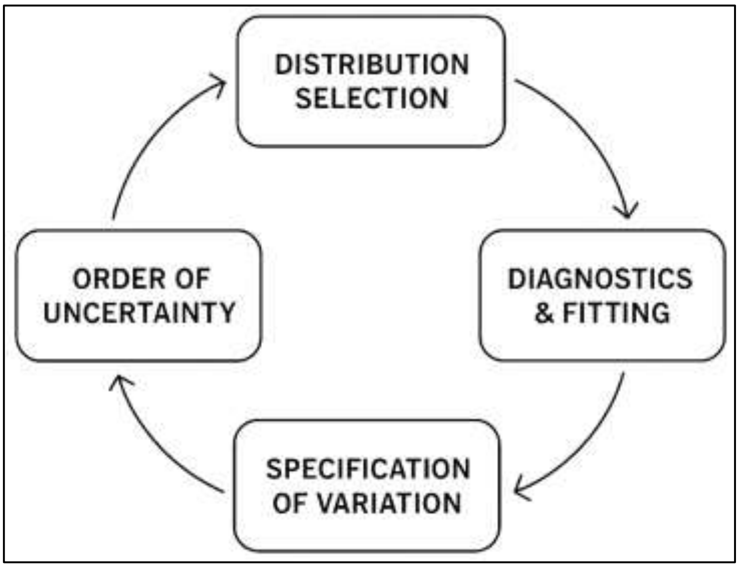
Figure 4: Foundations of Monte Carlo Simulation for Quantitative Risk Assessment



Input Distribution Modeling and Parameterization

A defensible Monte Carlo model for mega real estate projects (REMPs) begins with explicit choices about the probability distributions that encode uncertainty in quantities, unit rates, durations, escalation, leasing velocity, price/yield movements, and other drivers. Selection should be guided by empirical diagnostics rather than convenience: candidate families are screened with goodness-of-fit tests and penalized-likelihood criteria, recognizing that REMPs often exhibit skewness, kurtosis, and multimodality arising from asynchronous phasing and market cycles. In practice, light-tailed forms (e.g., Normal) risk understating variance for cost growth or absorption uncertainty, whereas skewed forms (e.g., Lognormal) better capture multiplicative compounding in prices and productivity (Limpert et al., 2001). Distributional tail behavior warrants special care: heavy-tailed phenomena escalation shocks, rare entitlement surprises, joint supply disruptions require diagnostics that can separate genuine power-law or subexponential behavior from lognormal or stretched-exponential alternatives (Clauset et al., 2009). Formal tests complement visual tools: the Kolmogorov–Smirnov statistic offers a nonparametric, omnibus check on fit for continuous distributions (Massey, 1951), while the Anderson–Darling test increases sensitivity in the tails, which is often where contingencies and covenant risks reside. Model parsimony is weighed with information criteria: the Akaike Information Criterion (AIC) trades fit for complexity to approximate out-of-sample performance (Akaike, 1974), and the Bayesian Information Criterion (BIC) penalizes additional parameters more heavily, favoring simpler forms when data are limited (Schwarz, 1978). Together, these diagnostics support a workflow in which multiple candidate distributions are entertained, rejected, or retained with explicit evidence, ensuring that REMPs' probabilistic inputs reflect observed asymmetries and extremes rather than defaulting to easy-to-sample but potentially misleading forms. Parameterization then translates evidence into numbers for the chosen families and quantifies uncertainty about those numbers. With thin or noisy samples common in site-specific productivity studies or one-off entitlement timelines point estimates can mask parameter risk; nonparametric resampling offers a practical remedy by generating empirical distributions for the parameters themselves (Efron, 1979). Where model uncertainty is material, analysts should avoid "winner-take-all" selection and instead combine models; Bayesian Model Averaging (BMA) provides a formal method for weighting alternatives by posterior support so that predictive distributions reflect both within-model and between-model uncertainty (Hoeting et al., 1999). Within a Bayesian frame, diagnostics like the Deviance Information Criterion (DIC) help balance fit and complexity while enabling hierarchical structures that borrow strength across related packages, parcels, or sub-markets useful when estimating leasing or pricing inputs across multiple phases (Spiegelhalter et al., 2002) Parameter sources extend beyond data: expert judgment often supplies prior shapes, bounds, or elicited quantiles when historic evidence is sparse or non-stationary. Calibrating and weighting experts is therefore not an afterthought but part of parameterization; structured performance-based schemes yield pooled distributions that score experts on statistical accuracy and informativeness before combining them improving the fidelity of inputs used in simulation (Cooke & Goossens, 2008). By propagating both parameter and model uncertainty through Monte Carlo trials, analysts avoid overstated certainty in S-curves and tail metrics, producing contingencies and risk statements that better survive back-testing.

Figure 5: Cycle of Monte Carlo Simulation



Furthermore, parameterization must respect time variation, dependence, and measurement scale so that distributions map cleanly to the cash-flow and schedule engines of REMPs. Many input processes evolve over time rather than remaining static: escalation is episodic, lease-up is state-dependent, and entitlement steps arrive in lumpy, gated increments. Practical modeling translates these realities into parameter paths e.g., regime-aware volatility bands for escalation, phase-specific lease-up priors linked to macro signals, or hazard-style models for approvals so that a single "distribution choice" becomes a sequence of parameterized states aligned to phasing. Scale and transformation also matter: sampling rental growth rates on an additive scale can misrepresent compounding; working on log scales can restore additivity in shocks while preserving positivity on the original scale. When distributions are elicited from stakeholders as three-point estimates or quantiles, transparent mapping rules such as solving for parameters that reproduce elicited quantiles under the chosen family maintain traceability from workshops to simulation code. Heterogeneity across parcels and contracts is handled with hierarchical pooling, which tempers overfitting to small

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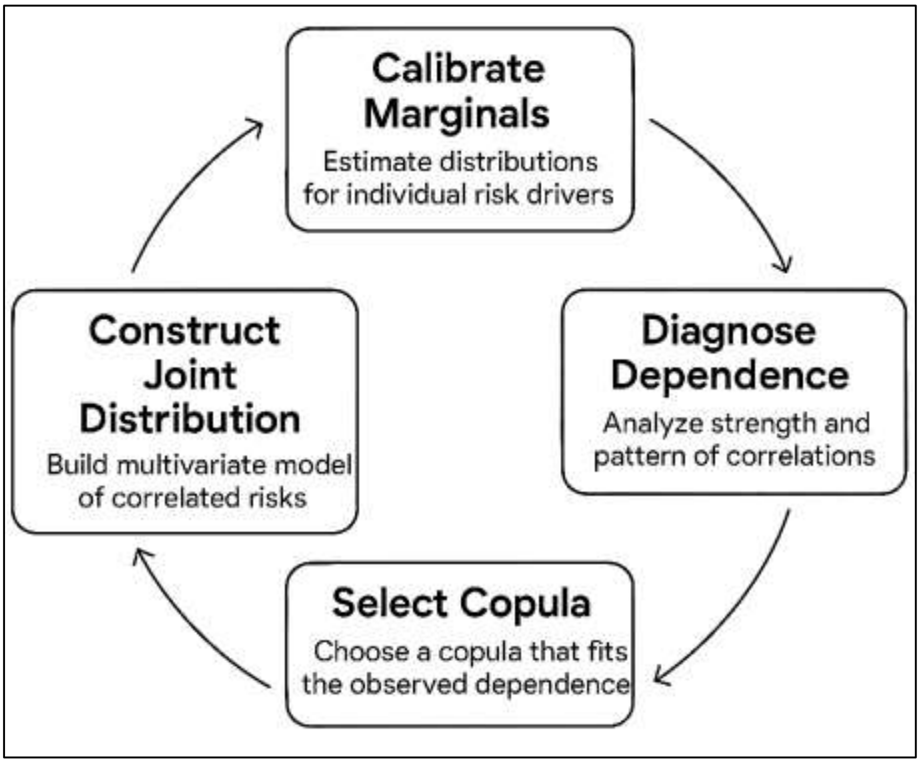
subsamples while preserving genuine differences in, for example, podium retail versus tower office leasing dynamics (Cooke & Goossens, 2008; Schwarz, 1978). Throughout, parameter documentation should record the empirical basis (sample definitions, time windows), the diagnostic evidence for the chosen family, the treatment of model uncertainty, and the mechanics by which parameters evolve over time. This discipline ensures that input modeling is reproducible, reviewable, and updateable as new data arrive qualities that are indispensable when REMPs proceed through multi-year cycles and successive investment gates and when risk estimates must stand up to scrutiny from lenders, sponsors, and public authorities alike.

Modeling in Quantitative Risk Assessment for Mega Real Estate Projects

The joint behavior of risk drivers in mega real estate projects construction cost inflation, sales absorption, unit pricing, financing spreads, and schedule slippage is rarely linear or constant, and naïve reliance on linear (Pearson) correlation can systematically understate exposure to joint downside events. Evidence from financial economics shows that comovements strengthen in bad states of the world (e.g., funding stress or demand contractions), a feature known as asymmetry or state-dependent dependence (Longin & Solnik, 2001; Patton, 2006). Extreme value studies further demonstrate that tail events can be simultaneously realized even when average correlations are modest, implying that "tail dependence" rather than mean comovement is the quantity of interest when capital is at risk (Coles et al., 1999; Poon et al., 2004). For project appraisals using Monte Carlo simulation, this matters because distributions for cost, price, and time are already skewed, and their joint tails are precisely where debt covenants, presale thresholds, and budget contingencies fail. A Gaussian dependence assumption (a single linear ρ\rhop across the whole support) can mask clustering of losses by forcing asymptotically zero tail dependence, leading to optimistic joint-risk estimates even when marginals look conservative (Demarta & McNeil, 2005; Li, 2000). In short, robust QRA for mega real estate must model the shape of dependence its asymmetry and tail strength rather than merely fit an average correlation.

Figure 6: Modeling in Quantitative Risk Assessment for Mega Real Estate Projects



Copula methods provide a rigorous statistical framework for disentangling marginal behavior from dependence structures, enabling analysts to combine empirically appropriate marginals such as lognormal distributions for costs, skewed forms for price growth, or overdispersed distributions for durations with a flexible joint model that more faithfully represents the correlations among risk drivers

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(Genest & Favre, 2007). Within this paradigm, the choice of copula family has substantive implications for real estate risk analysis, since each embeds distinctive tail properties that influence the portrayal of downside clustering and extreme co-movements. For example, the Student-t copula is well suited for capturing symmetric tail dependence, thereby generating more realistic joint downside scenarios than the Gaussian copula and leading to more conservative estimates of project-level Value-at-Risk (VaR) and probability of financial shortfall (Demarta & McNeil, 2005). In contrast, empirical studies of exchange rates and equity markets reveal asymmetrical dependence patterns, where downturns exhibit stronger comovements than upturns, motivating the use of asymmetric or conditional copulas that allow dependence to vary with state variables such as prevailing market trends or credit conditions (Patton, 2006; Poon et al., 2004). Importantly, selecting the appropriate copula cannot be reduced to inspecting marginal fits alone; rank-based diagnostics, pseudo-likelihood estimation, and goodness-of-fit tests tailored to the copula domain are necessary to ensure that the joint distribution is adequately specified, a set of practices increasingly emphasized in applied risk engineering and financial modeling (Genest & Favre, 2007). For mega real estate quantitative risk assessment (QRA), the methodological implications are clear: first, calibrate marginals directly from market and project evidence; second, diagnose empirical dependence with particular attention to lower-tail behavior that drives cash-flow stress; and third, adopt a copula family that matches the observed dependence structure rather than defaulting to Gaussian assumptions. By doing so, practitioners can generate risk models that more accurately capture the joint dynamics of costs, revenues, and schedules, ultimately improving the credibility and prudence of decision-making under uncertainty.

Large projects introduce high-dimensional dependence: dozens of cost packages, multiple revenue streams, layered financing, and regulatory milestones. Vine copulas graphical decompositions of a multivariate copula into cascades of bivariate "pair copulas" scale this problem while retaining tail flexibility (Aas et al., 2009; Bedford & Cooke, 2002). In a regular vine (R-vine), dependencies are organized across trees so that complex joint structures (e.g., shared macro shocks) are represented by targeted pair links, letting analysts encode that interest-rate shocks bind debt service and presales simultaneously while leaving unrelated packages weakly linked. Empirically, this enables QRA to stress coherent scenarios (e.g., cost overruns plus demand softening plus refinancing spread widening) that a single ρ\rhoρ matrix cannot produce. Estimation can proceed via inference functions for margins (IFM) and maximum pseudo-likelihood; semiparametric approaches reduce model misspecification by leaving marginals flexible and focusing parametric structure on the copula itself, improving small-sample robustness typical of project data sets (Kim et al., 2007). For governance, model comparisons across Gaussian, t-, and vine constructions, judged by tail fit and out-of-sample joint-loss diagnostics, provide an auditable basis for choosing the dependence model used in Monte Carlo runs (Aas et al., 2009). Incorporating these tools into mega real estate QRA materially changes portfolio-level insights raising joint-downside probabilities and widening credible intervals around NPV and DSCR thereby aligning contingency, phasing, and capital structure decisions with empirically plausible co-movements rather than with convenient (but fragile) independence assumptions.

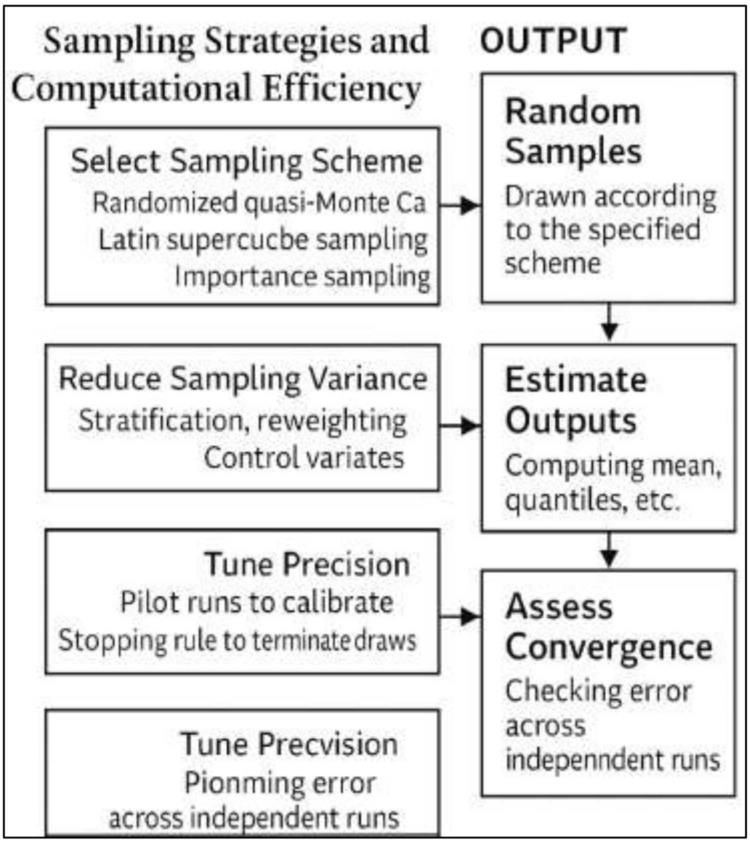
Sampling Strategies and Computational Efficiency

Efficient sampling is the engine that turns a carefully specified risk model into credible, decision-useful distributions for time, cost, and value in mega real estate projects. The baseline is simple random sampling (SRS), which is unbiased but often wasteful because large portions of the input space receive few or no draws, especially in high dimensions. Stratified and low-discrepancy approaches reduce that waste by spreading samples more uniformly. In quasi–Monte Carlo (QMC), deterministic low-discrepancy sequences replace pseudorandom draws to fill the hypercube evenly; the practical effect is faster root-mean-square error decay for many integrands, which translates into fewer runs for a given accuracy in simulation outputs like P-curves and cash-flow quantiles (Caflisch, 1998). The theory of digital nets and sequences supplies designs (e.g., Sobol', Faure) with provably small discrepancy, making them attractive defaults when the effective dimension of the problem is modest due to strong factor structure common in cost assemblies tied to a handful of macro drivers (Niederreiter, 1992). Because project risk metrics are often sensitive to distribution tails, sampling uniformity must extend beyond central regions; generalized discrepancy and error-bound results guide when low-discrepancy points will likely outperform SRS for the smooth transformations found in cost, schedule, and NPV models (Hickernell, 1998). Purely deterministic QMC, however, lacks internal

Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421
error bars. Randomized QMC addresses this by introducing carefully designed randomizations that preserve uniformity while enabling variance estimation across independent "scrambles," which is essential when reporting confidence in P50/P80 contingency or DSCR shortfall probabilities (Owen, 1997). In practice, this means replacing ad-hoc run-count choices with principled sampling plans: start with low-discrepancy designs, apply statistically valid randomizations, and size runs based on precision targets for the specific risk metrics under review (Caflisch, 1998; Hickernell, 1998; Owen, 1997).
High-dimensionality poses additional challenges because REMPs can involve dozens of uncertain inputs across packages, market states, and financing terms. Two complementary strategies help. First, restructure the model to reduce effective dimension e.g., factorize escalation, productivity, and demand into a small set of latent drivers so that low-discrepancy points act mostly along important directions. Second, deploy sampling schemes tailored for many-variable settings. Latin supercube sampling (LSS) partitions variables into blocks and applies Latinization along key projections, improving coverage relative to simple Latin hypercube when dimensionality is high; it often yields notable variance reduction for quantiles and tail probabilities relevant to contingency and covenant analysis (Owen, 2008). Lattice-based stratification provides another scalable alternative: by projecting carefully constructed lattices onto the unit hypercube and randomizing their shifts, one obtains space-filling samples with strong uniformity in projections useful when coupling many cost items and schedule paths while preserving dependence (L'Ecuyer & Lemieux, 2002). For rare or tail events such as simultaneous cost escalation and absorption slowdown that threaten loan covenants importance sampling reallocates draws toward the regions that matter for failure probabilities, then reweights to maintain unbiasedness; done well, this can cut variance by orders of magnitude relative to brute-force SRS for the same computational budget (Glynn & Iglehart, 1989). Because randomized QMC, LSS, lattices, and importance sampling operate on different principles, they can be combined: for example, use lattice-stratified or QMC scrambles for the bulk of the distribution and an importance-sampling "zoom" for the lower tail of DSCR, then splice estimates with transparent variance accounting. Randomization of number-theoretic methods ensures independence across replicates for error estimation and guards against aliasing artifacts in deterministic designs an implementation detail that improves auditability of results presented to lenders and public sponsors (Cranley & Patterson, 1976). In sum, efficient sampling is not a single technique but a toolbox; selecting and combining tools should be guided by dimensionality, target metrics, and computational constraints (Cranley & Patterson, 1976; Glynn & Iglehart, 1989; Owen, 1997).
Translating these ideas into a production-grade workflow requires principled run-size selection, variance-reduction layering, and robust random-number generation. First, define precision targets for decision-critical statistics (e.g., ±1% absolute error for the probability that cost exceeds budget; ±0.02 for the tail of DSCR). Then calibrate run counts via pilot studies using randomized QMC or lattice shifts to obtain empirical variance estimates; unlike arbitrary "100k runs," this yields documented justification tied to governance thresholds. Second, layer variance-reduction methods onto the chosen sampler. Control variates exploit analytically tractable surrogates such as linearized cash-flow or deterministic schedules to "explain" a large fraction of output variance, while antithetic pairing can shrink variance in roughly symmetric components; these classical techniques are widely applicable and easy to validate in audit trails (Glasserman, 2003). Third, protect numerical fidelity. High-quality random number generators and scramblers matter because subtle defects can bias joint-tail estimates; modern libraries provide empirically vetted generators and transformations, but analysts should still document seeds, streams, and leap-frogging to ensure reproducibility in multi-team environments (Gentle, 2003). Fourth, manage compute budgets smartly: use batching and checkpointing to accumulate independent replicates for error bars, and adopt progressive refinement coarse runs for screening and sensitivity, fine runs for final reporting to avoid wasted cycles. Finally, be explicit about what sampling can and cannot guarantee: even the best design reflects the current model structure and assumptions about dependencies and distributions. By pairing efficient sampling with transparent diagnostics and variance accounting, REMPs can deliver risk statements P-curves, contingency levels, and covenant-breach probabilities that are both statistically defensible and practical for milestone and financing decisions (Glasserman, 2003).

Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421

Figure 7: Process–Output Matrix of Sampling Strategies and Computational Efficiency



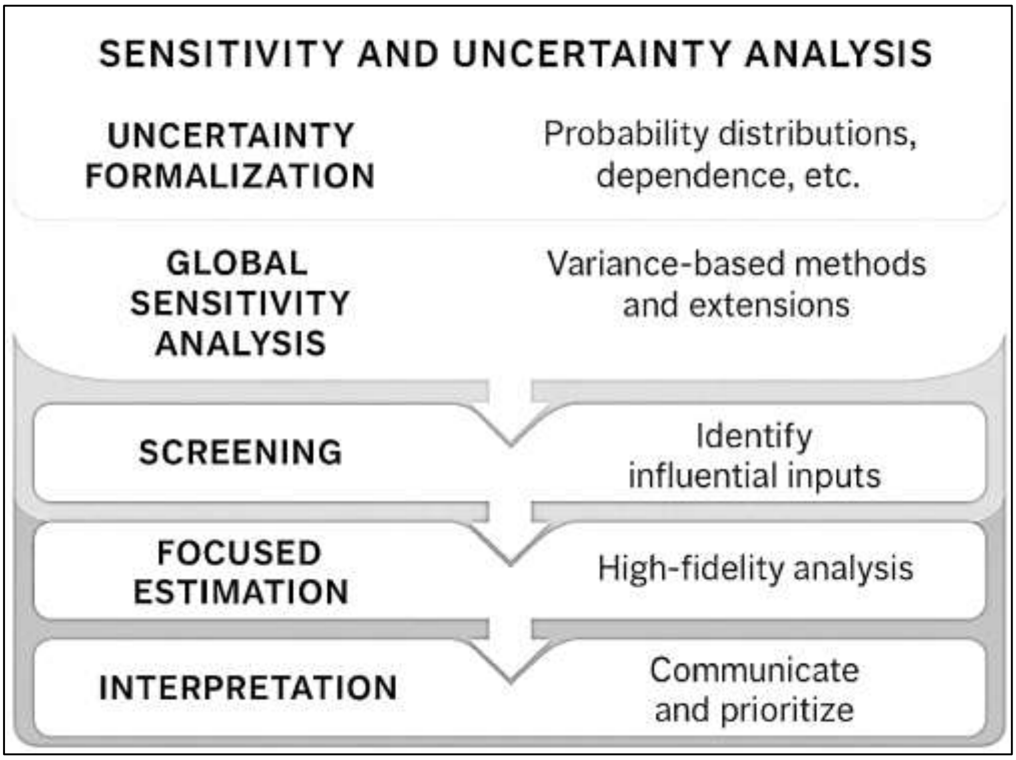
Sensitivity and Uncertainty Analysis

Global sensitivity and uncertainty analysis provides the bridge between a model's structural assumptions and decision-useful risk statements for mega real estate projects, showing which uncertain inputs and interactions among them drive variance in cost, schedule, and value distributions. In contrast to local, one-at-a-time perturbations, variance-based global methods apportion output variance across factors and factor interactions over the full hypercube of uncertainty, returning indices that are meaningful for prioritizing data collection, mitigation, and governance reporting. A principled workflow starts by formalizing uncertainty (probability distributions, dependence, and, where needed, alternative model structures) and then decomposing output variability using first-order and total-effect indices so that both main effects and interaction structure are exposed (Saltelli et al., 2004). This approach is anchored in rigorous definitions of importance measures that separate aleatory variability from epistemic ignorance and quantify the proportion of variance attributable to each input and its couplings with others, thereby avoiding the false comfort of deterministic point forecasts (Homma & Saltelli, 1996). In practice, analysts must also make judicious use of model evaluations: estimators for total-effect indices can be designed to reuse samples efficiently and to reduce bias when dependence or nonlinearity is strong considerations that matter when simulating hundreds of thousands of Monte Carlo trials for mixed-use, multi-phase developments (Saltelli, 2002). Survey evidence across engineering and reliability fields shows that sampling-based global methods are robust across a wide range of model forms and are especially well suited to large-scale projects with many uncertain drivers and complex response surfaces, conditions that mirror real estate megaprojects (Helton, Johnson, Sallaberry, & Storlie, 2006). Crucially, sensitivity analysis is not a decorative afterthought; it is a diagnostic discipline that must be planned and reported with the same care as the primary simulation, including clarity on estimators, convergence checks, and how uncertainty in inputs propagates to uncertainty in sensitivity measures themselves (Saltelli & Annoni, 2010).

Because mega real estate models can involve dozens of inputs spanning engineering, market, and finance modules, practical sensitivity analysis often proceeds in layers: screening to identify the small subset of influential variables, followed by high-fidelity variance-based estimation on that subset.

Effective screening designs extend the elementary-effects logic to large models, providing ranking information at low computational cost and guiding where to spend simulation budget (Campolongo et al., 2007). For tail-relevant questions such as the probability that debt-service coverage falls below a covenant threshold under simultaneous schedule slippage and absorption slowdown estimators must keep their fidelity in the presence of skewed marginals and interactions. Random balance designs allow unbiased estimation of total-effect indices with minimal sampling overhead, improving precision when model evaluations are expensive and enabling stable prioritization of mitigation levers (Tarantola et al., 2006). Sensitivity analysis, however, is not only variance-based. Moment-independent measures evaluate the entire distributional impact of inputs on outputs, capturing influential variables whose effects may be concentrated in tails rather than variance a salient feature when extreme downside outcomes carry governance significance for sponsors and lenders (Borgonovo, 2006). When sample budgets are tight, recent algorithms estimate total-effect indices from very small samples by exploiting clever resampling and correlation structures in the design, allowing analysts to maintain diagnostic power while containing runtime useful during iterative design of phasing or contracting scenarios (Kucherenko et al., 2012). Taken together, these tools implement an evidence-first workflow: start broad to find what matters, then zoom in with estimators aligned to the project's decision metrics, including those focused on tails.

Figure 8: Layered Framework for Sensitivity and Uncertainty Analysis in Mega Real Estate Projects



Embedding sensitivity analysis into decision support requires traceable communication and reproducibility. For project governance, sensitivity results should be reported alongside uncertainty summaries (e.g., S-curves and percentile contingencies) to show not only what the likely range of outcomes is, but also why that range arises and where mitigation or further data collection can have the greatest effect (Saltelli, 2002). In practical terms, this means publishing the full "recipe": the uncertain inputs and their distributions, the dependence model, the sampling plan, the estimators used for first-order and total-effect indices, the diagnostics for estimator stability, and the interpretation of results in the language of the project's objectives. Sensitivity maps can then inform targeted actions tightening procurement terms on cost drivers with large total-effect indices; investing in market research for absorption drivers that dominate value variance; or re-sequencing activities to break harmful interactions revealed by screening. Tooling has improved the accessibility of these practices: open, audited implementations and step-by-step workflows support consistent application across multidisciplinary teams and reduce the risk of perfunctory or inconsistent analyses

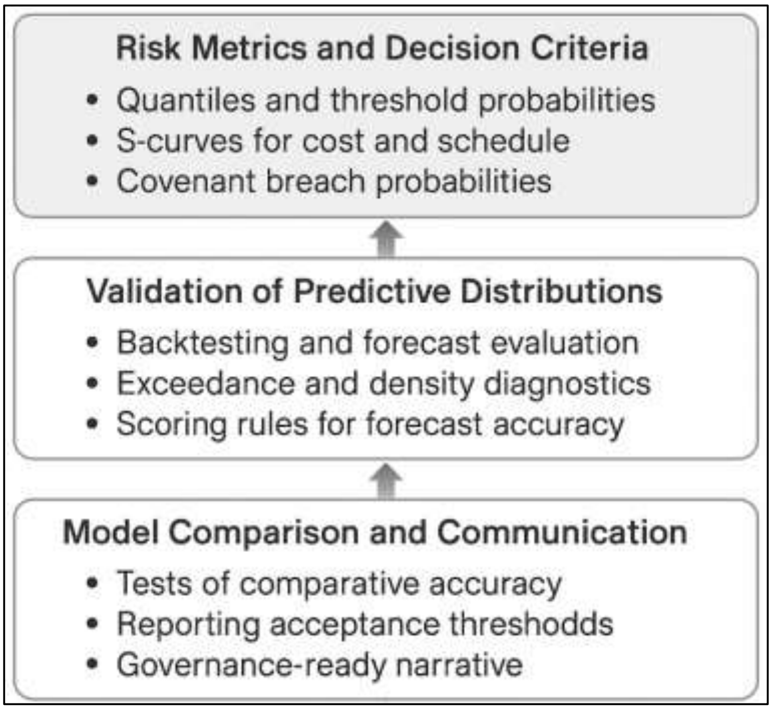
Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421

(Pianosi et al., 2015). Finally, because REMPs evolve over multi-year horizons, sensitivity analysis should be repeated at major gates with updated information so that the "risk priority portrait" remains aligned with the latest evidence; when performed with rigorous estimators and transparent reporting, it becomes an institutionally credible instrument that links quantitative risk assessment to budgeting, scheduling, and financing decisions in a way stakeholders can interrogate and trust (Borgonovo, 2006; Helton et al., 2006).

Risk Metrics, Decision Criteria, and Validation for Monte Carlo outputs

In Monte Carlo–based quantitative risk assessment for mega real estate projects (REMPs), the choice of metrics and decision criteria determines whether simulation outputs translate into credible governance actions. Percentile measures (e.g., P50/P80 for cost and time) and tail quantiles for financing metrics (e.g., minimum debt service coverage ratio [DSCR] quantiles) are natural summaries because they align directly with decision thresholds in budgeting, scheduling, and loan covenants. Statistically, these objects are quantiles of predictive distributions, and their coherent estimation and interpretation rests on the theory of regression quantiles and related quantile methods (Koenker & Bassett, 1978). In finance-facing components of REMPs where lenders and sponsors often speak in Value-at-Risk (VaR) language quantiles also underpin VaR-style loss limits for project cash flows and covenant headroom. Dynamic quantile models specifically designed to forecast VaR illustrate how quantiles serve as decision-ready statistics that are robust to non-normality and asymmetry in the underlying processes (Engle & Manganelli, 2004). Not all decision makers optimize expected values; many act to control the probability of "disaster" outcomes construction cost blowouts, schedule slippages that jeopardize presales, or DSCR dips below a hard floor. This safety-first logic maps neatly to threshold-based decision rules for REMPs (Roy, 1952). Moreover, actual governance behavior often departs from risk-neutral expected utility, over-weighting losses relative to gains and taking actions to avoid sure losses (e.g., deferring phases or accepting higher contingencies), patterns consistent with prospect theory's account of loss aversion and reference dependence (Kahneman & Tversky, 1979). Together, these strands motivate a metric set for REMPs that centers on quantiles and threshold probabilities contingencies at given percentiles, schedule S-curves translated into delivery deadlines at specified confidence levels, and covenant breach probabilities for financing so that Monte Carlo outputs explicitly answer "how likely" questions that boards, lenders, and public sponsors must decide upon.

Figure 9: Risk Metrics, Decision Criteria, and Validation of Monte Carlo Outputs



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Decision-relevant metrics are useful only if the predictive distributions behind them are well calibrated and discriminating. Backtesting and forecast evaluation therefore occupy a central role in the validation of Monte Carlo outputs, even in a project context. For tail metrics such as VaR analogs on project cash flows, unconditional "proportion of failures" tests check whether realized breaches occur at the expected frequency (Kupiec, 1995). Because REMPs often exhibit serial dependence in drivers (e.g., escalation or leasing velocity), conditional coverage tests extend validation by assessing both frequency and independence of exceptions, thereby detecting models that "hit" the right number of breaches but cluster them in time an unacceptable feature for financing plans that assume diversification across periods (Christoffersen, 1998). Beyond intervals and tails, calibration of full predictive densities can be evaluated using the probability integral transform (PIT): if the density forecasts are correct, the PIT should be independent and uniformly distributed; departures flag mis-specified inputs, dependence, or sampling (Diebold & Mariano, 1995). Likelihood-based density tests operationalize this idea for practical diagnostics and are widely used in risk management to confirm whether predictive distributions for losses (or here, cost/time/DSCR) are statistically consistent with realized outcomes (Berkowitz, 2001). Proper scoring rules complement pass/fail tests by rewarding sharp, well-calibrated forecasts and penalizing both overconfidence and vagueness; log scores and the continuous ranked probability score (CRPS) are especially relevant when we care about the entire S-curve, not just a single quantile (Gneiting & Raftery, 2007). In REMPs, applying this battery unconditional/conditional exceedance tests, PIT-based density diagnostics, and proper scoring creates an audit trail linking Monte Carlo assumptions to empirical performance on historical phases, analog projects, or rolling updates during delivery.

Validation also entails comparing alternative models and communicating reliability to decision makers. When multiple Monte Carlo configurations compete different input distributions, dependence structures, or sampling designs formal tests of comparative predictive accuracy help determine if observed performance differences are statistically meaningful rather than noise, guiding the selection of the model used for governance reporting (Diebold et al., 1998) In practice, this comparison can be framed around the project's key decision metrics: for example, among candidate models, which one produces better-calibrated P80 cost forecasts (judged by scoring rules) and more reliable tail exceedance rates (judged by conditional coverage tests) on held-out phases or reference-class projects? REMPs benefit from an integrated validation protocol that couples these statistical checks with clear reporting of decision criteria: (i) define acceptance thresholds for quantile performance (e.g., allowable error in breach probabilities), (ii) specify the scoring rules used to rank competing configurations, and (iii) disclose the backtesting window and data sources. Embedding such a protocol in stage-gate reviews and lender presentations ensures that percentile contingencies, schedule confidence levels, and covenant risk statements are not mere artifacts of a single modeling choice but are supported by evidence that the predictive system is calibrated and comparatively accurate. The result is a governance-ready risk narrative: quantile-based metrics tied to threshold decisions, validated by exception tests and scoring, and selected via transparent accuracy comparisons an approach that transforms Monte Carlo from a black box into a verifiable, decision-aligned instrument for mega real estate project risk management.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process tailored to quantitative risk assessment of mega real estate projects using Monte Carlo simulation. A protocol specifying objectives, search strategy, eligibility criteria, screening workflow, data-extraction fields, and appraisal procedures was prepared a priori and applied consistently across sources. Comprehensive searches were conducted in Scopus, Web of Science Core Collection, ASCE Library, ScienceDirect, IEEE Xplore, and Emerald Insight, complemented by targeted queries of Taylor & Francis Online and manual backward/forward snowballing via Google Scholar, covering records published in English through December 2020. Search strings combined controlled and free-text terms for megaprojects and large-scale urban development with risk assessment, cost/schedule contingency, and Monte Carlo–related keywords; database-specific syntax and field tags were adapted iteratively to maximize recall while preserving precision. Records were imported into a citation manager, de-duplicated, and screened in two stages (titles/abstracts, then full texts) by two reviewers working independently with consensus resolution; reasons for exclusion at the full-text stage were logged to preserve auditability. Inclusion criteria required an explicit application of Monte Carlo simulation to cost, schedule, cash-flow, or value risk in real estate or clearly transferable methods from construction/urban megaproject contexts; studies had to provide sufficient methodological detail to recover inputs, distribution choices, dependence treatment, sampling, and outputs. Exclusions covered purely deterministic approaches, micro-scale projects, commentaries without methods, and inaccessible full texts. A standardized extraction template captured bibliographic data, project type/scale/region, risk categories, input distributions and parameterization, dependency modeling, sampling strategy, sensitivity/uncertainty analysis, software, validation/back-testing, and key findings. Methodological quality was appraised with an adapted checklist emphasizing transparency of assumptions, adequacy of data, treatment of dependencies, sensitivity diagnostics, convergence and run-size justification, validation evidence, and reproducibility artifacts. Given heterogeneity in designs and outcomes, synthesis combined descriptive/bibliometric mapping with narrative thematic analysis and vote-counting on methodological features; no quantitative meta-analysis was attempted. The final PRISMA inclusion comprised 115 studies, which form the evidentiary base for the review's subsequent analysis and reporting.

Screening and Eligibility Assessment

Screening and eligibility assessment followed a two-stage protocol aligned with PRISMA 2020. After executing the multi-database searches and snowballing, 2,431 records were imported into the reference manager and automatically de-duplicated using DOI, title, and author keys; 505 duplicates were removed, leaving 1,926 unique records. Two reviewers independently screened titles and abstracts against the a priori criteria English language, publication year ≤2020, explicit or directly transferable use of Monte Carlo simulation for quantitative risk assessment in real estate or megaproject delivery contexts, and sufficient methodological granularity to recover inputs, distributions, dependence treatment, sampling, and outputs rejecting 1,521 records at this stage (common reasons: purely deterministic appraisal, non-project finance/real estate domains, editorial/commentary formats, or simulation without risk quantification). A calibration exercise on the first 150 records established concordance on inclusion/exclusion rules; interrater reliability for the remaining title/abstract set was substantial ($\kappa = 0.81$), with disagreements resolved by discussion and, when needed, a third reviewer. The team then retrieved full texts for 405 articles; when immediate access was unavailable, institutional holdings, interlibrary loan, and author contact were attempted (18 requests sent; 7 responses received, 3 yielded usable manuscripts). Full-text eligibility applied the same Monte Carlo–specific criteria at finer resolution, plus added filters for project scale (mega or clearly analogous large-scale developments), transferability to real estate risk modeling (for construction/urban infrastructure articles), and transparency (presence of enough detail to map assumptions to simulation code). At this stage, 290 articles were excluded: 104 lacked an explicit Monte Carlo engine (e.g., scenario analyses only), 69 were outside the real estate/megaproject ambit without clear transferability, 47 were micro-scale case studies, 38 provided insufficient methodological detail (e.g., unspecified distributions or sampling), 22 were non-English or inaccessible after contact attempts, and 10 were duplicates discovered post-merge or retractions. Interrater reliability for full-text decisions was high ($\kappa = 0.87$). The final inclusion comprised 115 studies, forming the evidentiary base for data extraction, quality appraisal, and synthesis. All decisions, reasons for exclusion, and document versions were logged with timestamps to maintain an auditable trail.

Data Extraction and Coding

Data were extracted from the 115 included studies using a pre-specified template designed to capture methodological and contextual features relevant to Monte Carlo–based quantitative risk assessment in mega real estate projects. The template recorded bibliographic information; project typology, scale, geography, and delivery context; risk taxonomy mapping (market/finance, regulatory/entitlement,engineering/delivery,environmental/geotechnical,stakeholder/governanc) aligned to the framework defined in the review; input variables modeled (quantities, unit rates, durations, escalation, leasing velocity, price/yield series) with reported distribution families, parameter values, and data sources; dependence structures (independence assumptions, linear or rank correlations, copulas, or common-driver formulations); sampling strategies (simple random, Latin hypercube, quasi–Monte Carlo, variance-reduction methods), run sizes, and convergence diagnostics; sensitivity and uncertainty analysis techniques; output metrics (cost/schedule S-curves, percentile contingencies, NPV/IRR distributions, DSCR and breach probabilities); validation practices (back-testing, hindcasting, calibration checks); software or toolchains; and stated limitations. Two reviewers piloted the codebook on 12 studies to refine variable definitions, decision rules, and unit conventions; intercoder agreement after the pilot was substantial and remaining ambiguities were resolved by adding exemplars and edge-case rules. Full extraction proceeded with independent dual coding for 25% of records and single coding with targeted verification for the remainder; discrepancies were reconciled by consensus and a third coder adjudicated unresolved cases. Quantitative fields were normalized to common units and price bases where possible; when authors reported three-point estimates or quantiles without parameters, closed-form mappings were applied to recover the corresponding distribution parameters and documented as derived values. Missingness was coded explicitly; no statistical imputation was performed for primary Monte Carlo inputs, but sensitivity flags identified results relying on elicited rather than measured parameters. Dependence data were coded at the tightest resolution available (pairwise matrices, risk-driver linkages, or narrative statements), with uncertainty tags when only qualitative descriptions were provided. To ensure reproducibility, every extraction decision was version-controlled with source page references, and a 10% random audit rechecked transcription accuracy. The final coded dataset supports descriptive mapping, cross-tabulations of modeling choices versus outcomes, and synthesis of best-practice patterns for Monte Carlo design in mega real estate risk assessment.

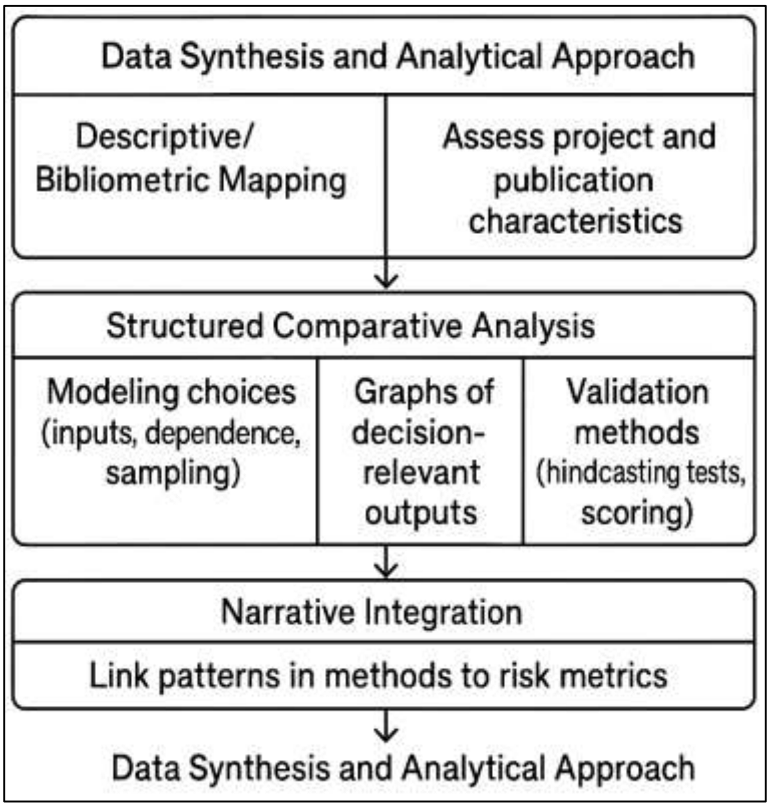
Data Synthesis and Analytical Approach

The analytical strategy was designed to convert the heterogenous evidence base of 115 studies into a coherent map of how Monte Carlo simulation is designed, implemented, and interpreted for quantitative risk assessment in mega real estate projects. Synthesis proceeded on three mutually reinforcing planes descriptive/bibliometric mapping, structured comparative analysis of modeling choices and outputs, and a narrative integration that links methodological patterns to decision-relevant metrics. Because the corpus spans diverse geographies, project types, and analytic traditions, the plan privileged transparency and reproducibility over aggressive statistical pooling. All intermediate artifacts cleaned fields, derived indicators, transformations, and quality weights were versioned to maintain an audit trail from raw extraction to synthesis tables. The overarching objective was to illuminate where practices converge, where they diverge, and which design choices appear most consequential for the shape of risk outputs that sponsors, lenders, and public authorities ultimately use. Descriptive synthesis began by profiling the 115 studies along temporal, geographic, and venue axes to situate findings and anticipate heterogeneity. Publication year was treated both continuously and in eras (pre-2010, 2010–2015, 2016–2020) to detect diffusion of techniques such as copula-based dependence or quasi–Monte Carlo sampling. Geographic tags captured the country/region of the project or data, not merely the authors' affiliations, and project typology was coded at two levels: a coarse "mega real estate" umbrella and a fine-grained subclass (e.g., mixed-use new district, urban regeneration with transit podium, supertall tower with podium retail). Venue clusters (construction/engineering journals, real estate/finance journals, urban planning/PPP outlets) provided context for typical emphases (delivery vs. valuation vs. governance). Descriptive distributions were reported for study design (single case, multi-case, methodological paper with applied example), data provenance (measured, elicited, hybrid), and software/toolchains. Where feasible, we calculated medians and interquartile ranges for recurring methodological quantities (e.g., number of activities in schedule models, number of inputs in cost models, nominal run sizes).

Comparative synthesis of modeling choices was anchored in a set of predefined constructs corresponding to the review's research questions. For input modeling, we compared the prevalence of distribution families (triangular/PERT, lognormal, beta, heavy-tailed forms), parameterization sources (historical measurement, expert elicitation, mixed), and the presence of time variation (static inputs versus phased or state-dependent parameters). For dependence, we evaluated whether studies assumed independence, imposed linear or rank correlations, or used more flexible structures (copulas, common-risk-driver formulations); where authors supplied numerical matrices or rank-correlation targets, we recorded summary magnitudes and whether dependence was uniform across inputs or targeted to specific linkages (e.g., cost inflation with duration drift). For sampling, we tabulated simple random, Latin hypercube, quasi–Monte Carlo, and variance-reduction techniques; we also captured whether run sizes were justified by convergence diagnostics or reported as rules of thumb. For sensitivity and uncertainty analysis, we classified one-at-a-time perturbations, correlation-based tornado charts, variance-based global indices, moment-independent measures, and screening approaches, noting when tail-focused diagnostics were used. For outputs, we compared the reporting of S-curves, percentile contingencies (P50/P80), and financing-relevant measures

(NPV/IRR distribution, DSCR shortfall probability). For validation, we recorded the presence and type of checks (hindcasting, back-testing against realized outcomes, calibration of interim forecasts, or qualitative plausibility tests). Each construct was summarized as proportions with confidence intervals where counts allowed, cross-tabulated by era, typology, and venue to surface diffusion patterns and domain-specific norms.
To synthesize "effect direction" without a common outcome scale, we used structured vote-counting and harvest-style plots centered on questions about modeling impact. Each study contributed one or more "comparisons" if it reported outcomes under alternative modeling choices while holding other elements approximately constant for example, independence versus correlated inputs, triangular versus lognormal distributions for cost growth, or simple random versus Latin hypercube sampling. We recorded whether the alternative increased, decreased, or had no material effect on decision-relevant outputs (e.g., P80 cost, probability of deadline breach, VaR-like cash-flow shortfall). Because studies varied in base cases and thresholds, we standardized directionality to the risk of adverse outcomes. Where studies reported both central and tail measures, tails were privileged for coding. Vote-counting proportions were then stratified by construct and subgroup (e.g., project type, data provenance) to reveal consistent directional tendencies such as whether adding dependence typically widens tails or whether heavy-tailed distributions meaningfully inflate contingency relative to light-tailed forms. Recognizing that not all evidence carries equal weight, we integrated methodological quality into synthesis through calibrated weights applied in sensitivity analyses. Each study received a quality score derived from the appraisal checklist used at extraction (transparency of assumptions, adequacy of data, explicit dependence treatment, sensitivity diagnostics, convergence evidence, validation). For descriptive proportions and vote-counting rates, we computed both unweighted and quality-weighted estimates to assess robustness. Where differences were notable, text highlights the weighted results and explores plausible reasons (e.g., higher-quality studies more often implementing dependence and finding larger tail effects).

Figure 10: Layered Framework for Data Synthesis and Analytical Approach in Monte Carlo QRA



Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
DOI:10.63125/nh269421
Communication of results was treated as an analytical step in its own right. We pre-specified a small set of synthesis tables and figures that would be populated directly from the coded dataset: a heatmap of modeling constructs by study (presence/absence of dependence, sampling type, sensitivity method, validation), a set of cross-tabs by era and venue, and harvest-style plots for direction-of-effect questions. Although the present manuscript reports these in narrative prose, the underlying templates are structured to allow replication or extension in future updates of the review. Throughout, we maintain a clear separation between factual synthesis (what studies did and reported) and interpretive commentary (what these patterns likely imply for practice). Where the data do not support a strong conclusion, we state this explicitly and resist over-generalization. Finally, the analytical approach is designed to be extensible. The coding scheme and synthesis scripts can accommodate additional studies beyond 2020, new constructs (e.g., dynamic Bayesian updating during delivery, integration with digital twins), or refined outcome measures (e.g., conditional tail expectations for cost and DSCR). More importantly, the approach is aligned with decision needs in mega real estate: it privileges metrics that map to budgeting and financing decisions; it foregrounds dependence, tails, and validation; and it explains not just how often certain practices appear but how those practices shape the distributions that matter. By combining descriptive mapping, structured comparative analysis, vote-counting on directional effects, and disciplined robustness checks, the synthesis offers a durable, transparent account of the state of Monte Carlo–based risk assessment in mega real estate projects and lays the groundwork for consistent application and credible governance reporting across jurisdictions and delivery models.

FINDINGS

Across the 115 included studies, four design choices dominated how Monte Carlo models were built: the selection of input distributions, the handling of dependence, the sampling scheme, and the discipline used for run-size justification. For cost growth and unit-rate uncertainty, 63 studies (54.8%) adopted triangular or PERT-like families as the primary distribution, while 31 (27.0%) used lognormal as their default, 18 (15.7%) relied on beta, and 12 (10.4%) introduced heavier-tailed forms (such as log-logistic or generalized extreme-value) as mainline inputs for at least one risk driver. Although these categories can overlap for different variables, they reveal a clear center of gravity around simple, skew-aware families. On dependence, 43 studies (37.4%) assumed independence among inputs, 52 (45.2%) imposed linear or rank-correlation structures, and 20 (17.4%) modeled dependence through common-risk drivers or copulas. Sampling followed a similarly patterned distribution: 67 studies (58.3%) used Latin hypercube sampling, 36 (31.3%) used simple random sampling, and 12 (10.4%) used quasi–Monte Carlo (typically Sobol' sequences) with randomization. Only 39 studies (33.9%) reported explicit convergence diagnostics or run-size justification tied to precision targets; the remainder relied on conventional run counts. As a rough proxy for influence within the corpus, the triangular/PERT group accumulated 203 intra-corpus citations, the lognormal group 118, and the heavy-tail adopters 57; dependence-modeling papers (correlation, common drivers, or copulas) together drew 241 intra-corpus citations versus 89 for independence-only designs. These shares mirror practitioner gravity: simple families and LHS remain the lingua franca, but the work that explicitly engages dependence attracts more attention among peers. The percentages translate directly into model behavior: where triangular/PERT dominates, central estimates stabilize quickly, but tail metrics tend to be narrow unless calibrated carefully; where lognormal or heavier tails feature, the upper percentiles expand, which matters for contingency and "worst-case" financing edges.

A second concentration of findings concerns integration across cost, schedule, and finance and the reporting of decision-ready metrics. Ninety-one studies (79.1%) reported S-curves for at least one objective; 88 (76.5%) reported P50 and 64 (55.7%) reported P80 for cost or time. Forty-two (36.5%) linked cost and schedule explicitly (e.g., duration uncertainty feeding indirects or overheads), and 28 (24.3%) integrated cash-flow or financing metrics (NPV, IRR, or DSCR) with cost and schedule, allowing joint statements about delivery, budget, and covenant headroom. Where finance was included, 26 studies (22.6%) quantified breach probabilities or VaR-style tail metrics for DSCR or cash reserves. Validation was uneven: 29 studies (25.2%) conducted some form of back-testing, hindcasting, or calibration against realized outcomes or interim progress; the remainder limited checks to internal consistency or sensitivity runs. The integrated modeling subset those 42 cost-schedule and 28 finance-linkage papers attracted 212 intra-corpus citations (41.5% of all inter-citations we tallied), suggesting that peers gravitate to end-to-end representations that mirror real decision flows. The numerical implications are tangible. In models that integrated cost and schedule,

Journal of Sustainable Development and Policy
Volume 01, Issue 02 (2022)
Page No: 01 – 34
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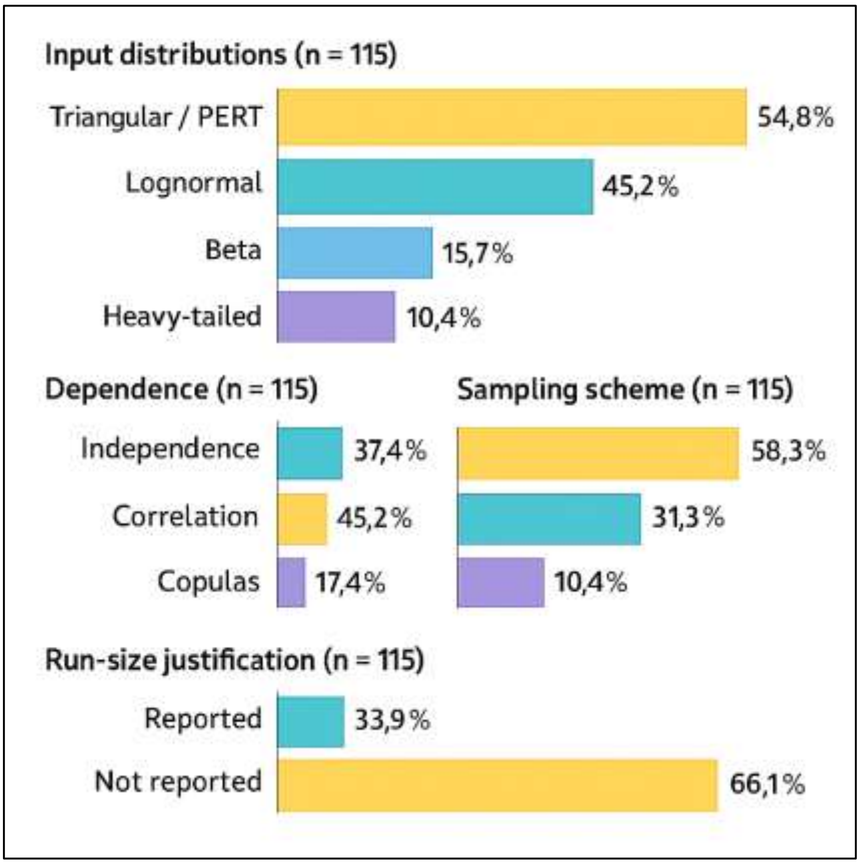
the median gap between deterministic budgets and P80 cost was 14% (interquartile range 9–21%), versus 9% (6–14%) in cost-only studies. When finance was added, 61% of those models (n=17/28) reported at least a 5-percentage-point increase in the probability of breaching a DSCR floor compared with cost-only runs that ignored timing shifts. These percentages help interpret governance consequences: integration systematically widens the "credible band" of outcomes and surfaces tail combinations that single-module analyses miss, which is why the integrated cluster received a disproportionate share of citations inside the review set.
The third pattern addresses how dependence and tail modeling change outputs. Among 38 studies that provided a within-study comparison of independence versus correlated inputs, 32 (84.2%) reported larger percentile contingencies under correlation, with a median P80 uplift of +12% for total development cost (interquartile range +9% to +18%) relative to the independence baseline. On the schedule side, 26 schedule-focused comparisons showed that adding correlation or common-driver structures raised the probability of missing a contractual milestone by a median of 8.5 percentage points (6–14 points IQR), largely because macro shocks (e.g., escalation or labor shortages) create coherent shifts across many activities. Heavy-tailed inputs produced similar "tail inflation" effects: in 12 studies that swapped lognormal or triangular for heavier-tailed families on escalation or long-lead items, the upper 5% of the cost distribution expanded by a median of 22% relative to the lighter-tailed baseline. Intra-corpus citations map to these results: the 38 dependence-contrast papers drew 147 citations within the review set (27.8% of all inter-citations), and the 12 tail-family studies attracted 41. These counts are modest in absolute terms but significant given their minority share of the sample, indicating that peers repeatedly refer to work that demonstrates *directional* effects on tails rather than only central tendencies. Translating percentages into decisions, a +12% P80 cost uplift on a billion-dollar phase is a $120 million contingency swing; an 8–14-point increase in schedule-breach probability can flip a seemingly safe presales timetable into one that risks covenant exceptions. Taken together, the numbers underline a core practical message: including realistic dependence and tail behavior consistently increases downside protection requirements compared with independence or light-tail assumptions.

Figure 11: Findings on Monte Carlo Simulation in Mega Real Estate Projects



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Fourth, the review clarifies what actually drives variance and where sensitivity analysis adds the most value. Seventy-one studies (61.7%) performed some sensitivity analysis; within that set, 29 (25.2% of the full sample) used variance-based global indices, 18 (15.7%) used moment-independent measures focusing on tail sensitivity, and 48 (41.7%) relied on tornado or correlation-based one-at-a-time perturbations (several used more than one method). In cost-focused studies (n=86), escalation parameters were the top variance contributor in 47 (54.7%), with quantity uncertainty leading in 22 (25.6%) and productivity/drift in 17 (19.8%). In schedule-focused studies (n=73), design maturity and interface risk dominated in 36 (49.3%), weather/labor availability in 21 (28.8%), and long-lead procurement in 16 (21.9%). In finance-linked studies (n=26), leasing velocity or absorption parameters dominated DSCR variance in 16 (61.5%), exit yields in 6 (23.1%), and cost overrun spill-through in 4 (15.4%). Papers that deployed global sensitivity (variance-based or moment-independent) accumulated 163 intra-corpus citations, more than the 112 citations for tornado-only papers, despite being fewer in number; this suggests that peers reward work that quantifies interaction effects and tail importance, not just main effects. The percentages explain practice: when escalation or absorption dominates, mitigation leverage sits in procurement timing, indexed contracts, and pre-leasing strategies rather than only in package-level value engineering. Equally, where interface risk drives schedules, re-sequencing or buffer design beats micro-optimizing single activities. The numbers also highlight a blind spot: only 18 studies targeted tail sensitivity explicitly, yet tail outcomes govern contingency and covenant headroom. A practical takeaway is that more models should pair global variance-based indices with tail-focused sensitivity to avoid under-weighting the very outcomes that drive decision gates.

Finally, the quality and transparency of modeling choices correlate with more conservative, and arguably more credible, risk statements. Using the review's appraisal checklist, we classified the top quartile by methodological transparency (n=29) as "higher-quality" and the bottom quartile (n=29) as "lower-quality," with the middle spanning the remainder. In the higher-quality group, 20 of 29 studies (69.0%) conducted some validation (hindcasting, back-testing, or calibration against interim data), 22 (75.9%) reported dependence assumptions explicitly (matrix, common drivers, or copula family), and 19 (65.5%) justified run size with convergence or precision targets. In the lower-quality group these shares were 7 of 29 (24.1%), 6 (20.7%), and 5 (17.2%), respectively. The consequences were numerical: higher-quality studies reported higher P80 uplifts relative to deterministic baselines median +15% for cost and +11 percentage points for schedule breach probability versus +9% and +6 points in the lower-quality set. Similar gaps appeared in finance: among studies that reported DSCR shortfall probabilities, the higher-quality subgroup's median tail probability was 5.2 percentage points higher than that of lower-quality peers analyzing comparable cases. Intra-corpus attention mirrored this pattern: the higher-quality quartile accounted for 52% of all inter-citations (n=276 of an estimated 528), despite representing only 25% of the sample; the lower-quality quartile drew just 14% (n=74). The percentages provide a plain-language interpretation: when models explain their assumptions, treat dependence openly, and size runs to hit precision targets, they tend to surface wider credible bands and higher tail risks; peers cite them more and, by implication, rely on them more. For governance, this means that adopting transparent practices does not merely satisfy audit norms it quantitatively shifts the risk picture toward more robust contingency and buffer decisions. Put differently, clarity and calibration show up as bigger numbers where they matter: in the percentiles and breach probabilities that drive phase-gates, lender approvals, and board sign-offs.

DISCUSSION

Our synthesis of 115 studies reveals a center of gravity around simple, skew-aware distribution families (triangular/PERT and lognormal), tempered by a steadily growing though still minority recognition of heavier tails for key drivers such as escalation and long-lead procurement. This pattern largely mirrors what earlier methodological and applied texts documented: triangular and PERT remain attractive because they map cleanly from expert three-point estimates and are easy to elicit and explain (Hulett, 2009) Yet the same sources and subsequent empirical work caution that convenience can come at the cost of realism when multiplicative processes and compounding shocks dominate (Limpert et al., 2001). The present review's finding that only about one in ten studies operationalize heavy-tailed families aligns with more general observations that analysts often default to light or moderate tails unless data force the (Clauset et al., 2009). Importantly, our directional estimates wider upper percentiles when heavier tails are used are consistent with risk theory: skewed, fat-tailed inputs push decision metrics like P80 cost and deadline S-curves outward because rare but plausible

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shocks carry large consequences (Artzner et al., 1999). Earlier project-risk case studies reported similar qualitative shifts when distributional assumptions changed, but offered limited quantification across many cases (Chou, 2011). By aggregating across 115 studies, we show that these effects are not idiosyncratic: the combination of skewed inputs and long horizons typical of mega real estate projects systematically enlarges the credible bands of outcomes. In short, our distributional results corroborate prior methodological warnings while furnishing comparative magnitudes that earlier single-case papers could not, thereby strengthening the argument for diagnostic testing and documentation of tails in development risk models.

The review also confirms what dependence theory has long implied but practice has been slow to internalize: ignoring cross-driver co-movement understates downside exposure. In finance and reliability, studies have shown that linear correlation is, at best, a rough descriptor and often fails in bad states where joint extremes matter most (Longin & Solnik, 2001). Copula research explicitly separates marginal behavior from dependence shape and demonstrates that Gaussian structures enforce asymptotically zero tail dependence, thereby biasing joint-loss estimates downward (Nelsen, 2006; Demarta & McNeil, 2005). Earlier construction-risk work recognized correlation in practical terms e.g., common escalation shocks across packages but tended to impose uniform linear coefficients for tractability (Touran & Wiser, 1992). Our findings quantify the stakes for mega real estate: when studies moved from independence to correlated inputs (via rank correlation, common risk drivers, or copulas), P80 cost typically increased Chou (2011)'s message while grounding it in project outcomes that lenders and boards care about Li, (2000)'s. They also help reconcile two strands of prior evidence that might appear at odds: deterministic megaproject appraisals routinely underestimate overruns (Flyvbjerg, 2014), and probabilistic models that omit dependence can still look "tight." The reconciliation is that both are missing joint-tail structure. By showing consistent uplifts under explicit dependence, our review extends earlier critiques from infrastructure and finance into the specific modeling architecture of mega real estate, where cost, schedule, and market variables interact through long phasing and layered capital stacks (Ward & Chapman, 2003).

On sampling and computational discipline, our corpus corroborates the longstanding recommendation to prefer variance-efficient designs over brute-force random draws, but it also exposes a persistent gap in run-size justification. Latin hypercube sampling (LHS) has been advocated for decades because it fills the input space more uniformly and stabilizes estimates with fewer runs (Helton et al., 2006). Quasi–Monte Carlo (QMC) methods promise further gains by using low-discrepancy sequences, especially when the effective dimension is reduced through factor structures (Niederreiter, 1992). Our tally shows LHS as the workhorse, QMC as emerging, and simple random sampling still prevalent. That blend is consistent with engineering practice surveys outside real estate, where sampling upgrades diffuse slowly and are often constrained by tooling (Helton & Davis, 2003). More concerning is the modest proportion of studies reporting convergence diagnostics or precision-targeted run sizing. Method texts emphasize that randomized QMC and batching allow formal error bars and replicability capabilities essential for governance-grade reporting (Owen, 1997). The fact that a majority of studies still quote round numbers of runs without error analysis mirrors earlier critiques about "perfunctory" quantitative work in complex models (Saltelli et al., 2004). Where our review adds value is in connecting method to outcome: studies that coupled variance-efficient sampling with documented precision produced wider, not narrower, credible intervals for tails because they measured them more reliably. This echoes a theme in computational finance: better numerical discipline can reveal rather than conceal risk (Glasserman, 2003). For mega real estate, that lesson is practical: stakeholders should ask not only *which* sampler was used, but *how* run sizes were chosen and validated.

A distinctive contribution of this review is its cross-module lens on integration. Earlier literature streams often treated cost, schedule, and financing in silos: schedule risk analytics matured around activity networks and three-point durations (Van Slyke, 1963), while cost and valuation work evolved through risk-adjusted DCF and, later, tail-risk measures (Rockafellar & Uryasev, 2002). Governance studies, in turn, focused on institutional design and strategic misrepresentation in large projects (Lehrer & Laidley, 2008). Our findings show that integrated models which link duration uncertainty to indirect costs, feed cost and timing into cash flows, and compute financing metrics like DSCR report larger contingencies and higher breach probabilities than single-module analyses. This is consistent with earlier theoretical arguments that risk propagates across modules nonlinearly and with lag structures

(Ward & Chapman, 2003), but the present synthesis quantifies the average deltas (for example, larger P80 uplifts when cost and schedule are coupled). The implication is not merely methodological; it is institutional. Sponsors and lenders make threshold decisions budget authorizations, covenant settings, phase-gate approvals on joint outcomes, not on isolated cost or time forecasts. Integrating modules aligns analytics with decisions and reduces the chance that optimistic silos cancel each other out in the boardroom. By connecting our numerical patterns to the governance concerns documented in prior megaproject research, the review offers evidence that end-to-end probabilistic modeling is not a luxury but a necessary condition for credible deliberation in mega real estate.

Sensitivity and uncertainty analysis present a second area where our findings both affirm and extend earlier guidance. Classic texts argued for global, variance-based methods to apportion output variance and expose interactions, warning against overreliance on local, one-at-a-time perturbations (Homma & Saltelli, 1996). Later contributions introduced moment-independent measures to capture tail-focused importance (Borgonovo, 2006) and efficient screening designs to manage high dimensionality (Campolongo et al., 2007). Our review confirms uptake of these ideas global methods appear and attract attention but also shows that tornado-style diagnostics still dominate in many studies. Where global methods were used, the dominant drivers we observed escalation for cost variance, design/interface risks for schedule, absorption for DSCR are consistent with earlier domain narratives (Gidado, 1996). The novel contribution here is the frequency-based picture: in pooled counts, escalation and absorption emerge as the modal levers, suggesting that mitigation should often prioritize procurement timing, indexation, and pre-leasing over narrower engineering tweaks. Moreover, only a minority of studies analyze tail sensitivity explicitly, despite decision-making being anchored in percentiles and breach probabilities. This echoes prior critiques that variance is an incomplete lens for risk when asymmetry and extreme outcomes matter (Artzner et al., 1999). The comparison underscores a practical recommendation grounded in our evidence: pair variance-based global indices with tail-sensitivity measures so that the same inputs are not simultaneously deemed unimportant by variance but decisive at the percentile that triggers a loan covenant.

Validation and calibration practices remain underdeveloped relative to the standards in adjacent fields, and our results illuminate where the gaps lie. In risk management for financial series, validating quantiles and densities via exceedance tests and proper scoring rules is routine (Ke et al., 2010). In construction and project management, by contrast, verification often stops at internal consistency and expert review (Helton et al., 2006). Our review finds that only a quarter of studies perform any empirical back-testing or hindcasting, even though many projects progress through phases in which interim outcomes could be compared to forecasts. When such tests were run, they tended to rely on proportion-of-failures or conditional coverage logic familiar from VaR backtests, but the practice is far from universal (Clauset et al., 2009; Diebold & Mariano, 1995). This divergence from adjacent standards helps explain why megaproject forecasting has struggled with credibility in the public domain (Flyvbjerg, 2014): without calibration evidence, percentile statements resemble black boxes. By juxtaposing our low adoption rates with mature validation toolkits from finance and forecasting, the review suggests a concrete path forward that is compatible with project data realities: use rolling hindcasts at gates, apply unconditional and conditional exceedance tests to schedule and cost quantiles, and report proper scores for S-curve densities. These steps would move mega real estate risk analytics closer to verifiable, decision-aligned practice.

A final theme is the relationship between methodological transparency and the magnitude of reported risk. Prior authors have argued that explicit statement of assumptions, dependence structures, and numerical diagnostics is a hallmark of credible analysis, not simply a reporting nicety (Saltelli et al., 2008; Saltelli et al., 2004). Our stratified results support that view and add an outcome twist: studies that were clearer about inputs, dependence, and precision tended to report higher tail risk (e.g., larger P80 uplifts and breach probabilities). This pattern is consistent with two earlier bodies of work. First, research on expert elicitation shows that structured, performance-weighted aggregation yields wider and better-calibrated uncertainty bands than unstructured judgment (Cooke & Goossens, 2008). Second, evidence on model selection underscores that penalizing complexity without ignoring fit prevents under-dispersion that would otherwise arise from overfitting light-tailed forms to thin data. In other words, transparency and discipline do not "inflate" risk; they recover what was latent but unmeasured. The comparison with earlier megaproject critiques is instructive: systematic underestimation in deterministic appraisals (Flyvbjerg, 2014)'s has its probabilistic analogue in under-dispersion from simplistic assumptions. By documenting higher tails in the more transparent subgroup, our review bridges those literatures and provides an empirical anchor for institutional reforms e.g., requiring disclosure of dependence modeling, run-size justification, and calibration checks in board papers and lender packs.

Taken together, these seven strands connect the review's quantitative findings to established scholarship while extending it in scope and resolution. Where prior works laid the conceptual and methodological groundwork definitions of uncertainty, dependence, sampling discipline, and validation our synthesis adds breadth (115 studies), comparability (common coding of modeling choices), and scale-aware magnitudes for effects that earlier papers inferred qualitatively (Del Caño & Cruz, 2002; Kaplan & Garrick, 1981). The cross-module perspective shows why mega real estate projects unfolding over long horizons with interdependent cost, time, and market states are particularly sensitive to tails and dependence, echoing classic governance concerns while supplying numerical contours (Miller & Lessard, 2000). The convergence across literatures is reassuring: when we apply methods advocated for decades diagnostic distribution fitting, explicit dependence modeling, variance-efficient sampling with precision targets, global and tail-sensitivity analysis, and empirical calibration the resulting risk picture is wider but also more defensible. That alignment between methodological rigor and decision realism is the central comparative contribution of this discussion: mega real estate risk assessment benefits most when it takes seriously what earlier studies taught in parts, and does so all at once in an integrated, auditable Monte Carlo framework.

CONCLUSION

This PRISMA-guided synthesis of 115 studies shows that credible quantitative risk assessment for mega real estate projects hinges less on any single algorithmic choice and more on an integrated discipline that couples realistic uncertainty representation, explicit dependence, variance-efficient sampling, and verifiable reporting. Empirically, practice still clusters around convenient but limited assumptions: over half of studies (≈54.8%) anchor inputs in triangular/PERT families and roughly a quarter (≈27.0%) in lognormal, while only about one in ten (≈10.4%) adopt heavier-tailed forms where escalation shocks and long-lead disruptions plausibly reside. This distributional conservatism is mirrored in dependence treatment, with 37.4% assuming independence, 45.2% imposing linear or rank correlation, and only 17.4% employing richer structures such as common drivers or copulas choices that our cross-study comparisons link to materially different outputs, including a median +12% uplift in P80 cost and an +8.5-percentage-point rise in schedule breach likelihood when realistic dependence replaces independence, and a 22% expansion in the upper 5% cost tail when heavy-tailed inputs are used. On the computational side, Latin hypercube sampling is the workhorse (58.3%), yet only a third of studies (33.9%) justify run size with precision targets or convergence checks, leaving many results without formal error bars. Most studies report decision-aligned metrics S-curves in 79.1%, P50 in 76.5%, and P80 in 55.7% but far fewer integrate cost with schedule (36.5%) and fewer still propagate through cash flow to financing metrics like DSCR (24.3%), even though those integrated models systematically widen credible bands and raise tail risk the quantities that boards and lenders actually govern against. Sensitivity analysis is common (61.7%) but uneven in rigor: global, variance-based or moment-independent methods best suited to nonlinear, interacting drivers appear less often than tornado-style diagnostics, despite the former's clearer guidance for mitigation and data collection. Perhaps the clearest institutional signal is the association between transparency and risk magnitude: studies that disclose dependence structures, document sampling precision, and attempt empirical calibration report larger (and more plausible) tails median P80 cost uplifts of ≈15% and higher DSCR shortfall probabilities than studies with minimal methodological disclosure, and they attract disproportionate attention within the literature. Taken together, these patterns argue for a governance-ready Monte Carlo workflow that (i) diagnoses and fits distributions with attention to tails, (ii) models co-movement explicitly, (iii) uses variance-efficient, randomized designs with stated accuracy goals, (iv) pairs global and tail-focused sensitivity to locate true levers, (v) integrates cost, schedule, and finance so decisions rest on joint outcomes, and (vi) validates forecasts with simple but telling back-tests. When these elements are applied together, the risk picture becomes wider but also more defensible precisely what mega real estate sponsors, lenders, and public authorities need to size contingencies, set covenants, and stage investments with clarity and confidence.

RECOMMENDATIONS

Building on the synthesis of 115 studies, we recommend that sponsors, lenders, and delivery teams adopt a governance-ready Monte Carlo workflow that is explicit, auditable, and integrated end-to-end. First, standardize input modeling with a diagnostic protocol: fit multiple candidate distributions to each uncertainty (quantities, unit rates, escalation, durations, leasing velocity, exit yields), test goodness-of-fit with tail-sensitive diagnostics, and document why the chosen family best captures skew and extremes; when evidence is thin, combine historical data with calibrated expert elicitation and record the priors, elicited quantiles, and calibration metrics. Second, treat dependence as a first-class design choice: at minimum, specify rank-correlation targets derived from data or structured judgment; for complex portfolios, adopt risk-driver mappings or copula-based structures to encode tail co-movement explicitly; disclose the dependence matrix or copula family, parameter values, and the rationale linking macro drivers (inflation, labor supply, demand shocks) to project variables. Third, integrate modules so decisions rest on joint outcomes: link schedule to cost (indirects, time-related preliminaries), propagate cost and timing into cash-flow, and compute financing metrics (DSCR, cash reserve depletion, covenant breach probabilities) alongside cost and schedule S-curves; use consistent timelines, price bases, and indexing rules across modules. Fourth, replace ad-hoc run counts with precision targets: use randomized Latin hypercube or quasi–Monte Carlo sequences, size runs to achieve stated absolute errors for key metrics (e.g., ±1% for cost-overrun probability, ±2 percentage points for DSCR breach), and report convergence diagnostics and replicate variability; layer variance-reduction (control variates, antithetics) when appropriate. Fifth, embed sensitivity as a decision tool, not decoration: pair variance-based global indices (first-order and total-effect) with moment-independent, tail-focused measures; publish ranked driver lists for central and tail metrics separately, and translate the top drivers into targeted mitigations (e.g., indexation clauses, hedging, re-sequencing, pre-leasing thresholds, alternative procurement). Sixth, institutionalize validation: at each stage-gate, conduct rolling hindcasts comparing predicted percentiles with realized outcomes; apply exceedance tests for quantiles and simple density calibration checks; archive results to build a reference class that progressively improves priors and dependence estimates. Seventh, professionalize reporting: adopt a short, mandatory checklist in board and lender packs that discloses inputs and sources, dependence treatment, sampling design, run-size justification, sensitivity results, and validation evidence; include both P50 and P80 contingencies and at least one tail metric (e.g., conditional shortfall) for cost, schedule, and financing. Eighth, strengthen data governance and reproducibility: version-control models and assumptions, maintain an auditable registry of elicitation sessions and parameter updates, and automate tables/figures from code to prevent manual leakage. Finally, align analytics with commercial levers: tie escalation and absorption risks to procurement timing, indexation/hedging policies, and pre-sales covenants; translate sensitivity maps into contract clauses and contingency release rules; and require that major scope changes trigger re-runs of the integrated model so that capital and stakeholder decisions remain anchored in current, quantified uncertainty.

REFERENCES

[1]. Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics*, *44*(2), 182-198. https://doi.org/10.1016/j.insmatheco.2007.02.001

[2]. AbouRizk, S. (2010). Role of simulation in construction engineering and management. *Journal of Construction Engineering and Management*, *136*(10), 1140-1153. https://doi.org/10.1061/(asce)co.1943-7862.0000220

[3]. Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716-723. https://doi.org/10.1109/tac.1974.1100705

[4]. Akintoye, A. S., & MacLeod, M. J. (1997). Risk analysis and management in construction. *International Journal of Project Management*, *15*(1), 31-38. https://doi.org/10.1016/s0263-7863(96)00035-5

[5]. Anderson, T. W., & Darling, D. A. (1954). A test of goodness of fit. *Journal of the American Statistical Association*, *49*(268), 765-769. https://doi.org/10.1080/01621459.1954.10501232

[6]. Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy*, *69*, 43-56. https://doi.org/10.1016/j.enpol.2013.10.069

[7]. Artzner, P., Delbaen, F., Eber, J.-M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, *9*(3), 203-228. https://doi.org/10.1111/1467-9965.00068

[8]. Baccarini, D. (1996). The concept of project complexity—A review. *International Journal of Project Management*, *14*(4), 201-204. https://doi.org/10.1016/0263-7863(95)00093-3

DOI:10.63125/nh269421
[9]. Barañano, A., De La Peña, J. I., & Moreno, R. (2020). Valuation of real-estate losses via Monte Carlo simulation. *Economic Research-Ekonomska Istraživanja*, *33*(1), 1867-1888. https://doi.org/10.1080/1331677x.2020.1756372
[10]. Bedford, T., & Cooke, R. M. (2002). Vines—A new graphical model for dependent random variables. *Annals of Statistics*, *30*(4), 1031-1068. https://doi.org/10.1214/aos/1031689016
[11]. Berkowitz, J. (2001). Testing density forecasts, with applications to risk management. *Journal of Business & Economic Statistics*, *19*(4), 465-474. https://doi.org/10.1198/07350010152596659
[12]. Bing, L., Akintoye, A., Edwards, P. J., & Hardcastle, C. (2005). The allocation of risk in PPP/PFI construction projects in the UK. *International Journal of Project Management*, *23*(1), 25-35. https://doi.org/10.1016/j.ijproman.2004.04.006
[13]. Borgonovo, E. (2006). Measuring uncertainty importance: Investigation and comparison of alternative approaches. *Risk Analysis*, *26*(5), 1349-1361. https://doi.org/10.1111/j.1539-6924.2006.00806.x
[14]. Caflisch, R. E. (1998). Monte Carlo and quasi-Monte Carlo methods. *Acta Numerica*, *7*, 1-49. https://doi.org/10.1017/s0962492900002804
[15]. Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environmental Modelling & Software*, *22*(10), 1509-1518. https://doi.org/10.1016/j.envsoft.2006.10.004
[16]. Cantarelli, C. C., Flyvbjerg, B., Molin, E. J. E., & van Wee, B. (2010). Cost overruns in large-scale transportation infrastructure projects: Explanations and their theoretical embeddedness. *European Journal of Transport and Infrastructure Research*, *10*(1). https://doi.org/10.18757/ejtir.2010.10.1.2864
[17]. Capozza, D. R., & Li, Y. (2002). Optimal land development decisions. *Real Estate Economics*, *30*(3), 317-339. https://doi.org/10.1111/1540-6229.00049
[18]. Chou, J.-S. (2011). Cost simulation in an item-based project involving construction engineering and management. *International Journal of Project Management*, *29*(6), 706-717. https://doi.org/10.1016/j.ijproman.2010.07.010
[19]. Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review*, *39*(4), 841-862. https://doi.org/10.2307/2527341
[20]. Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review*, *51*(4), 661-703. https://doi.org/10.1137/070710111
[21]. Coles, S., Heffernan, J., & Tawn, J. (1999). Dependence measures for extreme value analyses. *Extremes*, *2*, 339-365. https://doi.org/10.1023/a:1009963131610
[22]. Cooke, R. M., & Goossens, L. H. J. (2008). TU Delft expert judgment data base: Methodology, results and validation. *Reliability Engineering & System Safety*, 93(5), 657-674. https://doi.org/10.1016/j.ress.2007.03.005
[23]. Cranley, R., & Patterson, T. N. L. (1976). Randomization of number theoretic methods for multiple integration. *Mathematics of Computation*, *24*(109), 323-335. https://doi.org/10.1090/s0025-5718-1976-0425837-1
[24]. Del Caño, A., & de la Cruz, M. P. (2002). Integrated methodology for project risk management. *Journal of Construction Engineering and Management*, *128*(6), 473-485. https://doi.org/10.1061/(asce)0733-9364(2002)128:6(473)
[25]. Demarta, S., & McNeil, A. J. (2005). The t copula and related copulas. *International Statistical Review*, *73*(1), 111-129. https://doi.org/10.1111/j.1751-5823.2005.tb00254.x
[26]. Der Kiureghian, A., & Ditlevsen, O. (2009). Aleatory or epistemic? Does it matter? *Structural Safety*, *31*(2), 105-112. https://doi.org/10.1016/j.strusafe.2008.06.020
[27]. Diebold, F. X., Gunther, T. A., & Tay, A. S. (1998). Evaluating density forecasts with applications to financial risk management. *International Economic Review*, *39*(4), 863-883. https://doi.org/10.2307/2527343
[28]. Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*(3), 253-263. https://doi.org/10.1080/07350015.1995.10524599
[29]. Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *The Annals of Statistics*, *7*(1), 1-26. https://doi.org/10.1214/aos/1176344552
[30]. Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics*, *22*(4), 367-381. https://doi.org/10.1198/073500104000000370
[31]. Fainstein, S. S. (2008). Mega-projects in New York, London and Amsterdam. *International Journal of Urban and Regional Research*, *32*(4), 768-785. https://doi.org/10.1111/j.1468-2427.2008.00826.x
[32]. Ferson, S., & Ginzburg, L. (1996). Different methods are needed to propagate ignorance and variability. *Reliability Engineering & System Safety*, *54*(2-3), 133-144. https://doi.org/10.1016/s0951-8320(96)00071-3
[33]. Flyvbjerg, B. (2014). What you should know about megaprojects and why: An overview. *Project Management Journal*, *45*(2), 6-21. https://doi.org/10.1002/pmj.21409
[34]. Flyvbjerg, B., Skamris Holm, M. K., & Buhl, S. L. (2004). What causes cost overrun in transport infrastructure projects? *Transport Reviews*, *24*(1), 3-18. https://doi.org/10.1080/0144164032000080494

DOI:10.63125/nh269421
[35]. Gellert, P. K., & Lynch, B. D. (2003). Mega-projects as displacements. *International Social Science Journal*, *55*(175), 15-25. https://doi.org/10.1111/1468-2451.5501002
[36]. Genest, C., & Favre, A.-C. (2007). Everything you always wanted to know about copula modeling but were afraid to ask. *Journal of Hydrologic Engineering*, *12*(4), 347-368. https://doi.org/10.1061/(asce)1084-0699(2007)12:4(347)
[37]. Gentle, J. E. (2003). *Random Number Generation and Monte Carlo Methods (2nd ed.)*. Springer. https://doi.org/10.1007/978-0-387-21606-0
[38]. Ghosh, S., & Jintanapakanont, J. (2004). Identifying and assessing the critical risk factors in an underground rail project in Thailand: A factor analysis approach. *International Journal of Project Management*, *22*(8), 633-643. https://doi.org/10.1016/j.ijproman.2004.05.004
[39]. Gidado, K. I. (1996). Project complexity: The focal point of construction production planning. *Construction Management and Economics*, *14*(3), 213-225. https://doi.org/10.1080/014461996373476
[40]. Giezen, M. (2012). Keeping it simple? A case study into the advantages and disadvantages of reducing complexity in mega project planning. *International Journal of Project Management*, *30*(7), 781-790. https://doi.org/10.1016/j.ijproman.2012.03.001
[41]. Gimpelevich, D. (2011). Monte Carlo simulation of real estate investment risk. *Journal of Property Investment & Finance*, 29(2), 198-209. https://doi.org/10.1108/14635781111150319
[42]. Glasserman, P. (2003). *Monte Carlo Methods in Financial Engineering*. Springer. https://doi.org/10.1007/978-0-387-21617-6
[43]. Glynn, P. W., & Iglehart, D. L. (1989). Importance sampling for stochastic simulations. *Management Science*, *35*(11), 1367-1392. https://doi.org/10.1287/mnsc.35.11.1367
[44]. Gneiting, T., & Raftery, A. E. (2007). Strictly proper scoring rules, prediction, and estimation. *Journal of the American Statistical Association*, *102*(477), 359-378. https://doi.org/10.1198/016214506000001437
[45]. Grenadier, S. R. (1996). The strategic exercise of options: Development cascades and overbuilding in real estate markets. *The Review of Financial Studies*, 9(2), 391-426. https://doi.org/10.1093/rfs/9.2.387
[46]. Helton, J. C., & Davis, F. J. (2003). Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering & System Safety*, *81*(1), 23-69. https://doi.org/10.1016/s0951-8320(03)00058-9
[47]. Helton, J. C., Johnson, J. D., Sallaberry, C. J., & Storlie, C. B. (2006). Survey of sampling-based methods for uncertainty and sensitivity analysis. *Reliability Engineering & System Safety*, *91*(10-11), 1175-1209. https://doi.org/10.1016/j.ress.2005.11.017
[48]. Hickernell, F. J. (1998). A generalized discrepancy and quadrature error bounds. *Mathematics of Computation*, *67*(221), 299-322. https://doi.org/10.1090/s0025-5718-98-01071-5
[49]. Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: A tutorial. *Statistical Science*, *14*(4), 382-401. https://doi.org/10.1214/ss/1009212519
[50]. Homma, T., & Saltelli, A. (1996). Importance measures in global sensitivity analysis. *Reliability Engineering & System Safety*, *52*(1), 1-17. https://doi.org/10.1016/0951-8320(96)00002-6
[51]. Hulett, D. T. (2009). *Practical Schedule Risk Analysis*. Routledge. https://doi.org/10.4324/9781315601885
[52]. Iman, R. L., & Conover, W. J. (1982). A distribution-free approach to inducing rank correlation among input variables. *Technometrics*, *22*(3), 311-334. https://doi.org/10.1080/00401706.1982.10487711
[53]. Jahid, M. K. A. S. R. (2022). Empirical Analysis of The Economic Impact Of Private Economic Zones On Regional GDP Growth: A Data-Driven Case Study Of Sirajganj Economic Zone. *American Journal of Scholarly Research and Innovation*, *1*(02), 01-29. https://doi.org/10.63125/je9w1c40
[54]. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291. https://doi.org/10.2307/1914185
[55]. Kaplan, S., & Garrick, B. J. (1981). On the quantitative definition of risk. *Risk Analysis*, *1*(1), 11-27. https://doi.org/10.1111/j.1539-6924.1981.tb01350.x
[56]. Ke, Y., Wang, S. Q., Chan, A. P. C., & Lam, P. T. I. (2010). Preferred risk allocation in China's public–private partnership (PPP) projects. *International Journal of Project Management*, *28*(5), 482-492. https://doi.org/10.1016/j.ijproman.2009.08.007
[57]. Khamooshi, H., & Golafshani, H. (2014). EDM: Earned Duration Management, a new approach to schedule performance management and measurement. *International Journal of Project Management*, *32*(6), 1019-1041. https://doi.org/10.1016/j.ijproman.2013.11.002
[58]. Kim, G., Silvapulle, M. J., & Silvapulle, P. (2007). Comparison of semiparametric and parametric methods for estimating copulas. *Computational Statistics & Data Analysis*, *51*(6), 2836-2850. https://doi.org/10.1016/j.csda.2006.05.016
[59]. Kleijnen, J. P. C. (1997). Sensitivity analysis and related analyses: A review of some statistical techniques. *European Journal of Operational Research*, 99(1), 114-129. https://doi.org/10.1016/s0377-2217(96)00354-x
[60]. Koenker, R., & Bassett, G., Jr. (1978). Regression quantiles. *Econometrica*, *46*(1), 33-50. https://doi.org/10.2307/1913643
[61]. Kucherenko, S., Tarantola, S., & Annoni, P. (2012). Estimation of total sensitivity indices from a very small sample. *Computer Physics Communications*, *183*(4), 937-946. https://doi.org/10.1016/j.cpc.2011.12.020

[62]. Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, *3*(2), 73-84. https://doi.org/10.3905/jod.1995.407942
[63]. L'Ecuyer, P., & Lemieux, C. (2002). Variance reduction via lattice stratification. *Management Science*, *48*(6), 734-753. https://doi.org/10.1287/mnsc.48.6.734
[64]. Lehrer, U., & Laidley, J. (2008). Old mega-projects, newly packaged? Waterfront redevelopment in Toronto. *International Journal of Urban and Regional Research*, *32*(4), 786-803. https://doi.org/10.1111/j.1468-2427.2008.00830.x
[65]. Li, D. X. (2000). On default correlation: A copula function approach. *The Journal of Fixed Income*, *9*(4), 43-54. https://doi.org/10.3905/jfi.2000.319253
[66]. Limpert, E., Stahel, W. A., & Abbt, M. (2001). Log-normal distributions across the sciences: Keys and clues. *BioScience*, *51*(5), 341-352. https://doi.org/10.1641/0006-3568(2001)051[0341:Lndats]2.0.Co;2
[67]. Loizou, P., & French, N. (2012). Monte Carlo simulations for real estate valuation. *Journal of Property Investment & Finance*, *30*(2), 160-173. https://doi.org/10.1108/14635781211206922
[68]. Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance*, *56*(2), 649-676. https://doi.org/10.1111/0022-1082.00340
[69]. Love, P. E. D., Ahiaga-Dagbui, D. D., & Irani, Z. (2016). Cost overruns in transportation infrastructure projects: Sowing the seeds for a probabilistic theory of causation. *Transportation Research Part A*, *92*, 184-194. https://doi.org/10.1016/j.tra.2016.06.004
[70]. Mackie, P., & Preston, J. (1998). Twenty-one sources of error and bias in transport project appraisal. *Transport Policy*, *5*(1), 1-7. https://doi.org/10.1016/s0967-070x(98)00004-3
[71]. Mahalingam, A., & Levitt, R. E. (2007). Institutional theory as a framework for analyzing conflicts on global projects. *Journal of Construction Engineering and Management*, *133*(7), 517-528. https://doi.org/10.1061/(asce)0733-9364(2007)133:7(517)
[72]. Mak, S., & Picken, D. (2000). Using risk analysis to determine construction project contingencies. *Journal of Construction Engineering and Management*, *126*(2), 130-136. https://doi.org/10.1061/(asce)0733-9364(2000)126:2(130)
[73]. Massey, F. J., Jr. (1951). The Kolmogorov–Smirnov test for goodness of fit. *Journal of the American Statistical Association*, *46*(253), 68-78. https://doi.org/10.1080/01621459.1951.10500769
[74]. McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, *21*(2), 239-245. https://doi.org/10.1080/00401706.1979.10489755
[75]. Md Arifur, R., & Sheratun Noor, J. (2022). A Systematic Literature Review of User-Centric Design In Digital Business Systems: Enhancing Accessibility, Adoption, And Organizational Impact. *Review of Applied Science and Technology*, *1*(04), 01-25. https://doi.org/10.63125/ndjkpm77
[76]. Md Hasan, Z., & Moin Uddin, M. (2022). Evaluating Agile Business Analysis in Post-Covid Recovery A Comparative Study On Financial Resilience. *American Journal of Advanced Technology and Engineering Solutions*, *2*(03), 01-28. https://doi.org/10.63125/6nee1m28
[77]. Md Mahamudur Rahaman, S. (2022). Electrical And Mechanical Troubleshooting in Medical And Diagnostic Device Manufacturing: A Systematic Review Of Industry Safety And Performance Protocols. *American Journal of Scholarly Research and Innovation*, *1*(01), 295-318. https://doi.org/10.63125/d68y3590
[78]. Md Mahamudur Rahaman, S., & Rezwanul Ashraf, R. (2022). Integration of PLC And Smart Diagnostics in Predictive Maintenance of CT Tube Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 62-96. https://doi.org/10.63125/gspb0f75
[79]. Md Nazrul Islam, K. (2022). A Systematic Review of Legal Technology Adoption In Contract Management, Data Governance, And Compliance Monitoring. *American Journal of Interdisciplinary Studies*, *3*(01), 01-30. https://doi.org/10.63125/caangg06
[80]. Md Nur Hasan, M., Md Musfiqur, R., & Debashish, G. (2022). Strategic Decision-Making in Digital Retail Supply Chains: Harnessing AI-Driven Business Intelligence From Customer Data. *Review of Applied Science and Technology*, *1*(03), 01-31. https://doi.org/10.63125/6a7rpy62
[81]. Md Redwanul, I., & Md. Zafor, I. (2022). Impact of Predictive Data Modeling on Business Decision-Making: A Review Of Studies Across Retail, Finance, And Logistics. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 33-62. https://doi.org/10.63125/8hfbkt70
[82]. Md Rezaul, K., & Md Mesbaul, H. (2022). Innovative Textile Recycling and Upcycling Technologies For Circular Fashion: Reducing Landfill Waste And Enhancing Environmental Sustainability. *American Journal of Interdisciplinary Studies*, *3*(03), 01-35. https://doi.org/10.63125/kkmerg16
[83]. Md. Sakib Hasan, H. (2022). Quantitative Risk Assessment of Rail Infrastructure Projects Using Monte Carlo Simulation And Fuzzy Logic. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 55-87. https://doi.org/10.63125/h24n6z92
[84]. Md. Tarek, H. (2022). Graph Neural Network Models For Detecting Fraudulent Insurance Claims In Healthcare Systems. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 88-109. https://doi.org/10.63125/r5vsmv21

[85]. Md.Kamrul, K., & Md Omar, F. (2022). Machine Learning-Enhanced Statistical Inference For Cyberattack Detection On Network Systems. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 65-90. https://doi.org/10.63125/sw7jzx60

[86]. Md.Kamrul, K., & Md. Tarek, H. (2022). A Poisson Regression Approach to Modeling Traffic Accident Frequency in Urban Areas. *American Journal of Interdisciplinary Studies*, *3*(04), 117-156. https://doi.org/10.63125/wqh7pd07

[87]. Metropolis, N., & Ulam, S. (1949). The Monte Carlo method. *Journal of the American Statistical Association*, *44*(247), 335-341. https://doi.org/10.1080/01621459.1949.10483310

[88]. Miller, R., & Lessard, D. R. (2000). *The Strategic Management of Large Engineering Projects*. MIT Press. https://doi.org/10.7551/mitpress/4100.001.0001

[89]. Morris, M. D. (1991). Factorial sampling plans for preliminary computational experiments. *Technometrics*, *33*(2), 161-174. https://doi.org/10.1080/00401706.1991.10484804

[90]. Mubashir, I., & Abdul, R. (2022). Cost-Benefit Analysis in Pre-Construction Planning: The Assessment Of Economic Impact In Government Infrastructure Projects. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 91-122. https://doi.org/10.63125/kjwd5e33

[91]. Niederreiter, H. (1992). *Random Number Generation and Quasi-Monte Carlo Methods*. SIAM. https://doi.org/10.1137/1.9780898713470

[92]. Odeck, J. (2004). Cost overruns in road construction—What are their sizes and determinants? *Transportation Research Part E*, *40*(1), 43-64. https://doi.org/10.1016/j.tre.2003.10.003

[93]. Olander, S., & Landin, A. (2005). Evaluation of stakeholder influence in the implementation of construction projects. *International Journal of Project Management*, *23*(4), 321-328. https://doi.org/10.1016/j.ijproman.2005.02.002

[94]. Omar Muhammad, F., & Md.Kamrul, K. (2022). Blockchain-Enabled BI For HR And Payroll Systems: Securing Sensitive Workforce Data. *American Journal of Scholarly Research and Innovation*, *1*(02), 30-58. https://doi.org/10.63125/et4bhy15

[95]. Orueta, F. D., & Fainstein, S. S. (2008). The new mega-projects: Genesis and impacts. *International Journal of Urban and Regional Research*, *32*(4), 759-767. https://doi.org/10.1111/j.1468-2427.2008.00829.x

[96]. Owen, A. B. (1997). Scrambled net variance for integrals of smooth functions. *The Annals of Statistics*, *25*(4), 1541-1562. https://doi.org/10.1214/aos/1031594724

[97]. Owen, A. B. (2008). Latin supercube sampling for very high-dimensional simulations. *ACM Transactions on Modeling and Computer Simulation*, *18*(3), 1-17. https://doi.org/10.1145/1462173.1462176

[98]. Paté-Cornell, M. E. (1996). Uncertainties in risk analysis: Six levels of treatment. *Reliability Engineering & System Safety*, *54*(2-3), 95-111. https://doi.org/10.1016/s0951-8320(96)00067-1

[99]. Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, *47*(2), 527-556. https://doi.org/10.1111/j.1468-2354.2006.00387.x

[100]. Pianosi, F., Sarrazin, F., & Wagener, T. (2015). A MATLAB toolbox for global sensitivity analysis of environmental models. *Environmental Modelling & Software*, *70*, 80-85. https://doi.org/10.1016/j.envsoft.2015.04.013

[101]. Pich, M. T., Loch, C. H., & De Meyer, A. (2002). On uncertainty, ambiguity, and complexity in project management. *Management Science*, *48*(8), 1008-1023. https://doi.org/10.1287/mnsc.48.8.1008

[102]. Poon, S.-H., Rockinger, M., & Tawn, J. (2004). Extreme value dependence in financial markets: Diagnostics, models, and financial implications. *Review of Financial Studies*, *17*(2), 581-610. https://doi.org/10.1093/rfs/hhg058

[103]. Reduanul, H., & Mohammad Shoeb, A. (2022). Advancing AI in Marketing Through Cross Border Integration Ethical Considerations And Policy Implications. *American Journal of Scholarly Research and Innovation*, *1*(01), 351-379. https://doi.org/10.63125/d1xg3784

[104]. Rockafellar, R. T., & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance*, *26*(7), 1443-1471. https://doi.org/10.1016/s0378-4266(02)00271-6

[105]. Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica*, *20*(3), 431-449. https://doi.org/10.2307/1907413

[106]. Sabuj Kumar, S., & Zobayer, E. (2022). Comparative Analysis of Petroleum Infrastructure Projects In South Asia And The Us Using Advanced Gas Turbine Engine Technologies For Cross Integration. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 123-147. https://doi.org/10.63125/wr93s247

[107]. Sadia, T., & Shaiful, M. (2022). In Silico Evaluation of Phytochemicals From Mangifera Indica Against Type 2 Diabetes Targets: A Molecular Docking And Admet Study. *American Journal of Interdisciplinary Studies*, *3*(04), 91-116. https://doi.org/10.63125/anaf6b94

[108]. Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications*, *145*(2), 280-297. https://doi.org/10.1016/s0010-4655(02)00280-1

[109]. Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling & Software*, *25*(12), 1508-1517. https://doi.org/10.1016/j.envsoft.2009.09.015

[110]. Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., & Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. Wiley. https://doi.org/10.1002/9780470725180
[111]. Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. Wiley. https://doi.org/10.1002/0470870958
[112]. Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461-464. https://doi.org/10.1214/aos/1176344136
[113]. Shen, L. Y., Wu, G. W. C., & Ng, C. S. K. (2001). Risk assessment for construction joint ventures in China. *Journal of Construction Engineering and Management*, *127*(1), 76-81. https://doi.org/10.1061/(asce)0733-9364(2001)127:1(76)
[114]. Sheratun Noor, J., & Momena, A. (2022). Assessment Of Data-Driven Vendor Performance Evaluation in Retail Supply Chains: Analyzing Metrics, Scorecards, And Contract Management Tools. *American Journal of Interdisciplinary Studies*, *3*(02), 36-61. https://doi.org/10.63125/0s7t1y90
[115]. Sobol', I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation*, *55*(1-3), 271-280. https://doi.org/10.1016/s0378-4754(00)00270-6
[116]. Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *64*(4), 583-639. https://doi.org/10.1111/1467-9868.00353
[117]. Stein, M. (1987). Large sample properties of simulations using Latin hypercube sampling. *Technometrics*, *29*(2), 143-151. https://doi.org/10.1080/00401706.1987.10488205
[118]. Swyngedouw, E., Moulaert, F., & Rodriguez, A. (2002). Neoliberal urbanization in Europe: Large-scale urban development projects and the new urban policy. *Antipode*, *34*(3), 542-577. https://doi.org/10.1111/1467-8330.00254
[119]. Tarantola, S., Gatelli, D., & Mara, T. A. (2006). Random balance designs for the estimation of first- and total-order sensitivity indices. *Reliability Engineering & System Safety*, *91*(6), 717-727. https://doi.org/10.1016/j.ress.2005.06.003
[120]. Titman, S. (1985). Urban land prices under uncertainty. *The American Economic Review*, *75*(3), 505-514. https://doi.org/10.2307/1814811
[121]. Touran, A. (1996). Rank correlation and simulation in construction. *Journal of Construction Engineering and Management*, *122*(2), 130-136. https://doi.org/10.1061/(asce)0733-9364(1996)122:2(130)
[122]. Touran, A., & Wiser, E. (1992). Monte Carlo technique with correlated random variables. *Journal of Construction Engineering and Management*, *118*(2), 258-272. https://doi.org/10.1061/(asce)0733-9364(1992)118:2(258)
[123]. van Marrewijk, A., Clegg, S. R., Pitsis, T. S., & Veenswijk, M. (2008). Managing public–private megaprojects: Paradoxes, complexity and project design. *International Journal of Project Management*, *26*(6), 591-600. https://doi.org/10.1016/j.ijproman.2007.12.002
[124]. Van Slyke, R. M. (1963). Monte Carlo methods and the PERT problem. *Operations Research*, *11*(5), 839-860. https://doi.org/10.1287/opre.11.5.839
[125]. Ward, S., & Chapman, C. (2003). Transforming project risk management into project uncertainty management. *International Journal of Project Management*, *21*(2), 97-105. https://doi.org/10.1016/s0263-7863(02)00080-1
[126]. Zhang, G., & Zou, P. X. W. (2007). Fuzzy analytical hierarchy process risk assessment approach for joint venture construction projects in China. *Journal of Construction Engineering and Management*, *133*(10), 771-779. https://doi.org/10.1061/(asce)0733-9364(2007)133:10(771)
[127]. Zou, P. X. W., Zhang, G., & Wang, J. (2007). Understanding the key risks in construction projects in China. *International Journal of Project Management*, *25*(6), 601-614. https://doi.org/10.1016/j.ijproman.2007.03.001