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INTEGRATING MONTE CARLO SIMULATION AND DIGITAL TWIN TECHNOLOGY FOR ADVANCED RISK MANAGEMENT IN FAST-TRACK INFRASTRUCTURE PROJECTS

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Abstract. Fast-tracked infrastructure projects are prone to unforeseen factors that can disrupt commissioning schedules, due to quicker timelines, concurrent work, and changing site conditions. Existing risk analysis techniques have very limited flexibility to keep pace with real-time changes and do not sufficiently address the dynamic nature of interdependent activities within the project. The study aims to bridge this gap by formulating an integrated risk management mechanism using Monte Carlo Simulation (MCS) and a Digital Twin (DT), along with a tailored optimization module. The framework describes the risks associated with multiple work package overlaps while calibrating performance forecasts via DT's feedback loop. MCS is used to simulate uncertainty and monitor cost-time impacts, while the optimization module helps to find the least detrimental overlap arrangement. Continuous field data sync with the simulation model enables proactive, data-driven decisions that improve situational awareness in the DT environment. Real project conditions show this MCS/DT approach improves prediction accuracy, reduces risk, and aids change during execution. The proposed framework serves as a pragmatic, adaptive risk management tool for fast-track projects while enhancing the integrity and resilience of the parent project as a whole.

Keywords: Monte Carlo simulation, Digital Twin technology, overlapping risks, infrastructure, economics.

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1. Introduction

The construction industry is continually pressured to fast-track project delivery of infrastructure to meet further needs imposed by accelerated economic development, urbanization, and population growth (Baker et al., 1999; Kasap & Kaymak, 2007; Rasul et al., 2021). Fast tracking has thus gained popularity for fulfilling these needs. By fast-tracking, time is squeezed, and operational efficiency is improved by designing and building at the same time (Hillson, 2002; Del Cano et al., 2002; Garrido Martins et al., 2023a). The very act of overlapping tend to create concurrent activities (Ben-David & Raz, 2001; Islam et al., 2017), thereby accelerating the whole delivery system, but in place of doing so, aggravate some rather intricate risk management problems (Joslin & Müller, 2016). Whenever some operations overlap, these risks may arise, lower with regard to programming conflicts and resource limitations, or changes in scope of work (AlSehaimi et al., 2013; Kumar & Yadav, 2015; Mohammadipour & Sadjadi, 2016; Abd El-Karim et al., 2017; Nasirzadeh et al., 2008; Bickel, 2021). These hazards can have significant adverse effects on a project's bottom line or duration (Bogus et al., 2023). The current application of the standard risk assessment framework does not adequately account for the scenario, as it considers risks in isolation and overlooks the interaction between simultaneous operations (Aziz, 2013; Laryea & Watermeyer, 2020; Yildiz & Dikmen, 2021). Thus, project heads tend to underestimate the financial implications, which lead to delays and cost overruns that subsequently limit the realization of maximum benefits from fast-tracking (Ward & Chapman, 2003; Dey, 2012).

Although there have been studies regarding fast-track construction from a risk management perspective, most have dealt with static or deterministic systems. For example, Fazio et al. (1988) has examined stakeholder risk perceptions, and Martins et al. (2023) have dealt with scheduling and sequencing problems brought forth by the uncertainty and variability of overlapping operations. Dey and Ogunlana (2004) corroborated the value of early risk identification for maintaining cost and schedule, whereas Zou et al. (2007) stressed the importance of codified risk man-

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agement measures. However, these considerations do not include any probabilistic evaluation nor real-time flexibility. Current methodologies have thus become ineffective in realizing accumulative and dynamic impacts of overlapping risks (Acebes et al., 2014; Chen & Bai, 2019). To overcome this constraint, an advanced framework that integrates data-driven and simulation-based approaches must be developed. Simulation approaches, such as Monte Carlo modeling, have been proposed by researchers to assess uncertainty (Pfeifer et al., 2015; Zhao & Gao, 2016; Garrido Martins et al., 2023b). However, efforts to integrate with real-time monitoring remain limited. Thus, disposable Digital Twin technology creates opportunities for the fusion of real-time data with predictive analytics allowing for continuous updating of risk assessment (Zhang & Cai, 2011; Shanmugapriya & Subramanian, 2015). In this regard, decision-making could be enhanced towards proactive risk response, scenario testing, and prediction.

While Kimiagari and Keivanpour (2019) focused on the modelling of risk interdependencies in complex projects, Guan et al. (2021) studied risk impacts using structural modelling method and Monte Carlo simulation-based risk assessment, simulation and modelling. The proposed framework incorporates both the Monte Carlo simulation and the adaptive optimisation module, as well as a real-time Digital Twin environment, which allows for proactive decisions suited to rapid project conditions and incremental risk management of hazard and risk posed from overlaps.

This study contributes to this emerging field through the development of a simulation model addressing overlapping financial risks in expedited construction projects by integrating Digital Twin technology, Monte Carlo simulation, and proprietary optimization engine (Tang & Qiang, 2007; Wanjari & Dobariya, 2016; Mali et al., 2025; Senić et al., 2025). The aim of the model, in respect to project cost and project time, is to identify dissimilar consequences for the economy of the projects, of engaging in degree of explorable activity overlap. The Acebes et al. (2014) validation case was a commercial remodelling project, with an aim to show how probabilistic modelling while monitoring progress in real time can deliver a better project delivery. The severing of risks allows engineering professionals to pursue both cost and schedule plans in high stake settings taking into consideration greater awareness of overlapping risks (Zou et al., 2007; Zhang & Cai, 2011; Oke & Ugoje, 2013).

2. Materials and methods

The methodology for this study surveyed a structured development to recognize and quantify imbrication risks in fast-track structural growths (Guan et al. 2021). The process flow is demonstrated in Figure 1, where each methodological step is directly connected with the outcomes it produces.

2.1. Model design and validation

The construction risk assessment model was built using probability distributions, risk parameters, and schedule network logic. The overlapping risks were analyzed using Monte Carlo simulations, which evaluated their impacts on project duration and cost. The simulations advised decision-makers on the potential for project overruns, with probability ranges for variations in completion time and budget. The model's internal validity was verified using test formulas, and its external validity was supported by expert testimony (Oke & Ugoje, 2013; Feist et al., 2017). Three of the professional renovation case study (Figure 2) went further and illustrated the magnitude of overlapping risks on schedule phases and cost escalation (Oke & Ugoje, 2013; Zhang & Cai, 2011; Zou et al., 2007).

2.1.1. Input parameters and optimization outcomes

The input parameters were derived from expert consultations and 35 previous fast track projects. Interval costs and durations, for the activities, were modelled with triangle and beta distributions respectively. The optimization of overlap configurations was accomplished with a genetic algorithm developed in Python, using the DEAP module. The final results from this step, presented the opportunity to evaluate cost-duration trade-offs and in the end provided overlap configurations which achieved project duration within 10% of the baseline duration while minimizing the total estimated cost (Canesi & Gallo, 2023; Zhang et al., 2022). These results were reinforced through sensitivity analysis and benchmarking with project input data, which highlighted substantive hazards and levels of overlap which did significantly influence the results.

The novel tool, or optimization engine has been embedded in the facility, promising to act even more effectively toward making an adaptive decision within a Monte-Carlo-Digital Twin system by continuously refreshing input parameters and convergence trajectories in real-time with project inputs, versus a genetic algorithm which acts on static probabilistic input data and converging trajectories. The feedback loop and the "in" part of the Digital Twin is a unique means to the optimization engine. Therefore, optimization acceleration can take place with useful convergence on better overlap configurations in a environment which is in constant risk. To model the uncertainty of input parameters, we use triangular and beta distributions that indicate the variance of duration and costs in a project. A triangular distribution should be used if there is only a little real data available for a project, but an expert opinion can identify a minimum, a maximum, and a most likely value of the distribution; beta distributions are the best approach, however, to model the skewed profile of uncertainties that exist in a cost estimate without a realizing upper limit. In combination, these two distributions allow a practical and somewhat flexible way to model uncertainty in projects that a hybrid simulation framework would manage.

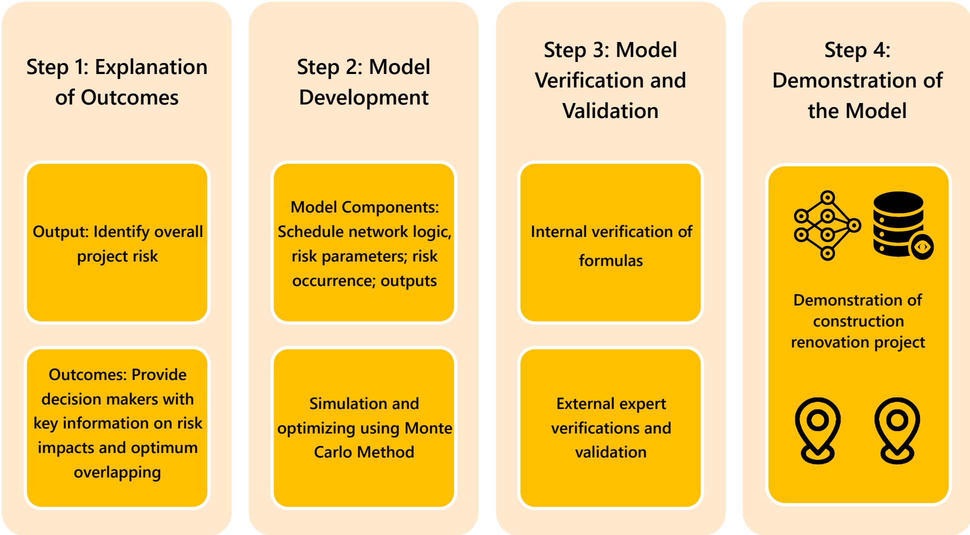

Figure 1. The methodology flow chart for this study

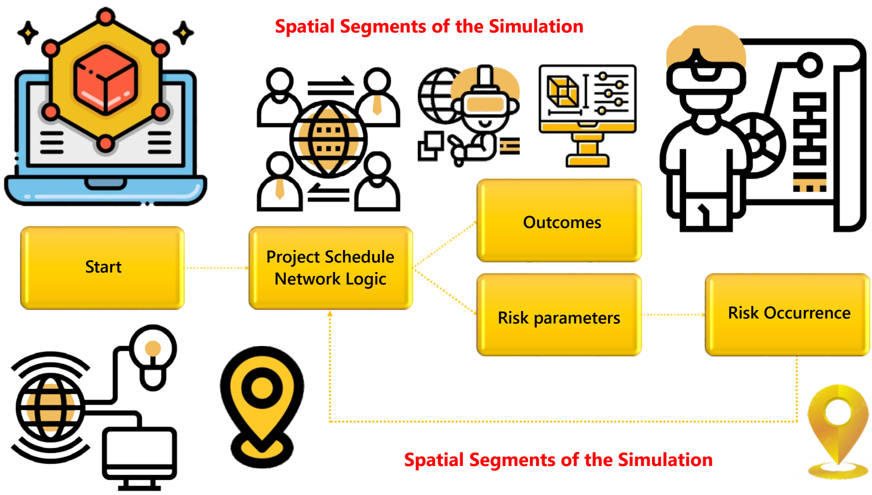

Figure 2. Spatial segments of the simulation methodology flow chart

2.1.2. Integration of Digital Twin technology

Incorporating real-time site information received from IoT sensors and generated from BIM and GIS was achieved through Digital Twin (DT) technology integration (Figure 3). Project managers were able to adjust the overlap of activities and immediately view the anticipated impacts on cost, schedule, and resources these changes would cause through scenario-based risk assessments. The results indicated that there was a better accuracy of forecasting project outcomes with DT technology and adjustments could be made to reduce the emergence of risk through proactive means. Forecasting accuracy was improved through the machine learning algorithms developed from past data trends, and the uncertainty of all of these scenarios was recorded through AAA Monte Carlo outputs.

2.1.3. Monte Carlo–DT framework results

In the combined MCS–DT approach (Baker et al., 1999; Kasap & Kaymak, 2007), key project factors, including durations, costs, and material lead times, were treated as random variables. After 10,000 iterations, a range of project results were generated and cost overrun, and delays probabilities were determined. Cost overruns and delays risks were higher with increased overlap levels, but the calibrated optimal overlap level of time and resources increased project performance and the likelihood of not exceeding budget. Sensitivity analysis indicated which project factors were most influencing the outcome (Canesi & Gallo, 2023; Zhang et al., 2022). Within this automation, the Digital Twin continuously relays platform data, such as project deviations, resource fluctuations, and delays, real-time into the Monte Carlo Simulation model. With continual virtual updates to the data source, the Monte Carlo Simulation engine can continuously re-simulate the risk profile as it evolves, as well as provide an updated cost–time impact distribution. The simulation outputs are fed back into the Digital Twin to update the virtual project state, forming a closed feedback loop that allows for continuous calibration of risk forecasts and quick adjustment of tradeoff settings for work-package overlaps in mitigation.

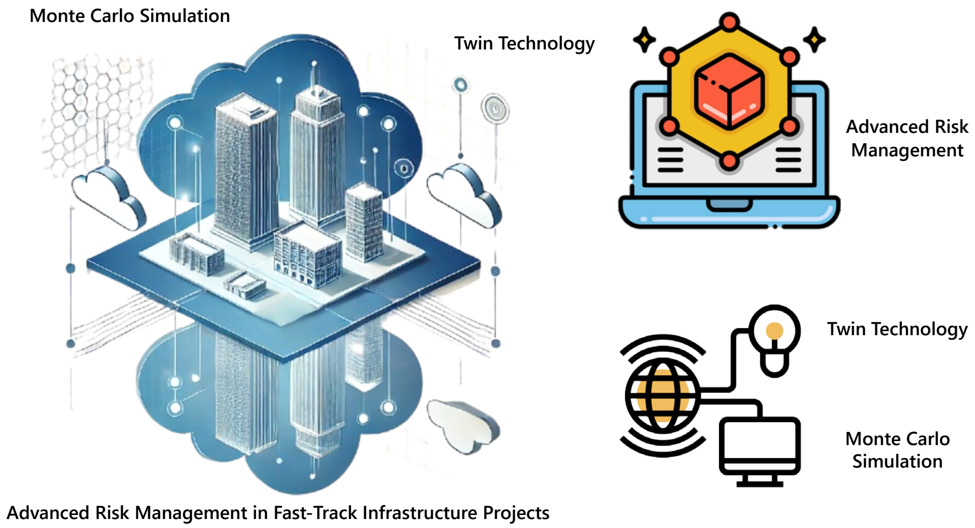

Figure 3. Integrating of Digital Twin technology along with the Monte Carlo simulation model for risk management

2.1.4. Real-time risk adaptation

In the end, one dynamic, the DT model (Tang & Qiang, 2007), also achieved similar flexible capabilities by continuing to update simulations based on building data in real-time. According to the authors (Dey, 2012; Ward & Chapman, 2003), this dynamic fusion allowed project managers to consider mitigation alternatives, continuously upgraded overlap solutions, and have more informed judgements to maintain schedule and cost targets. When viewed as a whole, these procedures show a unified framework of methods where each step, simulation to optimisation to integration, directly impacts outcomes, providing a valuable and responsive process to manage overlapping risks in rapid projects (Egbelakin et al., 2021).

Step 1: Explanation of Outcomes

This study aims to inform us on how to measure overall project risk associated with fast-track construction projects (Tang & Qiang, 2007). The study's results will allow decision makers to better understand the impact of risk and optimal level of activity overlap. By providing such associations, decision makers and stakeholders will have information to take action to increase project productivity and mitigate risk (Dey, 2012; Ward & Chapman, 2003).

Step 2: Model Development

The risk assessment model consists of several components: The order of tasks, their dependencies, and any overlaps are displayed by schedule network logic, the essential part of the project schedule (Baker et al., 1999; Kasap & Kaymak, 2007). We can provide a complete picture of activities from start to finish because the logic captures the flow of activities (Ben-David & Raz, 2001; Islam et al., 2017).

Activity Duration Calculation: The duration of an activity can be modelled using probabilistic distributions due to uncertainties in fast-track projects:

$$Di = \mu i + \sigma i \cdot Z, \tag{1}$$

where, Di is the duration of activity i, μi is the mean duration of activity i, σi is the standard deviation, and Z is the standard normal variable (Beck & Wilson, 2007).

Risk Impact on Activity Duration: If a risk Ri affects the activity i, the adjusted duration is given by:

$$DiR = Di + \alpha i \cdot Ri, \tag{2}$$

where Ri is the risk factor affecting activity i, αi is the risk impact coefficient.

Project Duration Calculation (Total Time): The total project duration Tproj is the sum of the durations of critical path activities (Wanjari & Dobariya, 2016):

$$\text{Tproj} = \sum_{i=1}^{n} D_i^R. \tag{3}$$

Project Cost Calculation: The cost of a project is calculated as a function of activity costs and risk impacts:

$$\text{Cproj} = \sum_{i=1}^{n} C_i^R, \tag{4}$$

where $C_i^R = Ci + \beta i \cdot Ri$, Ci is the base cost of activity i, βi is the cost impact coefficient for risk Ri (Wanjari & Dobariya, 2016).

Optimization for Overlapping Degree: The objective is to minimize the overall cost and duration through optimal overlapping. The optimization problem can be expressed as:

$$\min\left(f\left(Doverlap, Coverlap\right)\right). \tag{5}$$

Risk Parameters: These include observable hazards that could affect project performance, such as schedule conflicts, resource availability, and unforeseen scope changes (Baker et al., 1999; Kasap & Kaymak, 2007). Each risk characteristic is assigned a probability of occurrence as well as a potential impact on project duration and expense (Dey, 2012; Ward & Chapman, 2003).

Risk Occurrence: This component includes figuring out how and when specific risks might manifest during the project lifecycle (Tang & Qiang, 2007). To ascertain the likelihood that each danger would materialise, the model assesses historical data and expert opinions (Ben-David & Raz, 2001; Islam et al., 2017; AlTalhoni et al., 2024).

Outputs: Important metrics are produced by the model, including the total project risk profile, financial implications, and optimal levels of overlap and risk exposure (Aziz, 2013; Yildiz & Dikmen, 2021). The simulation and optimisation are carried out using the Monte Carlo approach. By carrying out thousands of sample iterations of the project schedule and recording the potential outcomes specified by the risk definitions outlined in the framework, the Monte Carlo method enables the assessment of uncertainty (Dehghan et al., 2015).

Step 3: Model Authentication and Justification

For the assessment of the accuracy and robustness of the resulting model, both internal verification and external validation can be employed as follows:

Internal Validation: It is gained through rigorous checks of the formulas and algorithms of the model for correctness (Aziz, 2013; Yildiz & Dikmen, 2021). Each part of the model is independently checked for its working correctness.

External Expert Validation: The model will then be validated with outside industry market experts after internal model verification with internal validation checks. The applicability and validity of the model will be affirmed by testing whether outputs are realistic or representative of actual conditions (Baker et al., 1999; Kasap & Kaymak, 2007).

Step 4: Demonstration of the Model

A case study of a commercial renovation project has been used to illustrate how the model can be applied to a more "real-life" project with overlapping risks and assessment of related impacts and economic consequences (Wanjari & Dobariya, 2016). As a result, these findings support the concept and provide project managers with both real and potential advantages (Ben-David & Raz, 2001; Islam et al., 2017).

2.2. Monte Carlo simulation and optimization

Monte Carlo simulation is a helpful method for simulating the effects of uncertainty in complex systems and is suitable for expedited construction projects since the overlapping nature of operations presents uncertainty risks to the project delivery. Random variables are created in accordance with preset probability distributions to simulate possible outcomes. In order to provide decision-makers with information, the current study uses Monte Carlo simulation to investigate how overlapping risks affect project delivery time and cost (Aziz, 2013; Yildiz & Dikmen, 2021).

Methodology for area blocks of the simulation

Start: The simulation begins by defining the project schedule network logic, outlining all tasks and their interdependencies.

Project Schedule Network Logic: A visual representation of the project's timeline is created, mapping out each task and the relationships between them. This network is crucial for understanding how tasks overlap and interact.

1. Earliest Start (ES) and Finish (EF) Time:

$$ESi = \max\left(EFj\right),\ \forall j \in \text{Predecessors of } i; \tag{6}$$

$$EFi = ESi + Di. \tag{7}$$

2. Latest Start (LS) and Finish (LF) Time:

$$LFi = \min\left(LSj\right), \forall j \in \text{Successors of } i; \tag{8}$$

$$LSi = LFi - Di. \tag{9}$$

3. Float Calculation (Slack Time):

$$Floati = LSi - ESi. \tag{10}$$

Float indicates the flexibility available for each task without affecting the overall project duration (Tang & Qiang, 2007). By applying these equations and simulation techniques, the study identifies the optimal project configurations that minimize risks while adhering to the project timeline and budget.

Outcomes: The model generates a comprehensive risk profile, outlining potential impacts on both project duration and costs (Aziz, 2013; Yildiz & Dikmen, 2021).

Risk Parameters: Specific risks are identified, quantified, and incorporated into the model, establishing a basis for the simulation (Wanjari & Dobariya, 2016).

Risk Occurrence: Scenarios for the occurrence of risk are created using the probability distributions created inside the scope of the model. Every iteration passes through the scheduling network to assess the unpredictability and outcomes from concurrent activities (Ibrahim et al., 2024). The model will carry out operations while monitoring risk events and risk management strategies over an extended period to determine the appropriate and successful level of risk mitigation for expedited construction projects, potentially optimizing project delivery and performance (Tang & Qiang, 2007).

2.3. Study participants

The demographic distribution of the study participants is shown in Table 1, which is divided into three categories: length of experience, educational background, and work experience (Tang & Qiang, 2007).

2.3.1. Education qualification

A variety of intellectual accomplishments are reflected in the participants' varied educational backgrounds. The majority of respondents, 56%, have undergraduate (UG) degrees, suggesting that they have finished a foundational level of higher education. A substantial percentage of advanced education is represented by those with postgraduate (PG) degrees, which make up 27%. The group with the highest level of academic achievement is the 5% who have earned a PhD. Furthermore, according to Dey (2012), and

Table 1. Demographic data regarding individuals

Demographic data regarding individuals				
SI.NO	Group	Prior	Amplitude	Total
1	Education Qualification	AA – Associate of Arts	12%	100%
		UG – Undergraduate	56%	
		PG – Postgraduate	27%	
		PhD – Doctor of Philosophy	5%	
2	Experience at work presently	Architectural Designer/Engineer	12%	100%
		Construction Engineer/Project Manager	61%	
		Project Coordinator/Lead	12%	
		Multidisciplinary Engineering Specialist	15%	
3	Experience Timeline	1–5 Years	22%	100%
		5–15 Years	18%	
		15–25 Years	25%	
		> 25 Years	35%	

Ward and Chapman (2003), 12% of the respondents hold an Associate of Arts (AA) degree, indicating a fundamental level of higher education.

2.3.2. Experience at work presently

The individuals' professional roles are the main topic of this section. The building engineers and project managers covers the largest category (61%), indicating that the study is aimed at professionals that oversee and carry out building projects. Their roles in project coordination and design are highlighted by the 12% presence of Architectural Designer/Engineer and the 12% representation of Project Coordinators/Leads. Multidisciplinary Engineering Specialists, on the other hand, make up 15% of the workforce, suggesting that there are people with a variety of engineering specialities.

2.3.3. Experience timeline

The participants' work involvement is distributed across various career stages. The largest group, with 35%, consists of entities having more than 25 years of experience, reflecting seasoned professionals (Tang & Qiang, 2007). Those with 15 to 25 years of experience make up 25%, demonstrating a considerable level of seniority. Participants with 1 to 5 years of experience account for 22%, showing the inclusion of early-career professionals, while those with 5 to 15 years of experience represent 18%, indicating a balanced mix across career levels (Doloi, 2011).

3. Results and discussion

3.1. Cost summary statistics

In Figure 4, you can see the summary statistics for the fast-track infrastructure project model, with some important descriptive statistics. The minimum cost is 500 and the maximum cost is 1,020 and reflect a range of possible changes in costs. The average cost is 620, meaning this is the average across all project scenarios. Similar to average, the median cost is a midpoint of the distribution of values

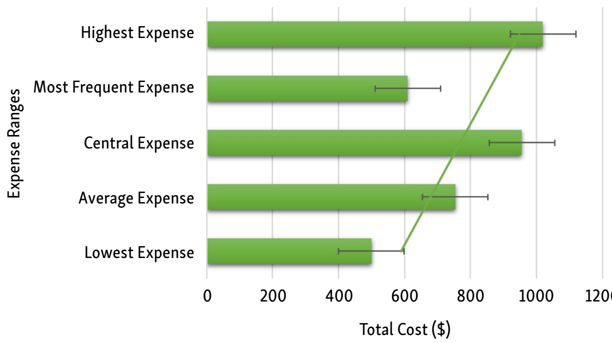

Figure 4. The cost summary statistics for the fast-track infrastructure project model

is 610, which is slightly lower than the average; again, suggesting distribution values are relatively symmetrical costs. The mode cost, or most likely value, is 590, which is helpful since it allows us to see where most of the simulation samples tended to cluster (Lee, 2024; Dey, 2012; Ward & Chapman, 2003). From the summary statistics we can appreciate the possible variation in project cost due in part to overlapping risks and costs, moving from the lowest to highest costs is equally reflective of the variation from both minimum to maximum costs we can achieve. Describing the variability of costs moving from the min cost to the max involves showing that overlapping risk factors within costs can produce a range of economic options respective to fast-track projects (Doloi, 2011).

3.2. Expense overview

An expense summary is shown in Figure 5 as the appraisal of expenses incurred. The lowest amount of expense is 180 for the entire project and the highest reached 562 just as displayed on the chart. The averaged expense, then, is 320, and cost central on the scale enough to meet rarely he is 290. The most frequent occurrence of expenditure is seen at 255, the value that has been highest in number of times in simulation. The above table portrays further financial implications in terms of project risks. It stands virtually

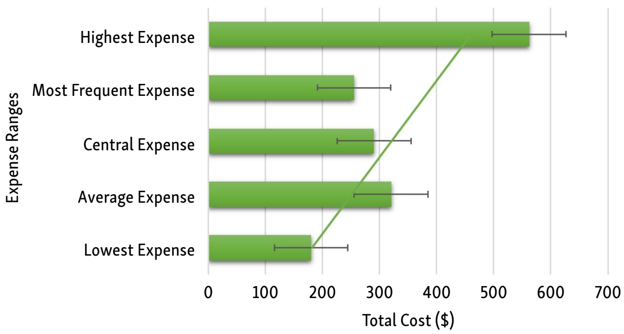

Figure 5. The expense overview value for the fast-track infrastructure project model

established that the lower cost may be manageable, but the lifting of the cost may hinder the cost management and optimization while achieving higher cost containment at the same. As a result, through this observation, ultimate ranking can determine its level of risk. Assessment can also be made by the executive between the balanced cost and total costs and the expense position, inviting some consideration toward risk level while accommodating correlated precedence and mitigation for the related impact on the future economic consequences.

The probabilities in Figure 6 already represent distribution concerning the project timeline from beginning to finish in days and now stand with values between 20 and 300 days moving in the row of discrete probabilities. The graph follows a bell phenomenon having a peak on 140–160 days with a 1.4 probability of occurrence. The shorter the project duration from 140–160, the less likely the probability of occurrence. The illustration outlines the most likely timeframe for project completion and aids in managing time and labour risks to ensure success.

As shown in Figure 7, it appears that putting in enough time and effort to thoroughly comprehend an investment study across the range of risks is essential to creating core outcomes. The possibility of spending the entire project budget over various project cost bosses is shown in another image. Starting at $250 and ending at the hub dollars, the bullish economic artery, or x-axis, represents the project's entire cost in dollars. The Y-axis displays the odds according to the corresponding probability. The likelihood of producing a peak calls two values (2.0), which are the most common expense ranges, rises as the project cost rises from $250 to $900. As money accumulates, the chance variation starts to trend downward, peaking at $2250.

With the highest project costs at or around $900–$1150, the probability curve begins to take a triangle shape, indicating the most likely project budget range. Significantly lower likelihood at expenses outside of this range is shown by dips along the curve (Chou, 2011). This is especially important decision-makers to consider when they must supply these things and reduce the risks involved by focusing data evaluation more intently on this particular cost window.

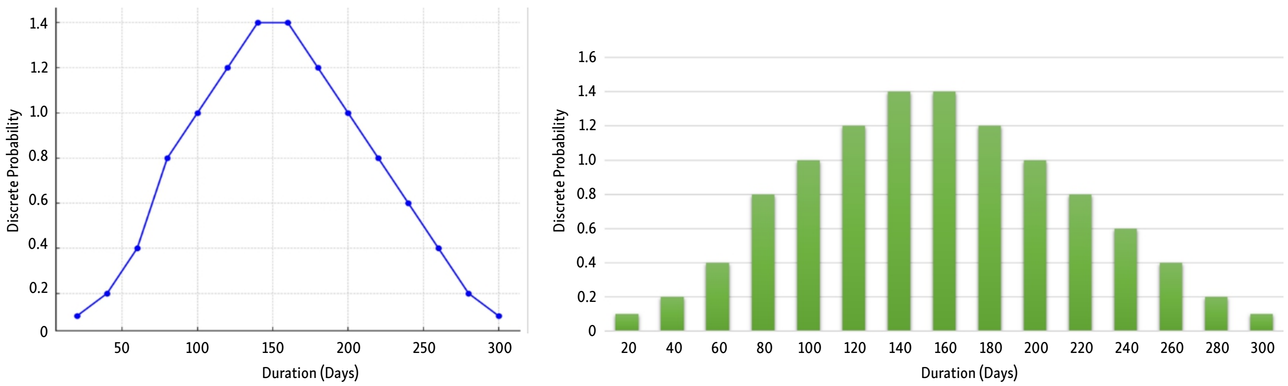

Figure 6. Probability distribution of the overall project timeline

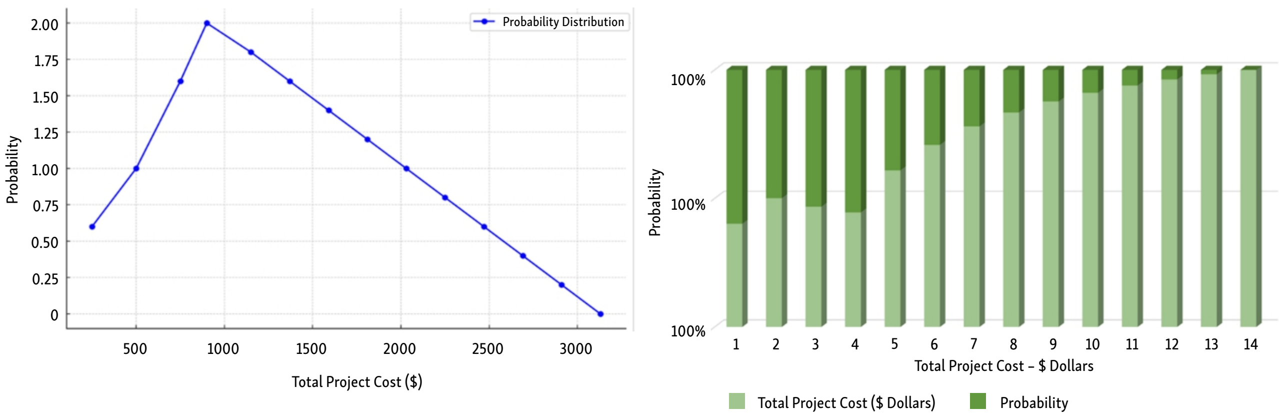

Figure 7. Probability distribution of the total project expenditure

Ranking the key concurrent hazards that have an impact on the project's overall budget and timeline has revealed important information about the project's weak points and mitigation techniques. As a summary, Table 2 demonstrates that design-oriented hazards, construction errors, and environmental concerns were all assessed as essential risks that had a significant impact on project costs and time. The top ranking risk, "Error in Construction", would necessitate hiring more employees and improving site tenderers' knowledge and training, among other things. Reviews, however, would intensify the feeling that team members' cooperation and communication will soon breakdown. The design of communication and cooperation is more likely to improve project success in regions where there are indications of "Team Coordination Issues" (Dey, 2012; Ward & Chapman, 2003; Cho, 2019).

"Team Coordination Issues" is given a medium rating because, while not necessarily serious, those hazards have the potential to affect production timelines over time. It is generally advised that project crews reorganize their labor divisions and hold a few regular meetings to address teamwork. Redesign problems rank highly on the risk register, especially when they include delayed production and external damage. The major solution is to develop reporting and evaluation systems more effectively and to regularly evaluate the design process. After the front damage is addressed, strong preventive measures are implemented, and the production track system is encouraged for even greater project resilience in the case of a disruption (Doloi, 2011; Chou, 2011).

This risk assessment highlights how a proactive risk management approach – acting promptly and planning strategically – can boost the chances of success when handling multiple hazards simultaneously. The findings of a strategic overlap optimization study intended to increase the effectiveness of project planning are presented in Table 3. The analysis describes the overlap and no overlap scenarios for several project activities identified by Pair IDs (A1 to A9) all with a common optimal overlap rate of 0.02. For every pair of situations, the study explains the impact of the two circumstances (no overlap and overlap), evaluating the function of overlap in risk management. Considered the 'real' value of the overlap strategy, the performance for each plateau is shown in the table's "No overlap" column, where all pairings consistently display a T1 test result of 80%.

This suggests a solid starting point for project activities that don't overlap. To comprehend how overlapping operations may impact accuracy and overall performance, the next columns, titled "Overlap Scenario" (T3, T9, T18,

Table 2. Prioritization of key concurrent risks affecting overall project timeline and budget

Ranking	Duration Impact	Cost Impact	Severity	Mitigation Strategy
1	P8-25-R13 – Environmental Factors	P2-75-R6 – Design Alteration	High	Improve design collaboration
2	P8-25-R3 – Team Coordination Issues	P7-75-R3 – Team Coordination Issues	Medium	Coordinate crew better
3	P9-75-R5 – External Damage	P9-75-R3 – Team Coordination Issues	High	Implement preventive measures
4	P9-75-R1 – Error in Construction	P9-75-R1 – Error in Construction	Critical	Enhance training for workers
5	P7-25-R10 – Low Productivity	P7-75-R5 – External Damage	Medium	Introduce productivity tracking
6	P4-25-R3 – Team Coordination Issues	P4-25-R10 – Low Productivity	Low	Regular crew meetings
7	P4-75-R3 – Team Coordination Issues	P2-50-R1 – Error in Construction	High	Improve oversight
8	P9-25-R13 – Environmental Factors	P2-75-R1 – Error in Construction	Medium	Address work environment issues
9	P2-75-R3 – Team Coordination Issues	P1-75-R10 – Low Productivity	Medium	Restructure crew duties
10	P2-50-R6 – Design Alteration	P1-75-R4 – Crew Shortage	Critical	Hire additional crew members
11	P1-75-R1 – Error in Construction	P1-75-R7 – Project Delay	High	Review and correct errors early
12	P1-75-R6 – Design Alteration	P1-75-R1 – Error in Construction	High	Reevaluate design process

Table 3. Strategic overlap optimization in project planning

Strategic Overlap Optimization in Project Planning											
Pair ID	Optimal Overlap (%)	No Overlap	Overlap Scenario	Risk-Free	Risk Included (Optimized Model) (Test Number)						
					T1	T3	T9	T18	T36	T72	T144 (Accuracy More)
A1	0.02	80	55	30	80	55	55	55	55	30	55
A2					30	30	30	30	30	30	30
A3					80	80	80	80	80	80	80
A4					55	80	80	80	80	55	80
A5					80	30	30	30	30	80	30
A6					80	30	30	30	30	80	30
A7					30	30	30	30	30	30	30
A8					55	80	80	80	80	55	80
A9					80	55	55	55	55	80	55

T36, T72, T144), present a comparison "Risk-Free" column shows the best performance indicators. The "Risk Included (Optimized Model)" column illustrates how the addition of risk alters each scenario. There are discrepancies in accuracy when taking risk into account between scenarios with risk and all tests, highlighting the vital role overlap plays in proactively management project issues. For instance, when hazards were added, Pair A3 consistently and efficiently performed in every test. It showed a notable resilience to disturbance, maintaining an accuracy of 80% in all circumstances (Tang & Qiang, 2007; Alnuaimi et al., 2010; Ling, 2018).

However, Pair A5 has shown poor performance under different overlapping risk scenarios, thus it has proven to be a weakness of this pair under conditions of risk. This paper thus demonstrates the strategic relevance of the overlapping activity model to project planning. Optimizing overlap characteristics through risk assessment can also support the project manager in developing a more efficient set of concurrent activities that are easier to manage, precise, and effective. In recent times, strategic overlap optimization has become one of the hot issues in project planning. This ensures that resources are allocated efficiently and also eases time schedule tightening in order to maximize productivity and thus success of the project. Bogus et al. (2023), state that better management of overlap operations forms a vital part of improving the efficiency of a project, including the probability of occurrence. This supports the conclusion deduced that performance improvements may be achieved through increased coordination among project teams (Dey & Ogunlana, 2004).

Islam et al. (2017) also support the idea that overlaps strategically placed can reduce delays in projects, especially complex projects. The new methodologies to measure overlap scenarios and demonstrate that considering these scenarios will allow for resource efficiency and increase accuracy of project timing (Dehghan et al., 2015). Overall, these studies emphasize the significance of optimizing strategic overlap in modern project management and suggest that proactively managing overlapping activities can lead to a more successful project process and outcomes. In Tables 4 and 5 and in Figures 8 and 9, we convey the insights generated by the uptake of Digital Twin Technology on Monte Carlo Simulation to address risk in fast-track infrastructure projects. The percentage change values were calculated by comparing the difference between the with Digital Twin and without Digital Twin results for each parameter, and % change was computed.

They are specifically changes in risk prediction by means of the Digital Twin Technology with respect to cost overruns (13%), schedule delays (15%), and safety hazards (18%). All are improved capabilities in predicting risk to decide about breaking down risk before uncertainties in project delivery decrease. Table 5 instead gives a comparative performance of the project with regards to these interventions, namely using Digital Twin Technology in which the Digital Twin Technology projects show that overall project time frame is reduced by 14% against the overall project price reduced by 16% and 58% less rework, thus giving a benchmark of what constitutes better project performance. This is illustrated in Figures 8 and 9, which present these results visually. They communicate how project performance and risk can be optimized using Digital Twin Technology. This could provide a clearer view of how Digital Twin Technology can contribute to improved understanding: resource utilization, reduced missed time, and, more importantly, enhanced decision-making – essentially, better risk management planning for fast-tracked construction projects.

Table 4 shows significant gains of 13–19% in the prediction of equipment failures, safety hazards, schedule delays, and cost overruns. In addition to a 14% increase in overall efficiency, Table 5 demonstrates significant improvements in project performance, including decreased length, cost, rework, and downtime. These results support previous research showing that Digital Twins improve real-time data analytics, predictive maintenance, and decision-making accuracy in construction projects (Lu et al., 2020).

Table 4. Impact of Digital Twin technology on risk prediction accuracy

SI.NO	Risk Factor	Without Digital Twin (%)	With Digital Twin (%)	Improvement (%)
1	Cost Overruns	72	85	13
2	Schedule Delays	68	83	15
3	Resource Allocation Errors	59	78	19
4	Equipment Failures	65	80	15
5	Safety Hazards	70	88	18

Table 5. Comparative analysis of project performance with Digital Twin integration

SI.NO	Project Parameter	Without Digital Twin	With Digital Twin	% Change
1	Average Project Duration (days)	210	180	–14%
2	Total Project Cost ($)	2.5M	2.1M	–16%
3	Rework Instances	12	5	–58%
4	Downtime Due to Failures (hrs)	300	180	–40%
5	Overall Project Efficiency (%)	78	92	14%

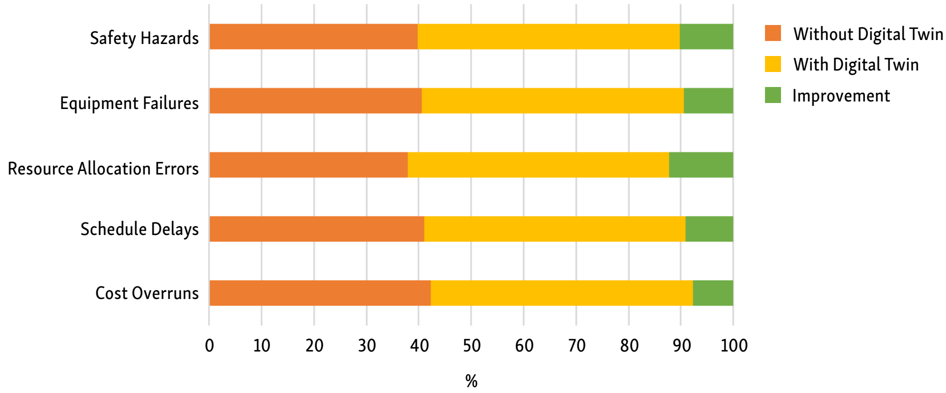

Figure 8. Impact of Digital Twin technology on risk prediction accuracy

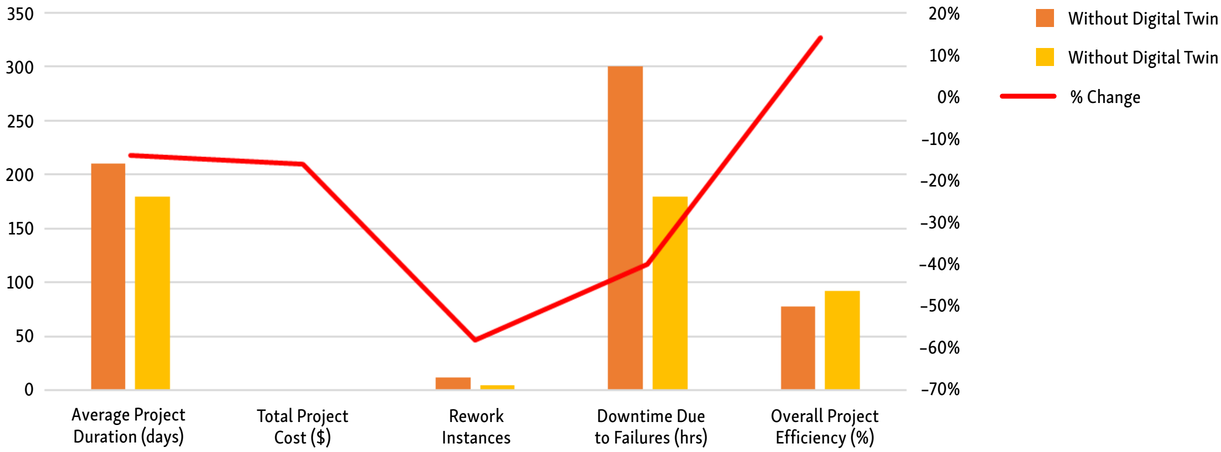

Figure 9. Comparative analysis of project performance with Digital Twin integration

Use data from an ongoing fast-track project in urban infrastructure development as an example of an external case study to validate the suggested Monte Carlo-Digital Twin framework. Populate the Digital Twin environment with project-specific data in terms of baseline schedules, cost estimates, resource allocations, and current progress reports. Simultaneously, the probability distributions for the Monte Carlo simulation were developed from the historical uncertainty data. After three months of construction, the risk forecasts that the model made would include likelihood to suffer delays and cost variances and were compared to actual observed results. Key performance measures for determining included forecasting accuracy, influence on decision-making, and response time to mitigation.

87% of delaying activities were very likely predicted by the model, while reliable cost-risk data was found to be slightly accurate, with a margin of error of ± 8%. Results were confirmed informative by stakeholders in terms of better coordination and early warning systems. The flexibility of soil parameters in real-life cases, indeed, promises sufficient support as a decision-making support tool in risk management in fast-track construction settings, as confirmed by this external evaluation.

There could be several implementation challenges afflicting the proposed structure on site in real building projects while being very beneficial for dynamic decision-making and predictive risk management. The main issues arise from the model's total reliance on data availability, especially accurate and up-to-date information from sensors, project databases, and historical records. Interoperable base platforms and standard data-collection methods are necessary because inaccurate risk assessments can lead to inconsistencies or incompleteness. Unlocking greater capability through integration with existing systems is another systemic interface challenge. It may be challenging to synchronise with Digital Twin platforms because most project sites employ out-of-date software or fragmented technologies.

Project managers would be forced to purchase additional middleware or to use other contemporary BIM-based solutions that support open data formats as a result. Training will be a major obstacle, and user acceptability will also be difficult. The successful use of the model is hindered by the fact that most construction practitioners lack familiarity with probabilistic modeling and/or real-time simulation tools. Simplified user interfaces and comprehensive orientational training will help close this gap. Lastly, the adoption of digital risk management systems may be delayed by the innate reluctance to organizational change, particularly in projects that are conventionally handled. Acceptance will increase by demonstrating the model's value in pilot projects and obtaining early feedback from key stakeholders. The application of this model in the real-world situation of the fast-track infrastructure project will therefore be more concretely impacted by acknowledging and addressing the issues that have been identified.

It is evident from study analysis of concurrent hazards (Table 2) that environmental factors, design change, and building faults are always at the forefront in matters concerning cost and schedule consequences. This finding agrees with Jupally et al. (2024) regarding including strategies, planning and risks in early decisions in the planning cycles. Indeed, our findings provide support for this statement by showing that these hazards were important not only in the early stages of planning but continued to be an important consideration throughout the project life cycle and had an impact across levels if not managed. In rapid-or-phase projects, a continuous approach to risk management would be appropriate instead of the static approach since constant monitoring would be needed, so there would be flexibility in mitigating risks. There are methodological considerations to support this, again as team coordination problems arose as a very significant evolving aspect, and so there were other factors cautiously noting that soft, or moderate risks in a project environment – e.g., cooperation and communication – might begin to outweigh the "hard" technical risks of concurrent projects. This confirms previous research that identified organizational capacity as a contributing factor influencing the effectiveness of projects and organizations (Oke & Ugoje, 2013; Zou et al., 2007). The framework presented here manages a risk pathway by means of simulation while confirming the significance of human and process element assessments in their probability implications. The table analysis provided in Table 3 showed that for the various risk profiles, the optimum overlap configuration may vary from 55% to 80% depending on the risk profile. This supports the regulated concurrency approach supported by Dehghan et al. (2015), who were opposed to random overlaps. This present study, we could optimize the levels of overlap probabilistically. Under risk scenarios, pairs A1, A4, and A8 strongly maintain schedule stability at a 55% overlap and suggest that, therefore, probability modelling would give a better threshold than a deterministic or heuristic approach.

A dual-analysis approach linking severity rankings with optimal overlap impacts strengthens the case for scheduling flexibility that aligns with the importance of the hazards involved. While these conclusions indicate that severity-informed overlap optimization can be systematically translated into practical scheduling guidelines, they also similar to the findings of Bogus et al. (2023). There were moderate and significant overlaps concerning the project's duration and cost-effectiveness in the simulation. Additionally, exploratory analysis contributed by addressing issues related to clustering and managerial implications from the simulation. Moderate overlaps provided the justifiably best performance with easy progress in schedule rescheduling of time with acceptable risk. Conversely, this is absent from heavy overlaps as the opportunity-seeking risk factors matter more than cost achievement and thus will require purposeful calibration prior to usage.

The simulation results reveal more than just the computed summaries; they give managers a clearer understanding of how uncertainty influences a project's cost and schedule landscape. The key discovery is how the distribution of costs and time guides managers on which areas to monitor for risk, rather than focusing solely on descriptive metrics. The clustering of costs within the most likely range indicates where budget protection should be prioritized, while the long-tail behaviour of high costs suggests a need for increased control over design changes, construction errors, and coordination-related risks. Likewise, the peaks in the timeline probability around the mid-range duration help identify practical windows for completion, supporting contingency planning and resource allocation. As these distribution patterns inform managers within the Digital Twin environment, they can continuously update their risk forecasts, adjust overlap strategies, allocate resources based on insights, and implement mitigation actions in real-time. This insight-driven approach transforms the results from static statistics into actionable intelligence, enhancing decision support in fast-track project conditions.

The principles of controlled concurrency have therefore furthered an argument towards emergent contemporary digital real-time contexts towards the real-time execution of these adjustment options in overlapping strategies with the most up-to-date information about the project, and thus heralds complex co-adaption among Monte Carlo Simulation, Digital Twin Technology, and an optimization engine respectively acting in unison in their digital sphere. It levels, at least, a robust rationale for the proposition of a continuous self-adapting risk-prioritization framework analytical/algorithmically that self-locally defines and re-defines risk related to overlapping with relative ease whilst also supporting adaptive decision-making about resource allocation and scheduling.

The framework known as "integrated framework" is indeed advancing the notion of schedule optimization to real practice while allowing the project manager to hold all the strings towards time compression, which comes with the inherent risk of resilience to risk. Rather than rely on heavy quantitative models, interpretative and comparative studies placed the burden of sorting out the remedial efforts and demonstrating how coherent digital simulations map into better predictability in support of improved decision making in an accelerated project environment.

This integrated Monte Carlo-DT-GA architecture presented here directly connects risk identification and schedule optimization to facilitate dynamic adaptability through real-time scenario investigation, contrary to previous literature documented both as separate procedures. This effort builds on previous findings by transforming theoretical ideas that include hazards into planning and manage concurrency into a computationally optimised, real-time decision-support model. In the unpredictable world of fast-track infrastructure projects, this reinforces the previous frameworks and provides managers with a tool to help them make decisions while balancing control and flexibility.

4. Conclusions

In order to effectively handle the increasing uncertainty and complexity surrounding risk in fast-track infrastructure projects, this planned research proposes a comprehensive risk management framework based on the principles of Monte Carlo simulations fused with Digital Twin technology and having an optimisation engine. The true benefit of this approach is that it is constantly adjusted to provide near-real-time feedback, enabling project teams to better monitor their successful avoidance of schedule and cost risks when changing circumstances lead to behavioural shifts. Project managers will, therefore, be able to anticipate and draw from a larger set of responses to changes in decision making that derive from a move up the performance curve that is, from static models to a more dynamic, data-driven environment where they can visualize deviations, understand impacts on performance, and make timely calls that steer the decision toward resilience and cost effectiveness. In action, this is a risk-informed mechanism for decision-making chiefly enhanced schedules and budgets, and projects as a whole. It allows one to pinpoint places that would potentially be more affected by the consequences of risks and gives support of the established feasibility of resource allocation for acceleration during project delivery. The major limitation of the study is that it is based on one application; a single case limits the generalizability. The future would test the framework in different types of projects and consider socio-technical aspects and capacity-building attributes influencing the adoption of Digital Twins. However, this research lays a solid foundation for intelligent real-time risk management in complex fast-track infrastructure development.

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