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Probabilistic risk assessment framework for cost overruns predictions in infrastructure projects using randomized simulations

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Abstract

This paper introduces PRIMoS (Probabilistic Risk matrix Integration with MOnte carlo Simulation), an advanced computational framework that enhances cost overrun risk assessment and uncertainty quantification in infrastructure project management. PRIMoS is an innovative Bayesian Monte Carlo simulation framework integrated with a probabilistic risk matrix, providing comprehensive cost risk analysis. The proposed framework simultaneously addresses both cost uncertainties and time uncertainties, the latter through discount rate assessment, extending beyond traditional cost-focused approaches. PRIMoS employs a novel method to define risk magnitude (RM) levels for all project components, enabling adaptive probability distributions for Monte Carlo inputs. This approach allows for the capture of specific cost-related interdependencies and evolving risk patterns within the financial aspects of the project lifecycle. The framework's efficacy was demonstrated through application to a large infrastructure project, showcasing its ability to provide more accurate and detailed cost overrun forecasts compared to conventional methods. The proposed model improved cost estimation accuracy by predicting an increase in contingencies, thereby reducing the estimation error to less than 5%. PRIMoS offers a powerful tool for proactive risk management and informed decision-making in large-scale infrastructure development.

1 | INTRODUCTION

Accurate estimation of costs and timelines is critical for the success of public projects across sectors. Mismanagement in this area frequently leads to delays and cost overruns, which are widespread across European countries. A comprehensive study by the European Court of Auditors found that approximately 45% of all public projects funded by European Union (EU) programs experienced delays, while nearly 30% exceeded their budget (European Commission, 2023). These challenges significantly impact the delivery of public services and the overall economic health of the regions involved. These inefficiencies often stem from underestimation of project complexity,

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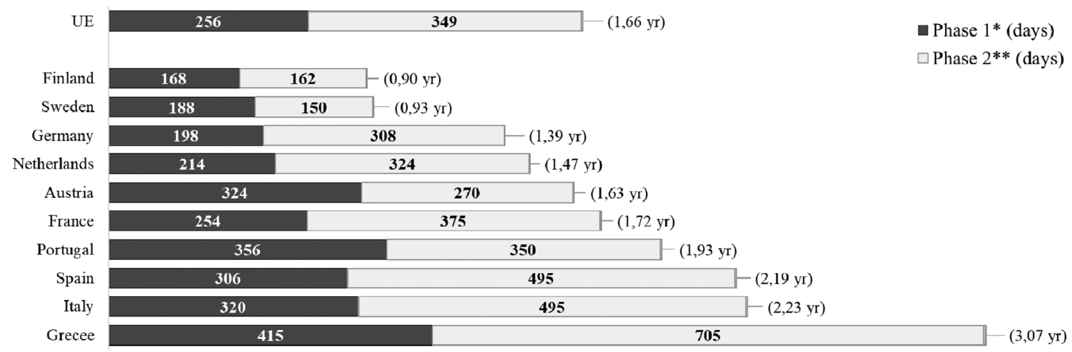

FIGURE 1 Life cycle of an infrastructure contract in 10 selected European Union countries by phase (year 2020). Infrastructure Project: Resurfacing of 20 km dual carriageway. *Source*: Authors' elaboration from World Bank Data-Doing Business 2020 (*pre-contract execution; ** contract execution).

unforeseen regulatory changes, and inadequate project management. A review of public works across member states conducted by the World Bank analyzes the relative performance in terms of the duration of a typical infrastructure procurement contract (Confartigianato Imprese, 2021). This report showed that in Italy, it takes an average of 815 days, approximately 2 years and 2 months, to complete the process—following the preparatory phases by the contracting authority to define the work—from the publication of the tender notice to the completion of the works, including the contractor payment.

The Italian timeline exceeds the EU average of 605 days by 210 days (a 34.7% increase), ranking Italy as the second-slowest in the EU for procurement process duration. Only Greece performs worse, with a process lasting 1120 days, which is 515 days longer than the EU average, an 85.1% increase (Figure 1).

In Italy, 320 days are spent from the publication of the tender notice to the start of works, and 495 days for project execution and contractor payment. These durations represent delays of 25.0% and 41.8%, compared to EU averages. In Italy, the first phase covers 39.3% of the procurement lifecycle, while the second phase is the longest part of the process, representing 60.7%, a share that is three percentage points higher than the EU average of 57.7%. The construction phase, therefore, appears to be the most critical stage in terms of both time and cost overruns. As previously highlighted, both cost and time overruns in the delivery of public works are substantial in public procurement in Italy, as observed by various (Guccio et al., 2014), despite the fact that regulations impose penalties in case of exceeding the planned timeframes (Mattera et al., 2023).

Italian extended public procurement processes indicate systemic inefficiencies in project timeline management. Initial delays often propagate, exacerbating time and cost overruns during project execution. Effective implementation of simultaneous engineering in the construction sector should be based on the seamless integration of construction management and scheduling with the design process (Adeli & Karim, 2001). This integrated approach is crucial in addressing the critical need for robust risk management strategies and accurate estimation techniques, which are essential to mitigate potential overruns and ensure the timely and cost-effective delivery of public projects. Precise cost estimation in construction project management is crucial to avoid disputes and legal issues. Traditionally, this task has relied on experienced estimators using subjective methods, which can lead to inconsistencies and potential errors. Addressing these limitations is essential for improving project outcomes and reducing risks (Adeli & Wu, 1998). This is particularly important in the context of public investments, where lengthy execution times not only penalize their effectiveness but could also potentially undermine European-funded initiatives. The multiplier effect of public investments is reduced by over a third within 5 years due to reduced efficiency in investment spending, such as longer execution times for public works and excessive costs (Busetti et al., 2019). Economists interpret the uncertainty associated with timelines and costs as the presence of information asymmetries that lead to contractual inefficiencies. In the field of engineering estimation, however, this uncertainty is frequently linked to strategic behavior by suppliers who intentionally underbid securing contracts. These strategies often lead to exceeding time and cost estimates during the construction phase, despite legal penalties for delays. Many analyses on large samples of public projects in Italy have shown that more than three-quarters of projects have experienced substantial delays (Banca d'Italia, 2011). As project complexity and contract values increase, delays and cost escalations also naturally increase. In particular, such costs and times become exponential in transport infrastructure projects, where a recent national study in 2023 reveals that high-speed railway projects, in the last 30 years, have faced cost overruns, with the final costs always higher than the preliminary costs, with cost variations presenting peaks of

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more than 360% and an average value of 165% (Bruzzone et al., 2023).

An analysis was conducted on a dataset of 359,960 public procurement auctions for public projects in Italy, of which 198,916 have been entrusted. This dataset was provided by the Italian National Anti-Corruption Authority (ANAC) for the period 2016–2022, with data processed by the Institute for Transparency, Updating and Certification of Procurement, through the Working Group of Regional Public Contracts Observatories (ITACA, 2023). The dataset includes information on reserve prices and award prices, number of public projects, supplies, and services, time overruns, and cost overruns. All data are categorized by regions and years. Key findings from the analysis reveal that the total value of awarded projects amounts to approximately €1.05 billion, with an average project value of €528,417. The national average price reduction is 16.3%, and the average number of bids per project is 8.6. The database provides significant insights into project execution. Notably, 41.4% of projects experienced a cost variation between the award phase and project completion. At the national level, the average cost overrun is 17.9%. Furthermore, the average time delay in project completion is about 113 days, based on an average project duration of 23 months. These increases are more significant in Southern Italy Regions, with Abruzzo, Sardinia, and Campania showing average cost deviations above the national mean, while Molise, Aosta, Lombardy, and Veneto fall below it. Despite the trends reported, current regulations prescribe that contingency allocations should be defined within a maximum threshold of 5% to 10% of the base tender amount, including safety costs (Annex I.7, Art. 5, Paragraph 2, Legislative Decree 36/2023, New Procurement Code). The amounts set aside as "contingencies" can be used to address various issues: increased costs resulting from price revisions, acceleration bonuses, and unforeseen circumstances that may disrupt the contract's balance. However, given the national and European averages for delays and cost overruns in public construction projects, these allocations prescribed by the National Code appear overly optimistic and unrealistic. There is a clear mismatch between prescribed contingency budgets and actual overruns, highlighting a potential gap in both ex ante assessment and risk management for public projects (Canesi & D'Alpaos, 2024). This situation highlights the need for more realistic budgeting approaches. It also suggests that policymakers and project managers may need to reassess the current guidelines to better align with the realities of project execution, especially in areas prone to higher cost variations.

The mitigation of temporal and financial deviations from initial projections represents a complex and relevant objective for Italian procurement entities in public project management. As mentioned earlier, estimates of investment costs for public works and infrastructure are closely linked to phenomena of uncertainty and risk that affect many aspects of public projects. In recent times, where the volatility of construction prices is high, project risk has increased, leading to a greater probability of cost and time overruns.

The substantial allocation of EU funds, including the European Structural and Investment Funds (ESIF) and the National Recovery and Resilience Plan (NRRP), to public projects emphasizes the critical need for accurate cost estimation. These funds, supporting initiatives in climate action, social inclusion, and innovation, come with stringent planning and reporting requirements. The high volatility in construction prices further complicates project management, necessitating more sophisticated forecasting tools and risk assessment methodologies. This combination of external funding pressures and market uncertainties underscores the importance of precise initial estimates and thorough project lifecycle monitoring to effectively anticipate and mitigate potential overruns. For this reason, cost overruns or delays can not only waste public resources but also hinder the achievement of strategic EU goals, including the green and digital transitions. To mitigate these risks, the EU has introduced stricter guidelines for project management and reporting. Recent directives emphasize the use of advanced tools such as building information modeling (BIM), risk management strategies, and ongoing project evaluation to improve the accuracy of cost and time estimates (Alnaser et al., 2024; Hussain et al., 2023). However, despite these approaches, which are typically applied during the execution and management phases of projects, the ex ante estimation phase remains crucial. There is a pressing need for models that can be applied by public administrations, contracting authorities, and economic operators, models that need to be precise and accurate, yet flexible and not overly complex for stakeholders who may not be computational experts. The aim of this study is therefore to develop a flexible and accurate model for ex ante cost estimation in public infrastructure projects, to integrate risk assessment and probability considerations into the estimation process. To address this need, this study introduces PRIMoS (Probabilistic Risk matrix Integration with MOnte carlo Simulation), an estimation tool designed to assist public decision-makers, contracting authorities, private investors, and contractors in the ex ante assessment of project costs and timelines. PRIMoS aims to mitigate, by estimating, the risk of cost overruns in public infrastructure projects by integrating a Bayesian Monte Carlo Simulation model with a double-entrance probabilistic risk matrix. By providing a robust and adaptable tool for risk-informed decision-making, PRIMoS represents a significant advancement in

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project planning and management for public infrastructure initiatives.

This study is structured as follows: Section 2 presents a systematic literature review on time and cost overruns' assessment approaches in public projects. Section 3 details the development and integration of the PRIMoS model in Phases, including a description of the case study used for validation. Section 4 discusses the results of the model, including validation procedures and sensitivity analysis. Section 5 concludes the paper, summarizing key findings, acknowledging limitations, and suggesting potential avenues for future research.

2 | LITERATURE BACKGROUND

The concept of trade-offs in construction project management has been a subject of research for decades. Adeli and Karim (1997), highlighting the intricate relationship between project cost and duration, underscored the complexity of decision-making in construction projects, where optimizing one aspect often impacts another. This fundamental observation sets the stage for understanding the challenges in managing construction projects, particularly in the public sector.

Construction time and costs are critical parameters for the success of public projects and depend on the co-presence of various factors related to, for example, technology, design, project management, and market trends (Asiedu & Adaku, 2020). Budget overruns occur when actual expenses surpass the initial financial projections for a project. This phenomenon, sometimes referred to as cost escalation or financial exceedance, typically results from inaccurate preliminary estimates during the planning stages (Avotos, 1983). Consequently, the project's financial requirements outstrip the allocated funds, potentially jeopardizing its successful completion. Similarly, schedule delays manifest when a project extends beyond its intended timeline. Such temporal overruns often result from setbacks in crucial project components, causing a ripple effect that pushes the entire endeavor past its planned completion date (Koirala & Shahi, 2024). Such delays indicate a failure to meet planned timelines, leading to extended timelines and potential complications in resource allocation and stakeholder expectations.

Researchers have long been interested in exploring the factors contributing to cost and time overruns in construction projects. A recent study, examining over 300 academic papers, provides a comprehensive overview of the field. This extensive analysis delves into various aspects of time and cost overruns, including regional and temporal patterns, the diverse nature of the projects under scrutiny, methodological approaches employed by researchers, and the primary drivers behind these financial and temporal discrepancies. By synthesizing a vast body of literature, this investigation offers valuable insights into the evolving topic of construction project management and the persistent challenges of maintaining financial and temporal targets in the built environment sector (Gómez-Cabrera et al., 2024). In addition, this study detects a tendency among articles to replicate research approaches and methods. These methods range from data collection approaches, such as surveys and interviews, to analytical models and case studies. Surveys and structured questionnaires are widely used to collect data from industry professionals, project managers, and contractors (Sadat & Thomas, 2024). They often include Likert-scale questions to assess perceptions of risk factors, causes of delays, and frequency of cost overruns. For instance, surveys have been effectively used to study factors influencing project delays across different geographical locations and project types, allowing researchers to analyze trends across responses statistically (Alhammadi et al., 2024; Bordat et al., 2004). Semi-structured or structured interviews are also employed to gather in-depth qualitative insights from stakeholders. Interviews with project managers, engineers, and contractors provide detailed narratives on specific issues that may not be easily quantifiable, such as interpersonal conflicts, regulatory delays, or unforeseen site conditions. This method is particularly valuable for identifying the causes of non-excusable delays caused by contractors or clients (Idrees & Shafiq, 2021). Regressions and statistical approaches, such as the Bayesian network classifier approach in addition to machine learning (ML) models, are applied to account for potential interrelationships between risk factors, cause of cost overruns and delays. They are often based on historical project data collected through government or industry records (Madihi et al., 2025; Sanchez et al., 2020). These studies are fundamental and form the basis for qualitative research in this field. By identifying the causes and relationships between factors leading to delays and cost overruns. The literature not only provides lists of causes but often categorizes these factors to facilitate analysis. Typically, factors influencing cost flows are classified into four main categories: technical, economic, psychological, and political (Herrera et al., 2020), or financial, political, cultural and market-related (Zayed et al., 2008). These classifications and listings will be instrumental in defining variables during the model development phase.

Fundamental to this study is also an examination of the approaches used in existing literature to estimate cost and time overruns in construction projects. Of particular interest is whether there are studies that have attempted to estimate both factors simultaneously. Two preliminary queries were initially run in the Scopus search engine,

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focusing on the Article Title, Abstract, and Keywords fields: (i) cost overrun/s, query: (TITLE-ABS-KEY (cost AND overrun); (ii) time overrun/s, query: (TITLE-ABS-KEY (time AND overrun). The engine provided a total of: (i) 4808 results; and (ii) 3356 results. The same search has been performed through the Web of Science (WoS) engine producing the following results: (i) 2952 results; and (ii) 2268 results. Narrowing the search only to Engineering Construction, Business and Management, and Computer Science Journals (called "Subject Area" in Scopus, and "Field" in WoS), the results provided in Scopus (i) 3864; and ii) 2405 results; in WoS (i) 1857 and (ii) 1665 results. Considering that the Scopus engine provided the highest number of results, the literature review was limited to this provider. The timeline report highlights, for both the queries, exponential interest in this field starting approximately in 2010, with a past 5-year production of (i) 1397; and (ii) 942 results; with an average fully yearly production of (i) 273 and (ii) 184 studies.

These studies encompass both researches focused on identifying the causes and factors of delays and cost overruns, as well as those proposing models and tools for estimating these factors. This study aims to concentrate specifically on the latter. To this end, the search was refined by modifying the query to include the non-mutually exclusive presence of "assessment OR estimation OR valuation OR prediction OR forecast," in the search terms. These last two queries led to (i) 533 and (ii) 316 documents found, respectively. Among these results, a higher frequency of various evaluative models was observed. These include statistical and regression analysis models, earned value management approaches, Bayesian belief networks, and stochastic approaches. Additionally, critical path method and program evaluation and review technique, Monte Carlo simulations, and multi-criteria decision analysis (MCDA) were prominent. Multi-attribute decision-making approaches, such as analytic hierarchy process, artificial neural networks, and multi-layer perceptron, were also frequently utilized. Fuzzy logic applications to reflect real-world vagueness (e.g., CoCoSo, Sugeno system) and system dynamics modeling featured prominently in the literature as well. Recent advancements in the field have introduced innovative applications, such as rough set approaches integrated with ML processes. These developments have significantly expanded the toolkit available for estimating delays and cost overruns in construction projects (Senić et al., 2024).

However, while these more recent mass appraisal models are useful for statistically verifying variabilities and supporting planning, they are less suitable for real "on-the-ground" estimates, particularly in complex and large-scale projects. Such projects often have unique administrative, social, and local characteristics that must be managed on a case-by-case basis by involved public and private experts and stakeholders. Falorsi and Alleva (2009) provide valuable insights into the distinction between interpretative and predictive models. Their work supports the notion that mass appraisal models, while rich in information and effective at highlighting interrelationships between variables, are primarily interpretative in nature. These models excel at analyzing complex datasets with numerous independent variables, making them ideal for understanding broad trends and relationships. However, they are not designed for making specific predictions, especially in unique or unobserved scenarios. A predictive model, conversely, has the primary objective of allowing us to forecast hidden values that are often not captured by statistical surveys. These models aim to uncover and estimate factors that may be overlooked or unmeasured in traditional data collection processes, providing insights into potential outcomes that are not readily apparent from existing data alone. This distinction underscores why mass appraisal models, while valuable for understanding general patterns in cost overruns and delays, may not be suitable for precise predictions in individual, complex infrastructure projects. This distinction is crucial in the context of infrastructure project management. While mass appraisal models can provide valuable insights into general trends and relationships, they are primarily interpretative rather than predictive. They can support the planning process by highlighting potential risk factors and their interrelationships, but they cannot accurately predict the specific cost overruns or delays for individual, complex projects.

For this reason, our literature review will focus on non-ML and non-mass appraisal models, concentrating instead on adaptable and customizable application tools that study both time and cost overruns. In particular, we will explore the Monte Carlo technique, as it offers a flexible approach that can be tailored to the specific needs of individual infrastructure projects, analyzing both cost and time overruns. Figure 2 illustrates the growth in the number of published articles over time, demonstrating the increasing academic interest in both cost and time overruns, as well as Monte Carlo applications in project management. This trend underscores the growing recognition of the importance of these topics in the field of infrastructure project planning and execution.

In the general scientific production of research concerning Monte Carlo models, as indicated in Figure 3, the map highlights clusters of interconnected research areas, with nodes representing key terms and links illustrating co-occurrence relationships.

Larger clusters associated with the keyword "Monte Carlo" include "overrun" in relation to "infrastructure project," "risk management," "construction industry," "causes," and "time," as well as "development" and

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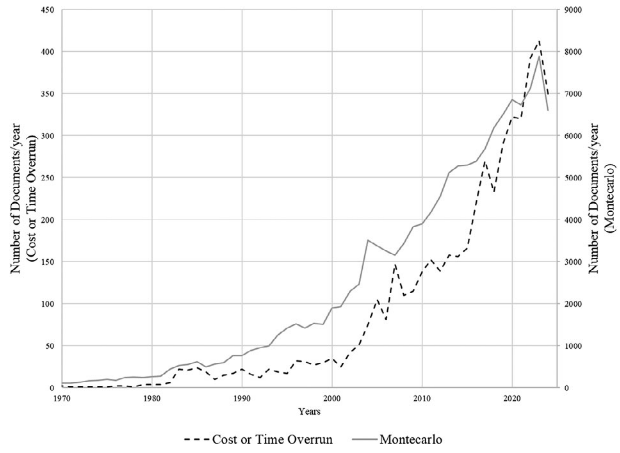

FIGURE 2 Number of published documents per years in Scopus Database: Documents on cost and time overrun VS documents on Monte Carlo applications. *Source*: Authors' elaboration from Scopus database.

"design." This visualization reflects the interdisciplinary focus and thematic relationships within this specific technique. The map provides a visual representation of the interconnected nature of research in Monte Carlo modeling, particularly in the context of construction and infrastructure projects.

It illustrates how concepts such as risk management, time overruns, and project development are closely linked in the literature, underscoring the multifaceted approach required in addressing project management challenges. The presence of terms related to both practical applications (like "construction industry") and methodological aspects (such as "development" and "design") highlights the balance between theoretical advancement and real-world implementation in this field of study. The results of the studies selected from the queries presented above were then cross-referenced and integrated with searches from WoS and Google Scholar, applying the same queries and limitations. This approach ensured a comprehensive overview of the work produced in this research area. After reading the abstracts of these articles, this number was reduced to 52, as the remaining ones were either not relevant to the thematic focus of this search string or did not propose estimation models but rather presented case study analyses or identified causes of delays and cost increases through surveys. Of these 52 articles, 28 were found to be specifically related to the use of Monte Carlo Simulations in the context of cost and/or time overruns. Table 1 summarizes their main characteristics and results. This process of systematic literature review and refinement allowed us to focus on the most relevant and methodologically aligned studies on Monte Carlo applications. By combining results from multiple academic databases and applying consistent criteria for inclusion, a thorough and representative sample of current research in Monte Carlo simulations applied to cost and time overruns in construction projects was ensured.

The systematic literature review revealed that among all the case studies, 12 focused on transportation infrastructure projects, of which four studies focus solely on cost overruns, two studies examine only time overruns, two studies investigate time both time and cost overrun keeping them separately, using separate or different model and approaches, and finally only two studies simultaneously investigate both cost and time overruns. Among the

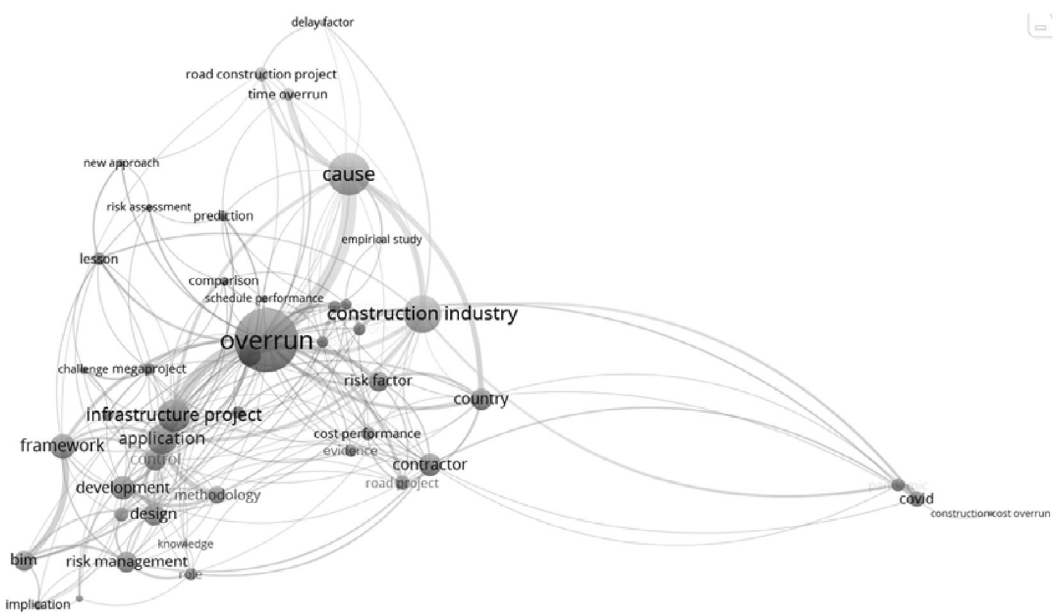

FIGURE 3 Network visualization of papers on "Monte Carlo" Topic. *Source*: Authors' elaboration using VOSviewer.

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TABLE 1 Literature review using the Monte Carlo approach for estimating costs and overrun times.

Reference	Number of risks	Case study: Country	Case study: Project type	Case study: Subtype	Prediction: Cost	Prediction: Delay
Afzal et al. (2020)	20	Pakistan	Generic transportation projects	Metropolitan transit project	x	
Asiedu and Gyadu-Asiedu (2020)	7	Ghana	Generic construction projects	Generic building construction		x
Bhargava et al. (2017)	3	USA	Road infrastructure projects	Highway expansion	x	
Bouayed (2016)	5	N/A	Generic transportation projects	Fictitious case study	x	
Brokbals et al. (2019)	26	Germany	Mixed building and road projects	Building construction, civil engineering, and road construction	x	
Chang and Ko (2017)	15	Taiwan	Sewerage projects	34 sewerage build-operate-transfer projects	x	
Eke and Elgy (2017)	N/A	UK	Educational building projects	120 educational facilities projects, various dimensions	x	x
Erol et al. (2017)	9	N/A	Residential building project	Fictitious case study		x
Ford et al. (2012)	N/A	USA	Road infrastructure projects	Highway		x
Iqbal and Purwanto (2022)	27	Indonesia	Road infrastructure projects	Toll road projects carried out with the PPP scheme	x	
Islam et al. (2022)	49	Bangladesh	Energy infrastructure projects	Thermal power plant project	x	
Jie and Wei (2022)	N/A	China	Commercial building projects	Fictitious case study	x	x
Kansal and Agarwal (2022)	32	India	Energy infrastructure projects	Hydroelectric power project	x	
Karabulut (2017)	17	Middle East	Residential building projects	Luxury villa		x
Lee et al. (2023)	11	Korea	Generic construction projects	Bridges, tunnels, seaports, and power plants	x	
Lowe et al. (2020)	16	India	Underground infrastructure projects	Metro corridor	x	x
Moghayedi and Windapo (2022)	4	South Africa	Road infrastructure projects	Highway expansion	x	x
Mohammadi and Spross (2024)	N/A	N/A	Underground infrastructure projects	Tunneling and underground space		x
Moret and Einstein (2016)	13	N/A	Railway infrastructure projects	Tunnels, viaducts, cuts, and embankments	x	x
Nguyen et al. (2024)	30	Germany	Railway infrastructure projects	Urban rail project	x	x
Peleskei et al. (2015)	8	Germany	Public building projects	Administrative buildings	x	
Rezaee Arjroody et al. (2024)	N/A	N/A	Road infrastructure projects	Early stages of road construction projects	x*	x*

(Continues)

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TABLE 1 (Continued)

Reference	Number of risks	Case study: Country	Project type	Subtype	Prediction: Cost	Delay
Sachchithananthan et al. (2024)	15	USA	Generic building projects	Twenty random building projects	x	
Sadeghi et al. (2010)	8	N/A	Generic building projects	Various generic construction projects	x	
Sihombing and Christin (2023)	66	Indonesia	Pipeline projects	Gas pipeline network development project	x	
Sobieraj and Metelski (2022)	18	Poland	Residential building projects	Large residential apartment complex		x
Sovacool and Ryu (2025)	2	Various	Energy infrastructure projects	Various	x*	x*
Steininger et al. (2020)	7	Germany	Railway infrastructure projects	Urban rail project	x*	x*
Vegas-Fernández (2022)	Vary	N/A	Construction projects	Various generic construction projects	x	

Note: x* = when the study investigates both cost and time overrun but using two separate models or approaches.

cases, only one (4%) relates to a European transportation infrastructure project. The literature review reveals an imbalance in the treatment of time and cost risks in infrastructure projects. While cost overruns are extensively studied, time overruns receive comparatively less attention, only six papers focus on time overrun. Only 18% of the studies examine time overruns exclusively, and a mere 26% investigate both cost and time overruns simultaneously. This disparity is particularly evident in transportation infrastructure projects, where out of 11 identified studies, as said, only one focuses solely on time overruns, while four address costs overrun exclusively. The underrepresentation of time risk analysis is a significant gap in the literature, especially considering the interdependent nature of time and cost in project management. The limited focus on time risks may be attributed to the challenges in modeling time-related variables. Unlike cost elements, which often comprise multiple components suitable for detailed Monte Carlo simulations, time is typically modeled as a single separated variable, as an overall project duration extension. This limitation in modeling complexity might explain the predominant focus on cost risks in existing literature.

Furthermore, this literature review reveals other important trends and gaps in the application of Monte Carlo simulations to cost and time overrun estimation in construction projects. While Monte Carlo methods are increasingly adopted to quantify uncertainty and variability, the literature remains fragmented in both geographical and sectoral terms. The distribution of studies across project types underscores a heavy focus on building and general infrastructure projects, with limited attention to transportation infrastructure, despite the latter's high exposure to complex risks. This gap is significant given that transportation projects are particularly susceptible to budget and timeline deviations, making them ideal candidates for probabilistic risk modeling.

Only five studies examine road transport infrastructure, and among them, just two conduct an integrated analysis of both cost and time overruns. These studies, combining cost and time overrun assessment, have demonstrated that a simultaneous estimation produces a superior model, compared to separately estimated models for cost and time overruns, as these factors are interdependent. The argument that cost and time variables should be included simultaneously, as they are interdependent, implies that they are influenced by similar factors such as the bid price, the degree of competition in the bids, the size of the project, and the type of project (Asiedu & Gyadu-Asiedu, 2020; Baloi & Price, 2003).

The critical insight from our literature review is the methodological fragmentation concerning the modeling of risk input variables in Monte Carlo-based models due to the absence of standardized or objective procedures for defining model inputs. This fragmentation suggests a significant constriction that limits the reproducibility and robustness of these models. Various studies acknowledge the challenge of defining accurate probability distributions and impact values, typically relying on expert judgment or historical analogies. While some degree of subjectivity is inherent and even necessary in such estimates, it need not be arbitrary. Most existing models adopting Monte Carlo simulations do not include a systematic procedure for defining input distributions, nor do they integrate a two-dimensional probabilistic structure that links risk magnitude (RM) to probability classes. This gap in methodology presents an opportunity for improvement in the field. Our effort with PRIMoS aims

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to bridge this lacuna by proposing a model that organizes and formalizes the estimation process. PRIMoS explicitly addresses these methodological gaps by introducing a double-entry probabilistic Risk Matrix combined with a Bayesian Monte Carlo simulation. This approach provides stakeholders involved in the estimation with a structured, verifiable framework for assessing probability and impact, rather than relying on randomized choices. By using standardized double-entry matrices to constrain the selection of probability distributions and variation ranges, our model offers a systematic method for incorporating expert knowledge into the valuation process. This approach improves the accuracy of risk assessment, providing a step-by-step process, enhancing reproducibility by public administrations.

3 | MATERIALS AND METHODS

3.1 | Transforming uncertainty into risk

In the context of economic investments, uncertainty stems from the imperfect present and future knowledge of the input variables employed in the assessment models and the approximations of the economic model that describe the investment. While the distinction between risk and uncertainty is well-established in the field, our focus is on how these concepts are operationalized in practical risk assessment models. Forward uncertainty, or uncertainty propagation, is applied in economic forecasting models by evaluating input variable uncertainty and quantifying corresponding output uncertainty (Tian et al., 2018). Parameter uncertainty reflects the lack of knowledge in assessing input values inside the forecasting models (Silva & Ghisi, 2014). In economic analyses, this may involve cost values, timing, discount factors, or other variables (Hopfe & Hensen, 2011). Uncertainty in design parameters arises from the different stages of design during which feasibility analyses are conducted. For example, preliminary feasibility analyses cannot depend on specific assumptions at the early design stages (Wei, 2013).

Economic valuations and forecasts inherently carry uncertainty. Regardless of the technique employed for economic analysis, the outcome can only be regarded as the "best estimate" of the result. Each estimate is influenced by various uncertainties, including unreliable information about the comparables, a lack of knowledge regarding current and especially future market conditions, and uncertain estimates of the input variables within the economic model. In the context of public infrastructure projects, market fluctuations can significantly impact cost estimations and project outcomes highlighted the importance of considering rate stability in project cost simulations, demonstrating that it significantly influences project cost variance (Wang et al., 2008). This concept aligns with the current volatile construction market, where prices for materials and labor can fluctuate rapidly. Uncertainties stem from both microeconomic factors and macroeconomic events. Various financial (Gu et al., 2018) and economic (Zhu et al., 2012) data are highly uncertain, impacting retrofit projects. Economic and financial conditions can experience unforeseen and rapid changes, as recently demonstrated by the Covid-19 pandemic (Gabrielli et al., 2023; Quaglio et al., 2021) and the outbreak of the War in Ukraine (Trojanek & Gluszak, 2022). These events, which significantly influence economic and financial variables (such as construction costs and discount/growth rates), will be introduced as input variables in PRIMoS model, which will serve to optimize the ex ante estimation of costs and time in public infrastructure projects. PRIMoS addresses these challenges by integrating concepts of probability and impact by a structured matrix that precedes the modeling of uncertainty via Monte Carlo analysis. This approach represents an advancement over traditional Monte Carlo simulations by providing a structured framework for assessing variability functions and ranges of variability.

The represented workflow in Figure 4 details all the phases of risk estimation model. After the case study definition, the research is divided into three phases. Specifically, PRIMoS employs a double-entry matrix in Phase II to assess the probability and impact of various risk factors. This structured approach provides a more robust foundation for the subsequent Monte Carlo simulation, ensuring that the input parameters are grounded in a thorough, project-specific risk assessment rather than relying on generic assumptions or subjective judgments. In Phase III, the model leverages the insights from the probability-impact matrix to inform the selection of appropriate probability distributions for each variable. This step is crucial as it bridges the gap between qualitative risk assessment and quantitative simulation, ensuring that the Monte Carlo model accurately reflects the risk profile identified in the earlier phases. Phase IV of PRIMoS integrates these elements into a comprehensive uncertainty modeling approach. The Monte Carlo simulation in this phase is critically informed by the structured assessments from the previous phases, ensuring that the random sampling process is based on well-founded, project-specific parameters. This approach enhances the reliability and transparency of the estimation process. This structured methodology represents a significant advancement over traditional Monte Carlo applications by guiding users through a systematic process of risk assessment and quantification, thereby improving the accuracy and reliability of project cost and time estimates.

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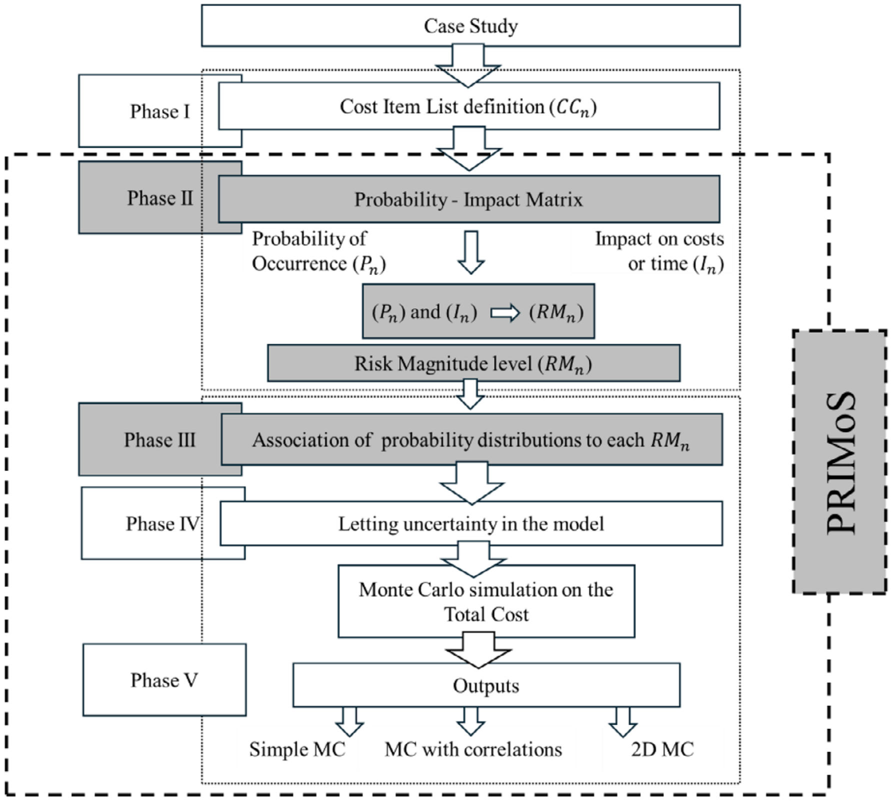

FIGURE 4 Workflow's phases (CC_n: cost item; P_n: probability of occurrence; I_n: impact; RM_n: risk magnitude level; MC: Monte Carlo).

FIGURE 5 Location of the case study.

3.2 | Phase I: The case study

The case study focuses on a major infrastructure project located in the province of Treviso, in the municipality of Vittorio Veneto, situated in the Venetian Prealps Region (Figure 5). This project was selected as our research example due to its complexity, long development history, and the numerous variations and successive phases it has undergone, making it highly representative of the challenges commonly faced in large-scale public infrastructure projects. The project, identified as the Variant of State Road No. 51 of Alemagna Vittorio Veneto, was commissioned through an integrated contract, which combines both design and construction works. This contracting approach is typically employed for projects with a high level of technological complexity, as it offers economies of scale advantages. Initiated in 1987 by the National Autonomous Roads Company (Azienda Nazionale Autonoma delle Strade, ANAS S.p.A.), the project has undergone several revisions and modifications over the years due to urban planning non-compliance issues, legal challenges, and technical necessities. These factors make it an ideal candidate for demonstrating the broad applicability and adaptability of the PRIMoS framework in managing evolving risk factors throughout a project's lifecycle. The primary objective of this project was to alleviate the historic and residential center of Vittorio Veneto from the heavy automobile traffic that currently traverses through it.

In Phase I, the original bill of quantities was reconstructed and broken down into n cost items (CC_n) as presented in Table 2.

The estimated costs (CC_e), derived from the detailed cost estimate prepared before the start of construction, amounted to €59,601,818 in the executive project, with an additional estimated contingency cost of €1,422,630 (2.39% of CC_e).

These estimated costs are compared with the actual costs (CC_a), which represent the as-built costs incurred during the project's execution and completion. As presented in Table 2, the actual costs after project completion amounted to €64,404,711 (CC_a), revealing a differential

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TABLE 2 Executive project's estimated costs (CC_e) and actual costs (CC_a).

Code CC_n	Cost item	Estimated costs[a] (€) CC_e	Actual costs[a] (€) CC_a	Cost difference (€) $CD = CC_a - CC_e$	% Difference $D_e = CD/CC_e$
CC_1	Construction costs	48,030,074	47,647,456	−382,618	−0.80%
CC_2	Engineering fees	395,158	878,737	483,579	122.38%
CC_3	Surveys	24,000	24,000	–	0.00%
CC_4	Interferences	210,000	1,089,803	879,803	418.95%
CC_5	Eminent domain	1,500,000	5,415,645	3,915,645	261.04%
CC_6	General office	183,179	93,327	−89,852	−49.05%
CC_7	Utilities	223,453	223,453	–	0.00%
CC_8	Taxes	3664	–	−3664	−100.00%
CC_9	Marketing	32,000	32,000	–	0.00%
CC_{10}	Testing and inspections	522,102	522,102	–	0.00%
CC_{11}	Financial costs	8,478,189	8,478,189	–	0.00%
TOTAL		59,601,818	64,404,711	4,802,893	8.06%
CC_{12}	**Contingencies**	1,422,630		4,802,893	337.61%

[a]All costs are NET, excluding VAT.

(delta) between CC_e and CC_a of €4,802,893 (8.06%). This difference, as specified in the introduction, represents the cost overrun. This resulted in an increase in Contingencies (CC_{12}) of 337.61%, compared to the initial estimate.

The grouping of costs (CC_n) identified in the detailed cost estimate followed the results from literature regarding the cost variables identified as most relevant in previous studies.

The purpose of PRIMoS model is to estimate potential cost increases ex ante, thus reducing the real gap (D_e) which, in this case study, resulted in an expenditure increase of 8.06%, with contingency estimates rising by approximately 3.4 times. The authors aim to verify whether PRIMoS model provides a more accurate economic quantification of unforeseen events, compared to traditional forecasting methods. By analyzing variability and uncertainty through probabilistic modeling, the objective is to determine if this approach enhances the reliability of predictions for public infrastructure projects.

3.3 | Phase II: Variables modeling

In Phase II, the risk assessment matrix was constructed, drawing upon the conceptual framework of risk and its classification as outlined by the National Anti-Corruption Authority (ANAC). This new matrix, which represents an original approach, tailored specifically for the needs of this study, aims to predict cost and time overruns in infrastructure public projects more accurately. This matrix was integrated into a Monte Carlo analysis, developing what has been called the PRIMoS model.

The Risk Matrix associates each variable to be included in the Monte Carlo simulations (e.g., costs, time, rates, etc.), with a qualitative probability of occurrence (P_n) and a categorized impact on costs or time (I_n). This approach aims to address overruns in by providing ranges of variability and probability distributions of occurrence for each considered variable. The impact intervals and probability levels were defined to enable the classification of risks and associated costs for modeling in the Monte Carlo simulation as presented in Table 3. This classification system forms the basis for the risk assessment framework utilized in the subsequent analysis. Probability is categorized into three levels: unlikely (P_a) ∈ [0%,30%]; likely (P_b) ∈ [30%,60%]; and very likely (P_d) ∈ [60%,100%]. Each probability interval was associated with a different probability distribution function, which is later applied to each input variable in the Monte Carlo model as presented later in this section. The intervals associated with impacts were revised to account for both negative (*Threats*, I_{max}) and positive (*Opportunities*, I_{min}) outcomes. As a result, the model incorporates ranges that accommodate positive, negative, and potentially neutral impacts. This bidirectional matrix considers both risks (increasing costs) and opportunities (decreasing costs) in its assessment, capturing potential negative and positive outcomes. As a result, it offers a more realistic representation of possible scenarios. As presented in Table 3, the impact on cost (I) is classified into four levels for each positive or negative impact. Each level on the left side of the matrix represents a potential cost decrease, and thus a positive impact (Opportunity) on the project cost estimate. These levels (I_{min}) are defined as follows: Light ($I_{min,a}$) corresponding to a −5% impact, Mediocre

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TABLE 3 Risks Magnitude matrix (authors' elaboration).

				Impact on costs (I)								
				Opportunities (I_{min})					Threats (I_{max})			
				Extreme	High	Mediocre	Light	None	Light	Mediocre	High	Extreme
				$I_{min,d}$	$I_{min,c}$	$I_{min,b}$	$I_{min,a}$	$I_{min,max,0}$	$I_{max,a}$	$I_{max,b}$	$I_{max,c}$	$I_{max,d}$
				−20%	−15%	−10%	−5%	0%	+5%	+10%	+15%	+20%
Probability (P)	Unlikely	]0%,30%[	(P_a)	RM_{min_4}	RM_{min_3}	RM_{min_2}	RM_{min_1}	RM_{0a}	RM_{max_1}	RM_{max_2}	RM_{max_3}	RM_{max_4}
	Likely	[30%,60%[	(P_b)	RM_{min_8}	RM_{min_7}	RM_{min_6}	RM_{min_5}	RM_{0b}	RM_{max_5}	RM_{max_6}	RM_{max_7}	RM_{max_8}
	Very likely	[60%,100%]	(P_c)	$RM_{min_{12}}$	$RM_{min_{11}}$	$RM_{min_{10}}$	RM_{min_9}	RM_{0c}	RM_{max_9}	$RM_{max_{10}}$	$RM_{max_{11}}$	$RM_{max_{12}}$
				Positive impact				**No impact**	**Negative impact**			

($I_{min,b}$) implying an impact of −10%, High ($I_{min,c}$) corresponding to a −15% impact, and Extreme ($I_{min,d}$) with an impact of −20%. Each level on the right side of the matrix instead represents a potential cost increase, and thus a negative impact (Threat) on the project cost estimate. These range from +5% ($I_{max,a}$) to +20% ($I_{max,d}$). These impacts represent the variability range (minimum and maximum values) assigned to each input parameter within the Monte Carlo simulation model. It is also considered that the maximum or minimum of these intervals may be equal to zero, representing a null impact ($I_{min,max,0}$), applicable to both the left and right sides of the interval. The proposed range of 0% to ±20% for impact levels was carefully chosen based on historical data from Italian public works projects, which show an average cost overrun of 17.9%, as mentioned in the Introduction section. This range allows us to capture typical variations observed in these projects, including potential underruns and slight overruns beyond the average, providing a realistic and data-driven framework for risk assessment in the Italian infrastructure context.

This matrix provides a systematic way to identify high-priority variables requiring attention and mitigation based on their combined probability and impact scores (ANAC, 2021, 2022, 2024). Thanks to this matrix, a negative Risk Magnitude (RM_{min}), and a positive Risk Magnitude (RM_{max}) can be associated with each risk. The probability and distribution associated with each variable in the Monte Carlo simulation are defined based on the RM_{min} and RM_{max} levels, as indicated by the combination of probability and impact in the risk matrix. These risk levels range from RM_1 (the lowest risk) to RM_{12} (the highest risk) and are used consistently for both positive impacts (RM_{min}) and negative impacts (RM_{max}).

As previously mentioned, each probability level is associated with a specific probability distribution function. These functions are assigned to reflect the expected likelihood of cost impacts. The shape of each distribution is chosen to best represent the associated probability level (P_n), with the range of possible impacts defined by the

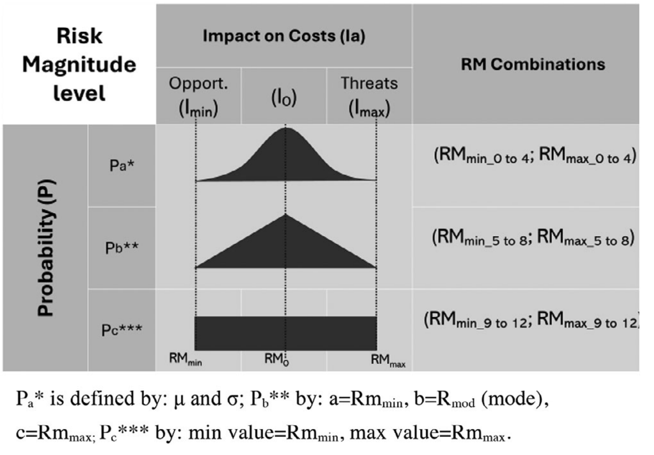

FIGURE 6 Frequency distribution assigned to each Risk Magnitude (Rm_n). P_a* is defined by: μ and σ; P_b** by: a = Rm_{min}, b = R_{mod} (mode), c = $Rm_{max;}$ P_c*** by: min value = Rm_{min}, max value = Rm_{max}.

minimum (RM_{min}) and maximum (RM_{max}) risk levels, as shown in Figure 6.

These distributions correspond to the different risk Probability levels outlined in Table 3. For unlikely risk scenarios ($RM_{1–4}$), a Gaussian (normal) distribution is used. This type of curve is centered around the most likely value, with a low probability of extreme cost deviations. It reflects situations where cost overruns (or savings) are unlikely, and impacts are generally stable and predictable. For likely risk scenarios ($RM_{5–8}$), a triangular distribution is applied. This assumes a higher likelihood of values near the most probable impact but allows for moderate variability. It reflects a balanced level of uncertainty, where cost changes are possible but not extreme. Finally, for very-likely risk scenarios ($RM_{9–12}$), a rectangular (uniform) distribution is used. In this case, all values within the RM_{min}–RM_{max} interval are considered equally likely, reflecting a high level of uncertainty. This means there is a higher probability of experiencing a wide range of impacts, including significant cost overruns or reductions. The selection of these

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TABLE 4 Infrastructure project's Cost and their Risk Magnitude classification.

Code	P_n	I_{min}	I_{max}	Interval (RM_{min}; RM_{max})
CC_1	P_b	$I_{min,0}$	$I_{max,d}$	(RM_{0b}; RM_{max8})
CC_2	P_b	$I_{min,0}$	$I_{max,c}$	(RM_{0b}; RM_{max7})
CC_3	P_b	$I_{min,0}$	$I_{max,a}$	(RM_{0b}; RM_{max5})
CC_4	P_b	$I_{min,0}$	$I_{max,a}$	(RM_{0b}; RM_{max5})
CC_5	P_c	$I_{min,0}$	$I_{max,d}$	(RM_{0c}; RM_{max12})
CC_6	P_b	$I_{min,0}$	$I_{max,b}$	(RM_{0a}; RM_{max2})
CC_7	P_a	$I_{min,0}$	$I_{max,b}$	(RM_{0a}; RM_{max2})
CC_8	P_a	$I_{min,0}$	$I_{max,b}$	(RM_{0a}; RM_{max2})
CC_9	P_b	$I_{min,0}$	$I_{max,b}$	(RM_{0b}; RM_{max6})
CC_{10}	P_b	$I_{min,0}$	$I_{max,d}$	(RM_{0b}; RM_{max8})
CC_{11}	P_b	$I_{min,a}$	$I_{max,a}$	(RM_{min5}; RM_{max5})

distributions is supported by their widespread use in project risk analysis literature (Vose, 2008) and by their empirical robustness in capturing varying levels of uncertainty.

The effectiveness of this distribution selection approach in reducing subjectivity was validated through a Fleiss' κ test, which showed 0.36 points increase in inter-rater agreement (from $\kappa = 0.22$ to $\kappa = 0.58$) when experts used our matrix for risk assessment, confirming the improved consistency and objectivity in probability risk evaluation. Each distribution provides a computationally efficient means to model uncertainty profiles that align with expert judgment and reflect observed variability in previous projects. Considering this approach, the proposed modeling allows the Monte Carlo simulation to reflect not only the range of potential cost impacts but also the shape of the uncertainty, depending on the associated risk level, according to a defined classification.

3.4 | Phase III: Data preparation

In Phase III, each cost item within the project estimated budget (CC_e), which can be associated with a risk component identified both from the risk list proposed by ANAC and by the analyzed literature, was evaluated. Each item was then assessed using the Risk Magnitude matrix presented in Table 3. This evaluation involved assigning two critical parameters: a cost overrun probability of occurrence (P_n) and its potential impact (I_n), as detailed in Table 4. This step is crucial in quantifying the uncertainty associated with each cost element. By applying the proposed probability/impact matrix, each cost item was associated with a qualitative Risk Magnitude Interval (RM_{min}; and RM_{max}). This step quantifies the uncertainty associated with each cost element, serving as a bridge to the Monte Carlo modeling analysis. Each Risk Magnitude corresponds to a specific probability distribution function as previously illustrated in Figure 6. These distribution functions are selected to best represent the nature of uncertainty for each risk level. The associated probability curve for each cost item will then be modeled through the computational Monte Carlo simulation algorithm. Furthermore, each Impact Interval will be incorporated into the Monte Carlo model as the minimum and maximum range associated with every selected cost item.

TABLE 5 Cash flow of the estimated costs in € (CC_e).

Costs	Year 0	Year 1	Year 2	Year 3
CC_1	9,606,015	19,212,030	14,409,022	4,803,007
CC_2	177,821	158,063	39,516	19,758
CC_3	10,800	9600	2400	1200
CC_4	42,000	84,000	63,000	21,000
CC_5	75,000	375,000	525,000	525,000
CC_6	54,954	54,954	36,636	36,636
CC_7	44,691	89,381	67,036	22,345
CC_8	916	916	916	916
CC_9	12,800	12,800	3200	3200
CC_{10}	182,736	182,736	52,210	104,420
CC_{11}	2,119,547	2,119,547	2,119,547	2,119,547
Total Costs	12,327,279	22,299,026	17,318,483	7,657,030
$1/(1+r)^n$	1.00	1.03	1.05	1.08
A.C.*	12,327,279	22,856,502	18,195,231	8,245,784
Total	61,624,796			

Note: A.C. = Actual Costs.*

3.5 | Phase IV: Data modeling

The economic analysis, in the discrete formulation, is structured in the form of an updated cost assessment according to the following equation (Formula 1) and represented in Table 5. The discount rate (r), which incorporates inflation, is calculated as the average of monthly Italian 10-year BTP gross yield rates from January 2010 onward.

$$TOTAL\ COST = \sum_{i=1}^{N} \sum_{t=0}^{T} \left\{ \left((\mathrm{CC}_n * d) * (1+r)^t \right) \right\} \quad (1)$$

$$\mathrm{t} \in \mathrm{N0}, \ldots, \mathrm{T}, \mathrm{T} = 4$$

$$\mathrm{n} \in \mathrm{N0}, \ldots, \mathrm{N}, \mathrm{N} = 11$$

The key inputs are as follows:

CC_n: future cash outflows (costs).
N: Total amount of cost items.

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TABLE 6 MCS input variables definition.

Input X	Estimated values (€)	Min (€)	V* (%)	Max (€)	V* (%)
CC_1	48,030,074	40,825,563	−0.15	55,234,585	0.15
CC_2	395,158	395,158	0.00	434,674	0.10
CC_3	24,000	21,600	−0.10	26,400	0.10
CC_4	210,000	189,000	−0.10	220,500	0.05
CC_5	1,500,000	1,500,000	0.00	1,725,000	0.15
CC_6	183,179	183,179	0.00	201,497	0.10
CC_7	223,453	223,453	0.00	234,625	0.05
CC_8	3664	3664	0.00	3847	0.05
CC_9	32,000	32,000	0.00	33,600	0.05
CC_{10}	522,102	522,102	0.00	600,418	0.15
CC_{11}	8,478,189	7,630,370	−0.10	9,326,008	0.10
D	0	0.08	–	0.22	–
R	0.03	0.01	−0.52	0.05	0.84

Note: *V* = Variation.*

r: discount rate.
t: the year when costs occur.
T: number of years over which it is thinkable to value the project.

Based on project estimates, a 4-year development timeline for the infrastructure project was modeled, and accordingly a cash flow projection spanning this duration was constructed (n). As a result, after a 4-year period of analysis, the total cost is €61,624,796, representing the total investment required for the operation. The cost model provides the most accurate estimate of the total cost. However, the total cost assessment relies on numerous variables that may deviate from the figures predicted by the valuer based on the knowledge available at the time of estimation. In practice, multiple factors may differ from the estimate or be influenced by unforeseen events not considered in the predictions. The Risk Magnitude assessment, and for each risk component of the above-described infrastructure project, has been defined as proposed in Table 6.

Uncertainty is incorporated into the cost model using a Monte Carlo simulation, defining uncertain parameters. To each input, such as costs, discount rate, or time is assigned a probability distribution that captures the variability of that parameter (Youssefi et al., 2022). Unlike previous studies that focused on estimating the costs associated with the highest magnitude risks, this analysis explores all cost items included in the Detailed Cost Estimate and adds the time dimension to the analysis. In addition to cost items, the model incorporates time as a factor through the discount rate, r, which represents the time value of money. This rate is adjusted within the magnitude matrix based on historical reference rate series. Specifically, the discount rate is modeled as an input that can be changed according to project duration and risk levels. This approach allows for a weighted present value calculation of cost capitals as time varies. By incorporating time-dependent discount rates, the model captures the temporal aspects of cost uncertainty, reflecting how the value of money and risk perceptions change over the project lifecycle. The distributions and the minimum and maximum values considered result from expertise in the field, specific market analyses, and literature reviews.

Each input variable (X), listed in Table 6, is therefore defined by a probability distribution P(X). These variables are assigned probability distributions that reflect their inherent uncertainty.

$$\forall\, \mathrm{X} \in \{\text{input variables of the cost model}\}\ \mathrm{X}/\mathrm{X}\ \text{is defined by}\ (\mathrm{X}_{\min};\ \mathrm{X}_{\max};\ \mathrm{P(X)})$$
$$\wedge$$
$$\forall\, \mathrm{X}\,/\,\mathrm{X} \in \{CC_n, r, d\},\ 1 \le n \le 11$$

The discrete model represented by the updated total cost, as presented in Table 5, is transformed into a stochastic forecasting tool as follows:

$$P\,(\text{TOTAL COST}) = \sum_{i=1}^{N}\sum_{t=0}^{T}\left\{\left(\mathrm{P}(\mathrm{CC}_n) * P\,(d)) * (1 + P\,(r))^{P(t)}\right)\right\} \tag{2}$$

$$\mathrm{t} \in \mathrm{N}0, \ldots, \mathrm{T}, \mathrm{T} = 4$$

$$\mathrm{n} \in \mathrm{N}0, \ldots, \mathrm{N}, \mathrm{N} = 11$$

The Monte Carlo simulation is used to model uncertainty in the forecast (Y) by performing a repeated random sampling of the inputs (X) to obtain a probability distribution of the possible numerical results. In this context, the MCS involves generating numerous possible scenarios for future cash flows, each based on the probabilistic distributions of the input variables (X). The outcome of the forecasting model will not be a discrete estimate but a probability distribution of that forecast P (total cost). The simulation process executes multiple iterations, with each iteration randomly sampling values for these input variables within their defined distributions. The resulting range of cash flow outcomes forms a probability of distribution that provides insights into the outcome. Specifically, three different MC simulations will be produced: the first will be a simple simulation to see the behavior of the model and how uncertainty propagates in it. The second simulation will set correlations between certain variables with the aim of improving the realism of uncertainty propagation. The third MCS will be a two-dimensional, to separate aleatory uncertainty from epistemic uncertainty.

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TABLE 7 Sensitivity analysis.

	Total cost (€)			Input[a]		
Variable	Downside	Upside	Range	Downside	Upside	Base case
CC_1	62,006,524	66,713,309	4,706,784	48,399,786	52,956,318	48,030,074
D	54,698,895	52,663,184	2,035,710	0.112	0.145	0.000
CC_{11}	61,301,139	61,948,104	646,965	8,166,578	8,789,800	8,478,189
R	61,721,434	62,357,727	636,293	0.026	0.034	0.030
CC_5	61,656,146	61,908,347	252,201	1,530,000	1,770,000	1,500,000
CC_2	61,627,720	61,665,917	38,196	398,200	435,688	395,158
CC_{10}	61,627,379	61,661,362	33,984	524,782	557,802	522,102
CC_7	61,626,559	61,644,251	17,692	225,367	242,841	223,453
CC_6	61,626,242	61,641,039	14,797	184,749	199,073	183,179
CC_4	61,625,178	61,632,038	6,860	210,539	217,180	210,000
CC_9	61,624,789	61,626,859	2070	32,164	34,188	32,000
CC_3	61,624,684	61,625,457	773	24,062	24,821	24,000
CC_8	61,624,654	61,624,951	297	3695	3981	3664

[a] CC_n in €.

This last simulation should be the most reliable, and the results will be discussed based on its outcome.

4 | RESULTS AND DISCUSSION

A sensitivity analysis was conducted prior to the MC simulation. This process identified the most influential variables, allowing for focused effort on shaping their probability distributions accurately. Less impactful inputs were represented with simpler assumptions. This analysis identified critical uncertainties requiring closer examination and those with marginal impact (Ariza & Zavala, 2025; Fajar & Tokimatsu, 2025). The sensitivity analysis was performed using Crystal Ball's percentile variation method to determine which assumptions primarily drive output dispersion. The analysis compares simulation results when input variables are at their 10th and 90th percentiles. The difference in forecast distribution indicates each input's influence on the model's output. Table 7 presents these findings, ranking inputs by their relative contribution. This approach distinguishes between parameters with marginal effects and those central to overall uncertainty.

4.1 | The MCS: The simple MC simulation

The first MC simulation, represented in Figure 7, conducted with the Crystal Ball software, an MS Excel plug-in, is a simple MC analysis performed with 1,000,000 trials that iteratively re-calculates the total cost forecast by randomly changing the inputs of the discounted cost model among their predefined probability distribution.

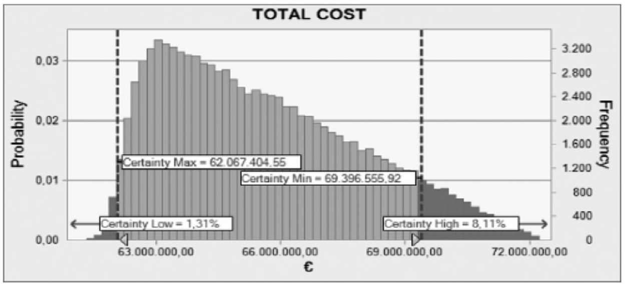

FIGURE 7 Simple MC simulation. Authors' elaboration.

The MC simulation was performed with Oracle Crystal Ball 11.1.3.0.0, on Microsoft Excel 365. To ensure reproducibility, a fixed random seed (12345) was applied. Convergence diagnostics were enabled for both the mean and the standard deviation, with a tolerance threshold of 1%.

The value predicted by the simple MC simulation shows a mean value of €65,574,348, which is different from the discrete use of the cost model, that is, €61,626,348. The standard deviation of the 1,000,000 simulations is €2,375,283, representing the uncertainty associated with the feasibility analysis. The skewness index is 0.55, and the kurtosis is 2.45, indicating the degree of symmetry of the distribution around the mean.

4.2 | The MC simulation: The simple MC simulation with correlations among the input values

A second MC simulation, illustrated in Figure 8, is performed to iteratively assess the total cost. The second sim-

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TABLE 8 Pearson correlation coefficients. Authors'elaboration.

	CC_1	CC_2	CC_3	CC_4	CC_5	CC_6	CC_7	CC_8	CC_9	CC_{10}	CC_{11}	*d*	*r*
CC_1	1.00	−0.11	−0.11	0.00	0.03	−0.11	0.99	1.00	−0.11	−0.11	−0.20	−0.29	0.10
CC_2	−0.11	1.00	1.00	0.00	−0.61	1.00	−0.36	−0.11	1.00	1.00	0.32	−0.09	0.55
CC_3	−0.11	1.00	1.00	0.00	−0.61	1.00	−0.36	−0.11	1.00	1.00	0.32	−0.09	0.55
CC_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CC_5	0.03	−0.61	−0.61	0.00	1.00	−0.61	0.33	0.03	−0.61	−0.61	0.04	0.00	−0.17
CC_6	−0.11	1.00	1.00	0.00	−0.61	1.00	−0.36	−0.11	1.00	1.00	0.32	−0.09	0.55
CC_7	0.99	−0.36	−0.36	0.00	0.33	−0.36	1.00	0.99	−0.36	−0.36	−0.17	−0.82	−0.06
CC_8	1.00	−0.11	−0.11	0.00	0.03	−0.11	0.99	1.00	−0.11	−0.11	−0.20	−0.29	0.10
CC_9	−0.11	1.00	1.00	0.00	−0.61	1.00	−0.36	−0.11	1.00	1.00	0.32	−0.09	0.55
CC_{10}	−0.11	1.00	1.00	0.00	−0.61	1.00	−0.36	−0.11	1.00	1.00	0.32	−0.09	0.55
CC_{11}	−0.20	0.32	0.32	0.00	0.04	0.32	−0.17	−0.20	0.32	0.32	1.00	−0.71	0.78
D	−0.29	−0.09	−0.09	0.00	0.00	−0.09	−0.82	−0.29	−0.09	−0.09	−0.71	1.00	−0.64
R	0.10	0.55	0.55	0.00	−0.17	0.55	−0.06	0.10	0.55	0.55	0.78	−0.64	1.00

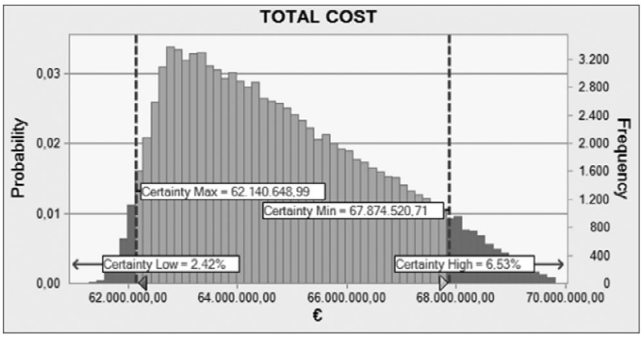

FIGURE 8 Simple MC simulation with correlations. Authors'elaboration.

ulation introduces some Pearson correlation coefficients between some the input variables, where a coefficient of +1 represents a perfectly positive correlation, −1 stands for a perfectly negative correlation, and 0 means the two variables considered are independent. The Pearson correlation coefficients have been defined through the pairwise analysis, specifically, given two variables named "*x*" and "*y*":

$$coeff\_person_{x,y} = \left[cov\left(x, y\right) / \left(\sigma_x * \sigma_y\right)\right]$$

where cov(*x*,*y*) is the covariance between the two variables, while σ_x and σ_y represent the standard deviation of the variables.

The coefficients reported in Table 8 have been defined through the pairwise analysis of the time series of the input data used in the cash flow model, collected from 2010 to 2025 (yearly average). The information was collected from Institutional sources such as Eurostat, European Central Bank, ANAC, and ISTAT (specifically, the consulted sources for each variable were the following: CC_1 and CC_8: ISTAT, 2024; CC_2, CC_3, CC_6, CC_9, CC_{10}: CNI, 2018; CC_5: Commissioni Provinciali Espropri, 2025; CC_7: Eurostat, 2024; CC_{11}: European Central Bank, 2025; d: ANAC, 2025; and r: Banca d'Italia, 2025).

The coefficients have been defined through the pairwise analysis of the time series of the data used in the model. The mean value predicted with this second run is €64,758,751, the standard deviation is €1,803,571 the skewness index is 0.53, and the kurtosis is 2.43.

4.3 | The 2D-MC simulation

Uncertainty analyses benefit from distinguishing between aleatory and epistemic uncertainty (Ragas et al., 2009; Zheng & Frey, 2005). Aleatory uncertainty stems from intrinsic data variability and is irreducible, while epistemic uncertainty arises from lack of knowledge and is potentially reducible with more information. This research employs a two-dimensional Monte Carlo simulation (2DMC) to separate these uncertainty types, enhancing the accuracy of risk factor analysis in the model. In a 2DMC simulation, uncertain inputs are sampled separately from variable inputs, and two iteration loops are generated. The inner loop simulates variability; the outer loop simulates uncertainty. When a parameter is subject to uncertainty, it is impossible to determine a specific value because of insufficient or incomplete information. The outer simulation theoretically aims to "eliminate" uncertainty caused by a lack of information by first iterating through the uncertain variables. Once these variables are frozen under the assumption that uncertainty has been eradicated (as the parameters are now defined), the "variable" inputs (irreducible uncertainty) are randomized in the second simulation loop. The parameter is subject to

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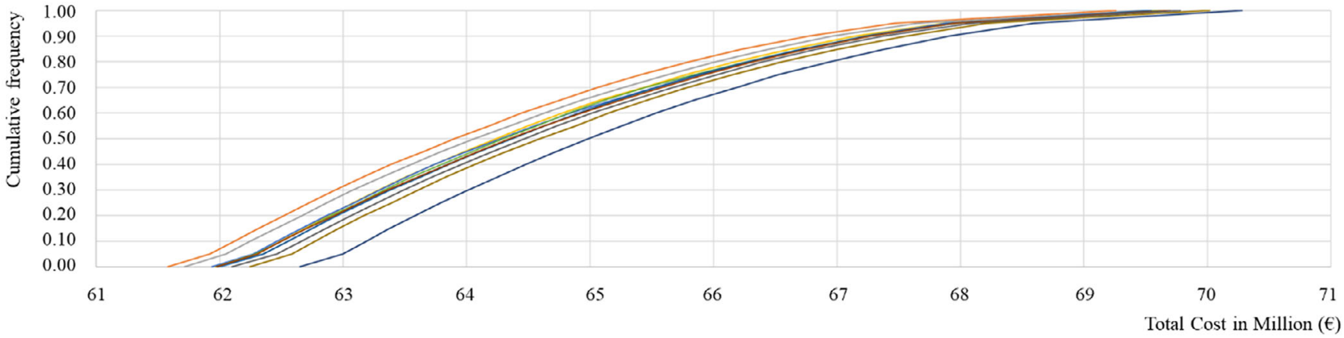

FIGURE 9 2D MC simulation with correlations. Authors'elaboration.

variability when it describes a "varying" population. It can naturally take on different values due to the same nature of the considered variable; their variability cannot be removed by additional hypothetical knowledge. In this simulation, the outer loop is performed by the variables: Interferences, Financial Costs, Discount od bids, Discount rate (BTP). This distinction, first introduced by Knight (1921) and taken up in numerous technical and methodological guidelines (Ayyub, 2003), is operationally implemented in this 2D MC. The inner loop randomizes the parameters: Construction Costs, Construction Site Security, Engineering Fees, Surveys, Eminent Domain, General Office Overhead, Energy Efficiency, Taxes, Marketing, Testing, and Inspections. Consequently, 1000 iterations are performed for the outer loop (uncertainty) and 1000 iterations for the inner loop (variability), leading to running the simulation 1,000,000 times. The simulation had a runtime of 1 h, 7 min, and 34 s on a DELL precision 5520, 32GB RAM. The mean value predicted with this second run is €64,654,383, the standard deviation is €1,765,561, the skewness index is 0.56, and the kurtosis is 2.40. The calibration analysis of the 2DMC model, Figure 9, indicates that the predicted value (€64,654,383) and the observed value CC_a = €64,404,711 both fall within the prediction interval bounded by P10 and P90. The estimated percentiles (P10 = €62,549,161, P50 = €64,351,174, and P90 = €67,277,873) confirm the consistency of the observation with the simulated distribution. The position of the observed outcome within the distribution suggests an overall satisfactory predictive validity.

In a two-dimensional Monte Carlo framework, the total variance (Var_{total}) is composed of the sum between the internal variance (Var_{within}) and the external variance ($Var_{between}$). Internal variance represents stochastic variability given fixed parameters, capturing inherent system randomness. External variance reflects uncertainty in parameters across outer loops. This approach distinguishes between inherent variability and parameter uncertainty in the model's results, offering a more comprehensive understanding of outcome variations. The percentage (PCT) of the two variances are calculated as $PCT_{within} = Var_{within} / Var_{total}$; and $PCT_{between} = Var_{between} / Var_{total}$. In this simulation PCT_{within} equals 24.7% and $PCT_{between}$ 75.3%.

TABLE 9 MCS results.

	Simulations		
Parameters	**Simple MC**	**MC simulation**	**2D MC**
Mean	65,574,531	64,758,751	64,654,383
Standard deviation	2,375,283	1,803,572	1,765,561
Skewness index	0.56	0.53	0.56
Kurtosis	2.45	2.43	2.40
Minimum	61,137,960	61,130,739	62,012,182
Maximum	73,234,320	70,525,254	69,694,656
Range width	12,096,360	9,394,515	7,682,474

The high $PCT_{between}$ indicates that most of the uncertainty is driven by incomplete knowledge of parameters, underscoring the utility of a 2DMC approach in separating parameter uncertainty from natural variability.

The mean value for the NPV simulations is quite similar in the three MC versions, but the standard deviation is reduced in the 2DMC. Besides, in the 2DMC simulation, the range width (maximum value—minimum value) is smaller if compared to other simulations, so at the same level of certainty, the 2DMC model produces a more robust range of results as represented in Table 9.

When conducting risk assessments through 2D MCS in the field of construction cost estimation, distinguishing between uncertainty and variability becomes essential. This is particularly relevant in civil engineering projects, which often involve intricate planning, several actors, and unpredictable external conditions.

By separating these two dimensions of risk, an analyst gains a clearer understanding of the underlying causes that influence the total project cost. Uncertainty pertains to factors for which information is incomplete or unreliable at the planning stage financial conditions, interactions with other projects (i.e., the choice of discount rate). These

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elements can be approximated but remain subject to judgment errors, limited data, or volatile external dynamics. In this context, uncertainty stems not from the nature of the process itself, but from gaps in knowledge or foresight. On the other hand, variability concerns elements such as cost components that exhibit inherent fluctuations even under optimal knowledge conditions. Such dispersion is normal in construction and arises from factors (i.e., supplier performance, price volatility, operational site efficiency). Variability is a built-in aspect of construction processes that cannot be eliminated but only be controlled through planning. Recognizing the distinction between these two sources of risk leads to more robust modeling, allowing practitioners to identify which risks may be addressed by improving data or predictive models, and which require financial contingencies or flexible strategies. In a sector where each project is essentially unique, integrating this differentiation within a 2D Monte Carlo framework enhances both the accuracy of cost forecasts and the quality of risk management.

The results of our study demonstrate the effectiveness of the PRIMoS model in improving cost estimation accuracy for complex infrastructure projects. Considering the 2D-MC simulation as the most sophisticated and accurate among the three approaches tested, we observe significant improvements in forecast precision. The mean value produced by the 2D-MCS (€64,654,383) closely aligns with the actual project cost, reducing the estimation error by 24.42%, compared to the initial estimated costs. This level of accuracy represents a substantial improvement over traditional estimation methods and addresses the critical need for more precise ex ante cost projections in public infrastructure projects as highlighted in our introduction. A second consideration can be drawn in terms of standard deviation. In a normal distribution, the spread of data follows a predictable pattern around the mean, that is, about 68.3% of the data falls within one standard deviation from the mean ($\pm 1\sigma$). Around 95.4% of the data is within two standard deviations from the mean ($\pm 2\sigma$). This is a much broader range, including most of the data points. Therefore, the standard deviations could be compared with the contingencies estimated at the design stage. The estimated contingencies were €1,422,630, while the real cost of contingencies turned out to be €4,802,893. Considering the 2D-MCS to assess the contingencies, the unexpected variations of costs around the best estimate, an average value between 2σ and 4σ can be assumed, which equals €5,296,683, which closely approximates the actual contingency costs of €4,802,893. This stark contrast with the initially estimated contingencies of €1,422,630 underscores the model's capability to more accurately predict and account for project uncertainties. This integrated structure incorporates expert judgment through the risk matrix while maintaining mathematical rigor via Monte Carlo simulations, accounting for both epistemic and aleatory uncertainties. It is crucial to note that regardless of the specific approach used within PRIMoS (simple MC, MC simulation, or 2D MC), the integration of the risk matrix modeling consistently yields improved estimates. These results are encouraging for stakeholders, demonstrating that the combination of Bayesian modeling preceded by a thorough risk and probability analysis in complex projects can help avoid cost overruns with precision under 5%. Our findings highlight a significant shortcoming in current public procurement practices, where contingency estimates are often determined as a simple percentage of costs. This approach is particularly adequate for large-scale infrastructure projects that require substantial economic, temporal, and financial commitments, supporting the identification of high-risk variables.

This feature aligns with the goal of providing stakeholders with a tool that enhances risk-informed decision-making. The model's step-by-step structure provides stakeholders with an efficient tool for objective project analysis, avoiding oversimplification and subjective judgments. Unlike mass appraisal or ML approaches that might overlook project-specific details and complexities, PRIMoS maintains sensitivity to the local socio-economic and political-administrative contexts that can significantly impact project costs and timelines. PRIMoS has been designed to complement, not replace, the expertise of competent professionals involved in the projects. It recognizes that certain critical aspects of project evaluation must be assessed on a case-by-case basis by experienced individuals with deep understanding of the specific project context. This human-centric phase of the approach ensures that the finer factors that can greatly influence project outcomes, such as local regulatory environments, community dynamics, or unique geographical challenges, cannot be left to automated learning systems alone. By combining the analytical power of the PRIMoS model with the irreplaceable insights of experienced project managers and stakeholders, we create a synergy that enhances the accuracy and reliability of project estimations while maintaining flexibility to adapt to the unique characteristics of each infrastructure project.

5 | CONCLUSION

This research provided a significant advancement for risk management in the field of infrastructure cost estimation by proposing a novel approach, PRIMoS, which integrates a Bayesian Monte Carlo simulation model with a risk matrix's Magnitude assessment. Through this approach, several key advantages emerged, contributing to more

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precise and informed decision-making in large-scale public projects.

First, unlike conventional deterministic models, this framework systematically incorporated probabilistic distributions and RMs. By assigning probability distributions to cost and time variables, stakeholders gain deeper insights into potential financial and scheduling fluctuations. By utilizing a structured risk matrix that associated each variable with a RM level, the model effectively refined input distributions, leading to more reliable estimations tailored to large-scale infrastructure investments. Previous studies primarily focused on cost estimation concerning high-magnitude risks, while this research expanded the analysis to encompass all cost components within the Detailed Cost Estimate while integrating the temporal dimension. Among the advantages of the proposed model, the Monte Carlo risk simulation stands out for its speed of execution, even with a very high number of iterations. This efficiency makes it particularly suitable for use in professional contexts characterized by tight deadlines and limited computational resources, while still offering reliable results and a solid basis for decision-making analysis.

By integrating both cost and time uncertainties, this approach enhanced strategic planning capabilities for project managers and policymakers.

One of the limitations of the model includes the reliance on the experience and judgment of stakeholders involved in the decision-making process, in filling the Risk Magnitude matrix. While this approach does not completely eliminate subjectivity, it provides a structured framework that channels expert knowledge in a way that produces more objective and reproducible results. The model acts as a guiding tool, providing a common language and framework for risk assessment, facilitating more effective communication and decision-making among project teams, public administrators, and other stakeholders.

The time variable was integrated into our analysis through the discount rate, an approach that captures the time value of money and its associated uncertainties. This method effectively represents the temporal aspects of the project within the economic framework, aligning with established practices in financial modeling and risk assessment. This approach offers several advantages. First, it maintains model parsimony, enhancing its accessibility and applicability across various project types. Second, it allows for a more nuanced exploration of economic risk factors, which are often the most critical in project decision-making. This approach does not limit the model's potential; it opens avenues for future research and applications, including dynamic time-cost interaction modeling, for example, implementing a feedback mechanism that allows time delays to directly impact costs. The flexibility of our framework allows for easy incorporation of more explicit time-related variables in future iterations, such as differentiated temporal distributions of costs or alternative time horizons.

While the current study focused on a single case to establish a clear baseline for the model's performance, the flexibility of PRIMoS allows for its application across a wide range of infrastructure projects. It is important to note that the model was tested in a blind manner, without prior knowledge of the actual ex post costs, which enhances its credibility and robustness. Future research could explore the model's adaptability to different project types and geographical contexts, further validating its robustness and versatility. An interesting prospect is the potential integration of PRIMoS model with BIM. This integration could be realized by embedding PRIMoS modules within 4D or 5D BIM environments, enabling real-time risk re-evaluation as design or schedule changes occur. This combination could enhance the model's application throughout the entire lifecycle of infrastructure projects, from initial planning to construction and maintenance phases.

Beside the research limitations, this research introduced a milestone for the innovative fusion of Bayesian modeling and risk assessment approaches, providing a methodological enhancement to traditional Monte Carlo simulations in cost estimation. By bridging financial analysis and risk assessment in a unified framework, the study advanced the discipline of infrastructure planning and risk-informed decision-making. By leveraging these methodological improvements, project stakeholders may minimize unforeseen cost overruns, improve scheduling accuracy, and strengthen long-term financial sustainability. This study underscored the need for probabilistic modeling in complex engineering projects, offering a robust foundation for future research and practical implementation in construction risk management. PRIMoS provides a powerful potential tool that can be further refined and exploited, for comprehensive risk management in infrastructure projects, supporting proactive decision-making and enhancing overall project sustainability and resilience. Through better estimation and management, public works can achieve their intended outcomes more effectively, ensuring that European funds are used efficiently and transparently.

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DATA AVAILABILITY STATEMENT

All data, models, and code generated or used during the study appear in the submitted article.

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