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Practical Implementation of AI-based risk management processes on construction megaprojects

Rhys Phillips, Dev Amratia, Carlos Ledzema, Richard Bendall-Jones, Vahan Hovhannisyan, Leonie Anna Mueck

Abstract

Recently, AI-Schedule Risk Analysis (AI-SRA) has emerged as a groundbreaking approach to construction project risk management. [1,2] Unlike traditional Quantitative Schedule Risk Analysis (QSRA),[3] AI-SRA leverages machine learning models, trained on extensive historical schedule data, to directly predict activity durations distributions based on data embedded in the schedule. As previously shown, AI-SRA surpasses traditional QSRA in both the accuracy of end-date forecasts and activity duration predictions. [4,5] Despite its proven effectiveness, practical implementations of AI-SRA within project organizations have so far been scarce and the practicalities of rolling out this new process are unstudied.

Here, a comprehensive study of how to implement AI-SRA successfully on megaprojects is presented. AI-SRA roll-out on five projects across different sizes and sectors shows that, generally, three challenges need to be overcome: Lack of trust in AI models; the unintuitive nature of AI-SRA results; and AI-SRA differing from tried and tested processes. These challenges can be overcome by clear steps towards understanding AI, visualizations to aid comprehension of the results, and demonstrations of equivalence of AI-SRA to traditional processes. As a case study, the specific application of these principles on a major UK rail project using AI-SRA is discussed.

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Introduction

Countering project delay with risk management

In the realm of large-scale construction projects, the issue of delayed completions and budget overruns has become pervasive. Public skepticism towards project timelines and budgets is not unfounded, empirical data validates it. A 2015 McKinsey report revealed that 98% of megaprojects suffer from cost overruns or delays.[6] Research indicates an average delay of 43% beyond planned schedules for large-scale projects, with only 0.1% meeting their original time and budget targets.[7]

An analysis of a large dataset encompassing over 740,000 schedules further underscores this trend, showing that 85% of large-scale construction projects experience delays. A quarter of projects are 230 days late, and 10% exceed their planned completion by over a year. The COVID-19 pandemic exacerbated this issue, increasing median project delays from 80 to 214 days.[8]

In response to widespread delays in construction projects, sophisticated risk, uncertainty and stakeholder management processes have been implemented. Particularly in mega-projects, the implementation of specific risk management strategies is often a mandatory requirement. The gold standard of these strategies is quantitative risk analysis, which is also an AACE-recommended practice RP 40R-08. This analytical approach, encompassing Quantitative Schedule Risk Analysis (QSRA) and Quantitative Cost Risk Analysis (QCRA), aims to quantify the impact of discrete threats and opportunities on project timelines and budgets. [9, 10, 11]

In this paper, the focus is on QSRA, but many aspects of the study translate directly to QCRA. It should also be noted that in this paper QSRA is used to refer to traditional CPM-based QSRA and not to parametric estimating. While parametric estimating has been shown to outperform CPM-based QSRA and QCRA [12, 13] it is traditionally used at project stage gates rather than in each reporting period. The projects referred to in this paper all use CPM-based QSRA and consequently the deployment of an AI-assisted Schedule Risk Analysis (AI-SRA) has focused on overcoming its limitations.

The use of QSRA is particularly prevalent in public infrastructure due to the scrutiny of those projects.

The shortcomings of QSRA

Quantitative schedule risk analysis generally follows the steps shown in Figure 1, top row. Despite its prevalence, critical literature that demonstrates the effectiveness of QSRA and QCRA has so far been missing [14].

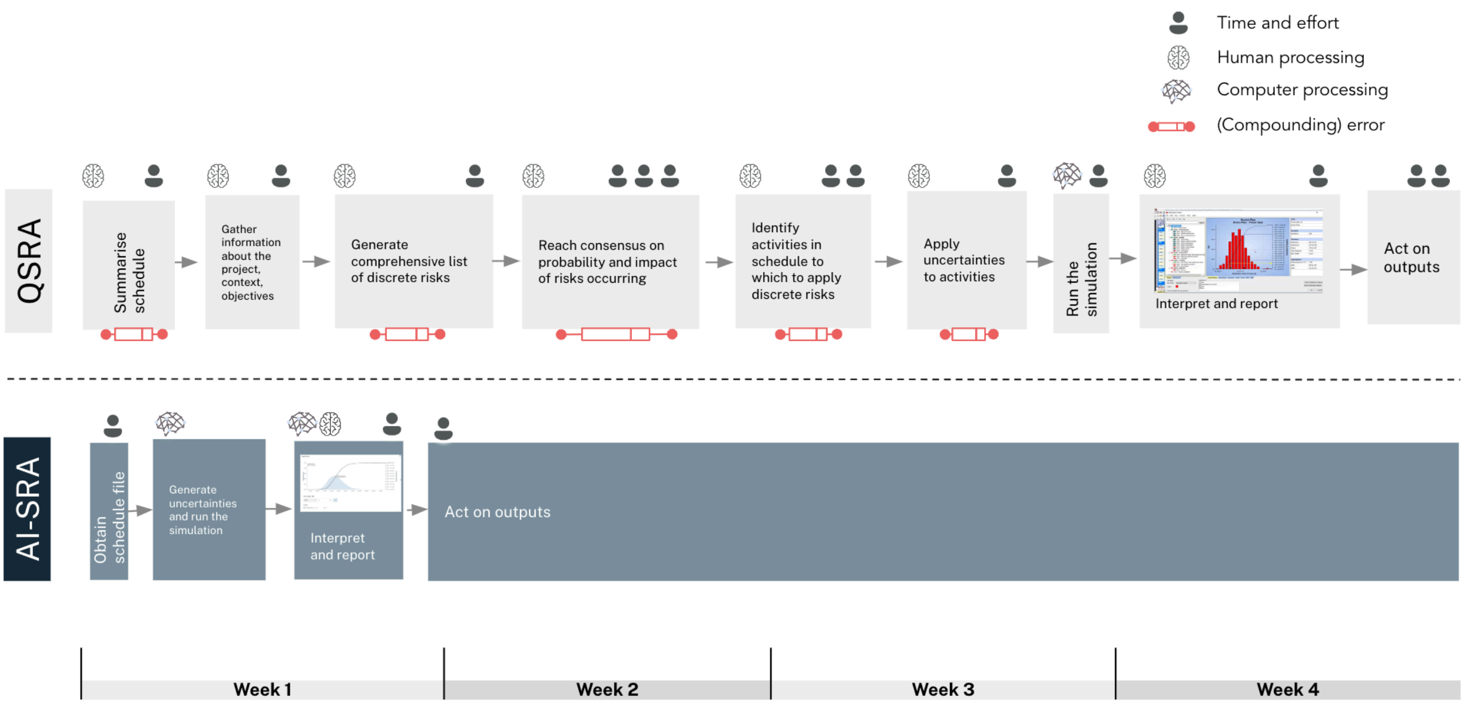

Figure 1: A comparison between quantitative schedule risk analysis (top) and AI-assisted schedule risk analysis (bottom).

In fact, there is consensus that QSRA has significant shortcomings that limit its accuracy and its impact on overall project outcomes:

1. **Limited human attention span**
   To generate a comprehensive list of threats and opportunities, QSRA requires workshops with experts who give their opinions on the potential risks, their impact and their likelihood of materializing. In a second step, probability distributions based on these estimates are applied to all activities in the schedule that may be affected by a specific risk. It is generally impossible for a human, given time and resource constraints, to do this for a schedule of tens of thousands of activities and schedules are summarized to a couple hundred of activities, introducing potential loss of logic and uncontrolled approximation.
2. **Sparing use of QSRA**
   Even with summarized schedules, QSRAs are labor intensive processes which most mega-projects only use sparingly. Quarterly or biannual cycles are the norm even in risk-mature organizations. In addition, QSRAs may be used to prepare for key milestones, such as possessions in the rail industry. This means that updated, quantitative risk positions are scarce, rendering delay mitigation difficult.
3. **Human Bias**
   QSRA results are inevitably affected by bias because the potential threats and opportunities and their likelihood and potential impact are collected from a group of humans. Awareness of these biases has notably increased in the past decade among the project controls and project management community, but they still influence the results today.
4. **Bounded distributions**
   In a typical QSRA, the use of bounded distributions – like uniform, triangular, or PERT [15] – to model duration uncertainty leads to an unrealistic assessment of project risk (see Figure 1) They fail to account

for the long-tailed nature of low-probability, high-impact risks that significantly contribute to project delays. Typically, the same types of distributions are assigned to each activity rather than accounting for their heterogeneity. Furthermore, the application of these bounded distributions in complex schedules artificially inflates certainty, fostering false confidence and underestimating risk exposure. This flawed approach in measuring activity delays and managing risks in QSRA results in flawed outputs, impacting project success.

AI schedule risk analysis

AI Schedule Risk Analysis (AI-SRA), represents a significant advancement in proactive risk management by amending human expertise with AI trained on extensive project data. [2, 16] AI-SRA leverages advances in AI, specifically deep learning with Graph Neural Networks (GNNs),[4] which learn from large datasets of project schedules to predict future project outcomes. This process simplifies forecasting, requiring only the project schedule for analysis, and promises remarkable accuracy and efficiency in predicting project timelines.
A step-by-step process of AI-SRA is shown in Figure 1, bottom row. AI-SRA addresses the limitations of traditional QSRA in several key ways which enhance the risk management process.

1. **Lower resource limitations due to AI**
   AI-SRA eliminates the need for schedule summaries. The AI can process millions of activities rapidly, exposing potential delays that might be hidden in summarized schedules. The process of risk identification and modeling, often time-consuming in traditional QSRA, is streamlined in AI-SRA. It allows workshop participants to focus on mitigating risks rather than in identifying and modeling them. This efficiency shift means more time is allocated to addressing risks.
2. **Continuous use of AI-SRA is possible and leads to action-oriented risk management**
   AI-SRA is much less resource intensive to run and can hence be employed continuously rather than sparingly. This allows for dynamic reactions to changes in the project plan, keeping risk exposure information current. AI-SRA focuses risk management on proactive strategies and continuous threat mitigation. Ultimately, AI-SRA places risk management at the forefront of project decision-making, fostering a culture of continuous, proactive risk management.
3. **Overcoming human biases**
   AI-SRA significantly reduces the impact of cognitive and behavioral biases in the risk analysis process. While biases can still influence risk mitigation, the initial identification and modeling of risks are objective, thanks to AI's involvement.
4. **Accurate probability distributions**
   The deep learning models employed in AI-SRA provide more accurate uncertainty distributions than human-tuned models, capturing the 'tail risk' that bounded distributions in traditional QSRA miss. This leads to a more realistic modeling of project uncertainties.

Numerical AI-SRA Performance

Previous papers [4] have systematically compared the results of using various PERT and Log Normal distributions see [4] to those generated with AI-SRA. As can be seen in Table 1, these AI models are at least twice more accurate than any version of QSRA for activity-level forecasts as measured by mean absolute error (MAE)), Continuous Ranked Probability Score (CRPS) [17] and likelihood (the probability density around the task's actualized duration, averaged over the entire test set.) Similar superiority of AI-SRA results was demonstrated for project end-date forecasts (see [4]).

In addition, AI-SRA calculations are near instant. Once the machine learning pipeline is set up and the model is trained, it takes a few seconds to produce accurate distributions for each activity's duration in the schedule.

Method/ forecast metric	**CRPS**	**MAE**	**Likelihood**
PERT	703.5	1514.1	0.012
Log normal	105.2	237.3	0.01
GNN	64.1	106.3	0.44

Table 1: Activity-level performance of AI-SRA based on GNN (graph neural networks) compared to QSRA results using PERT distributions and log normal distributions.

Goal of this study

Given the recency of AI-SRA, only a few mega-projects have introduced it into their risk management procedures. There have so far been no examples in the literature that discuss practical considerations of introducing AI-SRA, including onboarding, training, organizational changes and process changes that enable AI-SRA to unfold its potential. This article closes that gap in the literature.

Practical considerations when rolling out AI-SRA

Significant professional retraining and skepticism is to be expected when a gold standard such as QSRA is replaced by a process based on disruptive new technology such as AI. This section describes the main challenges that are encountered when practically implementing AI-SRA and how they have been overcome. The focus is on projects that are worth more than 500 million dollars as they have a complexity and organizational structure that makes traditional QSRA a time consuming and inefficient process.

The main body of evidence supporting the conclusions of this section are the implementations of AI-SRA on 5 megaprojects across the rail industry as well as the oil and gas industry. These implementations started in 2022 and are continuing to date. Total project costs of the projects considered ranged from £60M to £10B. The schedules on which AI-SRA was run ranged from a couple of thousand activities to tens of thousands of activities. Specific use cases of AI-SRA within these projects included 1) risk assessment before final investment decision; 2) risk assessment during early contractor involvement; 3) risk assessment after a rebaselining event and 4) risk assessment cycles during the construction phase.

From these experiences, three challenges have been identified that need to be overcome to make AI-SRA roll-out successful:

- **Challenge 1: Lack of trust in AI**
  The central component in the AI-SRA methodology is the artificial intelligence model [4, 5]. The use of a data-driven model is essential in avoiding cognitive biases such as availability, recency, saliency, and anchoring in QSRA workshops, [7]. In spite of its advantages, the use of AI requires the practitioner to overcome challenges in securing stakeholder buy-in. In particular, deep learning models are opaque to the reasoning behind why an activity was delayed in the past. Consequently, the people in charge of managing the risk must trust the delay assessment that the model has made.
- **Challenge 2: AI-SRA results are unintuitive**
  AI-SRA results look relatively familiar to risk professionals who are used to numerical outputs of QSRA. However, AI-SRA relies even more on quantitative rather than qualitative information than QSRA which makes AI-SRA outputs difficult to interpret particularly for professionals who are not used to probabilistic

thinking. In order for the AI-SRA process to be successful, all the stakeholders involved must reach consensus on the actions to be taken as a result of the analysis, meaning that AI-SRA results have to be intuitive for everyone involved.

- **Challenge 3: AI-SRA processes differ from tried and tested approaches**
  While there is a clear equivalence between AI-SRA and QSRA, there are differences in the process representing a training and skills challenge. This means professionals have to invest time to re-train which they weigh up with the efficiency gains that AI-SRA brings.

In the following, solutions to these challenges, that have been tested in megaprojects, are presented.

Harboring trust in AI models

To counter challenge 1, the lack of trust in AI models, a 4-step process, shown in Figure 2 has been included as part of the practical methodology. The objective of the process is to generate confidence in the deep learning models before decisions need to be made. The steps often need to be repeated with relevant stakeholders until buy-in is secured.

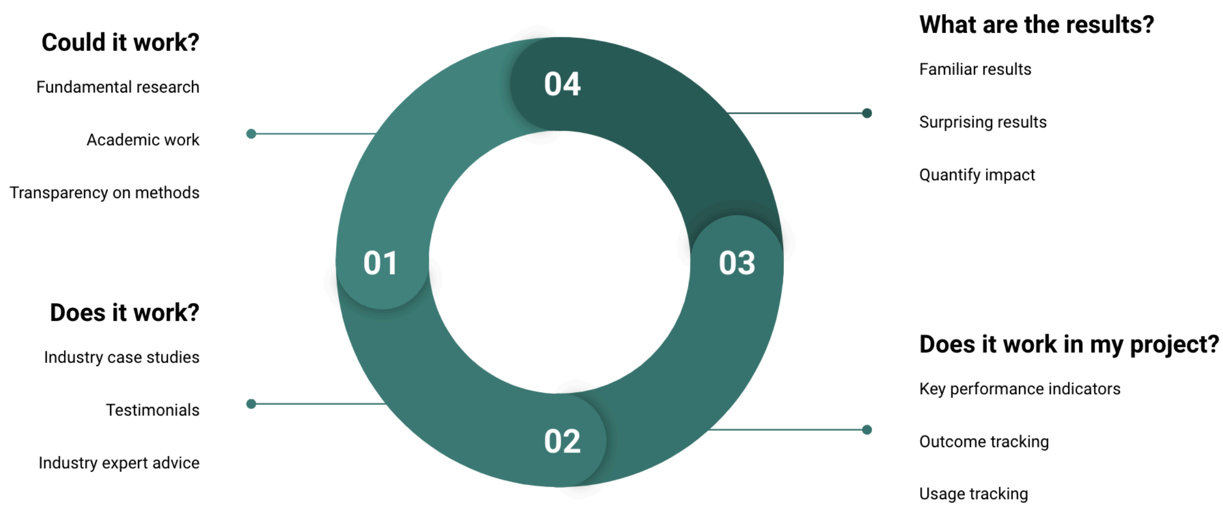

Figure 2: Four-step process to build trust in AI-based outputs.

In this study, the 4-steps have been facilitated as follows:

1. **Could it work?** - Stakeholders must have visibility on the science behind the methods. This can be facilitated by accessibly explaining general research on AI and its fundamental principles to stakeholders and by being transparent about the models that are used in the process.
2. **Does it work?** - Stakeholders require confidence that the fundamental research has also been applied in real life, successfully. This can be facilitated presenting use-cases in similar sectors or industries.
3. **Does it work in my project?** - Stakeholders must have confidence that the AI-SRA process is driving better outcomes for their specific and unique project. This can be facilitated via project-specific success metrics.
4. **What are the results?** - In order for the stakeholders to be able to take action on "surprising" results, the AI-SRA process must also provide a way for stakeholders to observe or query how their own assumptions rank in the analysis.[18] Presenting a balance of surprising results, which are more valuable, and results that reinforce their understanding of the project was found to be the best method to foster confidence in the AI-SRA methodology and drive better outcomes.

Making AI-SRA results intuitive through visualizations

Challenge 2 of rolling out AI-SRA in practice is the relatively unintuitive nature of some of the results. AI-SRA requires professionals to think probabilistically and to form risk narratives from a host of quantitative results. As has been established in other statistics-heavy fields [19, 20, 21], visualizations are key to place these numbers in context and to facilitate action. Visualizations also make it easier to communicate results to wider stakeholders.

Three visualizations are presented here for use in the context of AI-SRA: 1) Driving paths, a probabilistic version of critical paths; 2) Mitigation impact visualization; 3) Forecast information presentation.

Driving paths

AI-SRA produces several competing critical paths, with each one having a probability of being critical. A challenge of AI-SRA is attaining a clear understanding of the paths through the schedule where delay is most likely to accumulate and prioritizing the mitigation of one path over another.

The Gantt chart is the most commonly used visualization to show the attributes of a schedule (e.g. activities, their connections, their durations, the critical path). However, in the development of AI-SRA it has been determined that for large projects Gantt charts are impractical and uninterpretable when alongside forecast results.

The driving paths visualization (Figure 3) was designed to show which different sections of the schedule are likely to accumulate delay. The algorithm behind the visualization is designed to keep only relevant connections in the schedule, dropping paths that have no criticality or don't accumulate delay. Consequently, the visualization is a summarized version of the schedule file, which shows only information that is relevant for key stakeholders when deciding how to mitigate risk in the schedule.

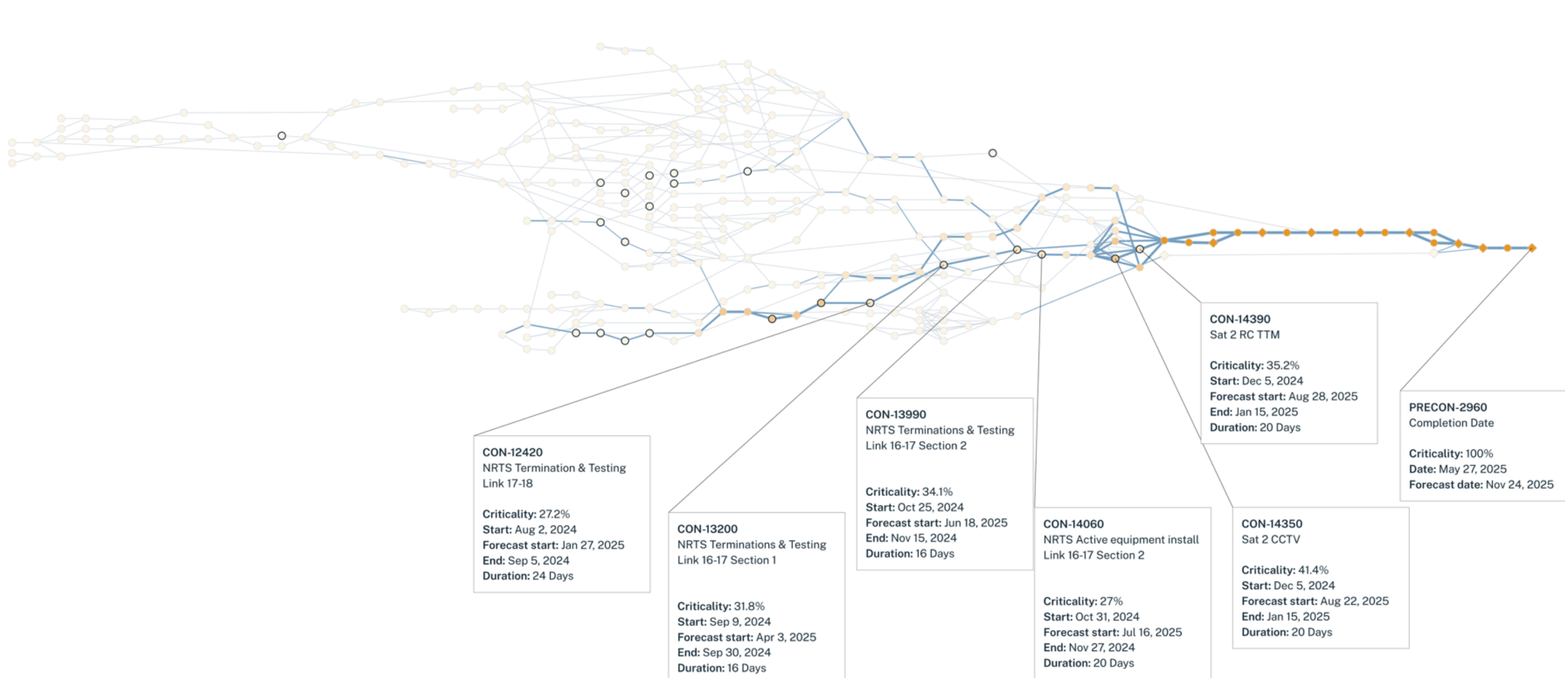

Figure 3: The Driving Paths visualization. This image summarizes a schedule containing around 1500 tasks. The activities highlighted on the main driving paths are those to which the completion date is most sensitive (which can be different to the critical path).

In the figure, each circular node represents an activity that was not omitted by the algorithm, each diamond node represents a milestone and the lines connecting the nodes are direct connections between the activities. The thickness of the lines represents the criticality that has been forecast for that path and the highlighted nodes are those to which the end date forecast is most sensitive.

This visualization can be used for three primary purposes:

1. Identify the top critical path that must be prioritized for mitigation action and compare it to the planned critical path.
2. Recognize previously ignored sub-critical paths that could potentially contribute to the delay of the project if left unchecked.
3. Immediately identify critical bottlenecks in logic that - due to merge bias - are almost certain to be delivered with delay.

Mitigation impact visualization

To generate trust in the AI-SRA process and elicit action from its results it was necessary to quantify and display the potential impact of mitigating the risks contained in the insights achieved via AI-SRA.

To this end, a visualization, presented in Figure 4 was developed that shows two probability distributions:

1. The “before action” distribution. Which presents the results from the AI-SRA simulations for an end date of interest.
2. The “after action” distribution. Which presents the sensitivity of the same end date to the probability of delay of a set of activities selected by the risk practitioner. The sensitivity is measured by “turning off” the prediction given by the ML model and forcing the task to complete as planned in all the simulations.

Figure 4: Mitigation impact visualization.

Presenting end date sensitivity in this manner had three benefits: 1) Risk practitioners could define impact in different ways, giving them versatility to approach the subject of impact with different stakeholders. 2) The effect of taking action could be observed on the entire distribution of outcomes; this leads to previously unavailable conclusions, such as being able to increase confidence in the delivery date, even if the date is still late. 3) Practitioners can also identify tasks which are irrelevant to mitigate since they have no effect on the possible outcomes of the end date.

Forecast information presentation.

A collection of visuals that enables the risk practitioner to observe what the machine learning outputs are and understand the context of its prediction was found to be important. Language must be easily accessible by any stakeholder in the AI-SRA process. Using risk jargon or specialist language constituted a barrier for adoption of the methodology.

The dashboard that was developed contains the following elements (see Figure 5):

1. The probability of duration of the activity in question. Here, the practitioner can directly observe the output of the machine learning model and qualify the probability and potential impact of the risks.
2. The potential savings quantify, in one number, the sensitivity of the project's end date to this individual activity. It gives a clear indicator of the potential impact that dedicated mitigation strategies can have on the project.
3. The forecasted criticality and the time remaining until the start of the activity provide an idea of the urgency of acting on this activity.
4. The activity neighborhood visual shows the direct predecessors and successors of the activity, giving the practitioner the data required to understand the context in which the task is taking place.
5. The possible delay causes (created using an AI model) give the practitioner a starting point for the threats that may affect this activity and materialize the forecasted delay.

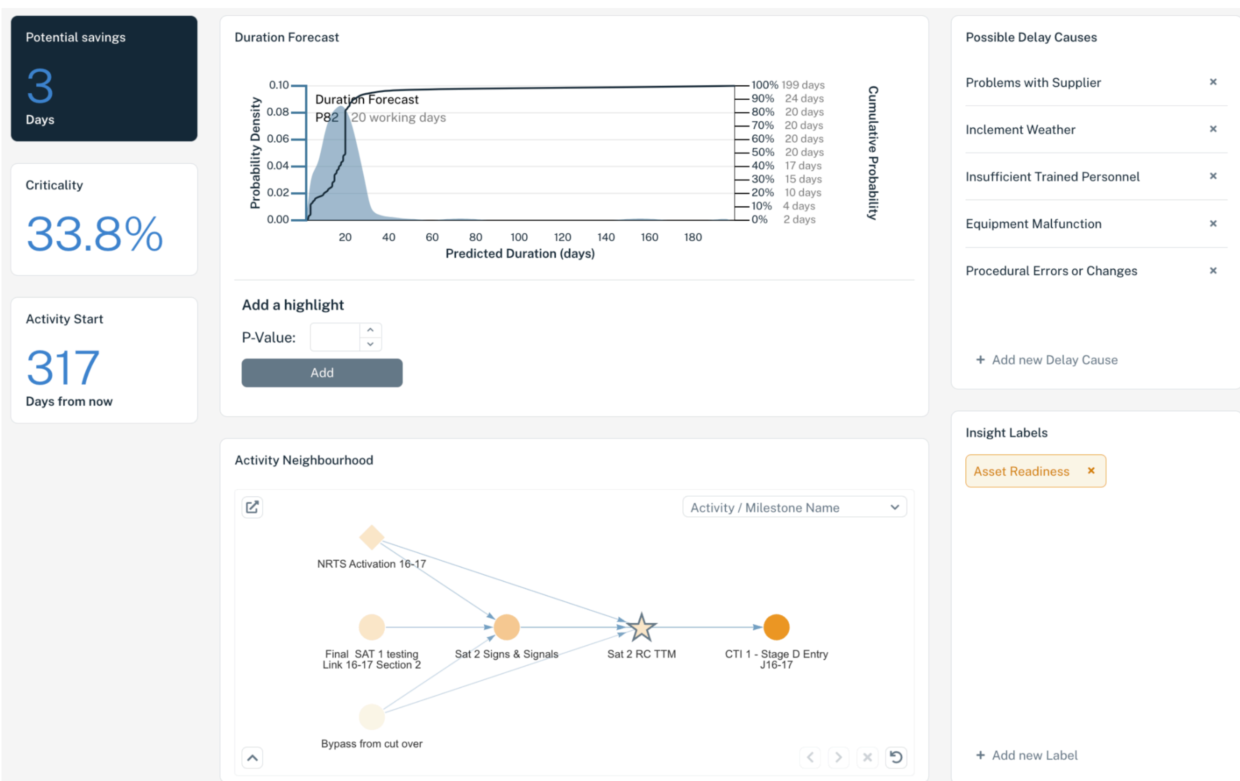

Figure 5: AI-SRA forecast information dashboard.

Familiarizing professionals with AI-SRA processes: The AI-SRA workshop

Challenge 3 revolves around the lack of familiarity with AI-SRA processes and the arising training. Here, experience has shown that demonstrating the equivalence and differences between QSRA and AI-SRA processes along with the gains from using AI-SRA are key. This is discussed here using the AI-SRA workshop as an example.

The risk workshop is a key cornerstone of traditional QSRA, addressing elements of risk quantification, stakeholder management, and lastly some action planning. Depending on the time available for the workshop and the concentration spans of the attendees, these efforts can become compressed. In this event, the quantification of risks and their application to the model takes priority. This means that action planning is often deprioritized. As a result, the workshop generates a body of risk that may affect a project, but little thought as to what to do about this risk. In some cases, the focus of the workshop can be to appease the reporting requirements set by an organization, rather than attempting to fully understand the risk position of the project.

Because AI-SRA can quantify risk without the need for human intervention, this changes the emphasis of the workshopping process significantly. Rather than spending the majority of the team's time on quantifying risk, the session can be spent on talking about risk that matters, and therefore what to do about it.

Furthermore, the fact that the data is already available means that the team is not starting from a 'blank page'; they are able to review the outputs from an objective starting point. As existing best practice, traditional approaches require the team to validate the quantifications in an existing (but largely subjective) risk register. More often, traditional workshops seek to quantify a complex risk item on the spot, without reference criteria, and solely relying on the judgment and experience of the room.

In comparison to a traditional QSRA, the AI-SRA agenda contains fewer discrete parts, and contains activities that are more likely to be appealing to action-oriented project teams, rather than the quantification of risk. This can enable project delivery and controls teams to have more meaningful discussions, which also help both disciplines to achieve their objectives in a less polarizing way (broadly speaking, risk managers need to quantify risk to create a risk model; project managers do not see this as an activity that directly benefits them). Because the outputs have already been produced, teams can interrogate the outputs to aid their discussion, facilitated by the visualizations described above.

Task sensitivity register															
Project X															
Milestone of interest		Activity		Sensitivity ID	AI-SRA impact level	Criticality to Milestone of Interest	Basis of Criticality (Total Float or Longest Path)	Task Duration			Risk owner	Who is primarily responsible ?	Potential causes of duration variance	Cause Type	Response strategy
What are the primary tasks that are expected to experience over-run and thus need to be prioritised?								Days				What will be the key causes of task duration over-run?			What are we going to do?
ID	Description	ID	Description			%		Planned	P20, P50, P80, P90	Mean					
1	Project end	a	Complete surveys	xxxx	5	72%	LP	20	12, 20, 27,39	23.3					
2		b	Snagging	xxxy	4	82%	FP	60	45, 60,78,100	70.05					
...	...	...	...	...	...	...	...	...	...	...					

Figure 6: AI-SRA workshop table prepared by a risk practitioner. The data in the blue cells was extracted from AI-SRA results, the amber cells were completed during the AI-SRA workshop.

Experience with practical implementations have shown that once the AI-SRA workshop format has been explained, it is embraced especially by action-oriented risk professionals because it allows them to focus on actions that arise from the analysis rather than spending most of their time and energy on the analysis itself. An example of an anonymized AI-SRA workshop table prepared by a risk practitioner is shown in Figure 6.

Additional materials were developed to further facilitate the adoption of AI-SRA. For example, the framework outlined in Figure 7 provides guidance on how the process should be run.

AI-SRA - How your rail project will run AI-SRA

This guidance note is produced to provide an overview of the process of running a QSRA through nPlan Insights for risk, planning, and project controls teams. A full guidance document is available here.

Model Setup & Forecasting

To generate a forecast and highlight the insights from the forecast simply export the schedule file from P6 to .xer and run regular schedule integrity checks using *schedule.nplan.io*, addressing key schedule integrity issues. Once complete, upload the xer to nPlan Insights. The results will then be available in Insights and prior to the workshop the forecasts and driving paths are reviewed to identify any updates to schedule logic required.

Risk Workshop

Prior to the risk workshop with the project team, risk managers should familiarise themselves with the outputs, including the key milestone forecasts, potential critical paths, and insights highlighted as the top risky activities. During the risk workshop these uncertainties should be analysed and the potential risks identified by the project team. The workshop can then focus on generating comprehensive mitigation plans for these risks.

Reporting

After (or prior to) the risk workshop scenario tests can be conducted to model the impact on the forecast of mitigating the risk to selected groups of activities. Actions to mitigate risk can be tracked in nPlan Insights and the project risk register updated with additional identified risks.

Monitoring

The Actions tab within nPlan Insights provides a simple overview of the actions in place to track the progress of each action. Once actions have been completed the insight can be dismissed and in future forecasts no uncertainty will be forecast on these activities.

Figure 7: A guidance note to project controls professionals on a major UK rail project.

Case study: UK rail program

AI-SRA was rolled out across a series of UK rail projects constituting a single mega-project. This section describes the specifics of how the three challenges described above - lack of trust in AI, unintuitive nature of AI-SRA results and familiarization with new AI-SRA processes - were addressed in this specific case.

Across the implementation, a total of 18 project control professionals were involved in adopting AI-SRA. They included the head of risk, the head of project controls and a variety of planners and risk managers. AI-SRA was used to inform investment decisions, prepare possessions, assure QSRA results and complete the contractually mandated risk analysis.

Gaining trust in AI through buy-in from upper management

As explained before, a key challenge in implementing AI-SRA is the lack of trust in AI. In this case study in particular, the stakeholders were concerned about the accuracy of the results and how to identify the reasons behind the delays highlighted by the deep learning model. The methodology explained in the section “Harboring Trust in AI models” was followed to address their concerns.

First, the support of the head of risk and head of project controls was secured by answering the first two questions of the methodology (i.e. Could it work? Does it work?). Through academic references, performance studies and case studies, the stakeholders became convinced that the use of deep learning models could lead to more accurate, reliable, and frequent risk management.

The buy-in from users such as risk managers and planners followed the buy-in from upper management. Some of the risk managers were skeptical at first about the ability of AI to be applicable to the individual projects. Training and onboarding sessions with the head of risk and the head of project controls in the room served to convince the wider user group. Creating advocates among the risk managers also helped in spreading awareness and usage of the new process. Upper management voiced their support for innovation and specifically called out the benefits AI-SRA would create for the team by enabling the team to become more effective.

Running QSRA and AI-SRA in parallel

In this case study, it was found that once the first challenge was addressed, the issues of understanding the AI-SRA results and updating processes could be addressed simultaneously. Once these final two challenges were addressed, the organization was able to transition entirely out of QSRA and run their risk processes via AI-SRA.

The transition started with running both methodologies in parallel for a year. During this time the teams had the opportunity to familiarize themselves with the novel visualizations presented in section “Making AI-SRA results intuitive through visualizations” and with the materials and workshops presented in section “Familiarizing professionals with AI-SRA processes: The AI-SRA workshop”. Additionally, participants could be onboarded onto the AI-SRA methodology using live project data, thus improving engagement with the new process and without compromising their existing risk processes. Finally, participants also found it valuable to compare the novel visualizations and results to the narratives that were possible with the traditional QSRA to observe differences and gain confidence in transitioning to AI-SRA.

At the end of this period, the participants concluded that the AI-SRA methodology was easier to run when compared to traditional QSRA. In particular, the ease of producing forecasts and simulating hundreds of scenarios for risk mitigation proved a stark difference from QSRA, where simulating scenarios is a slow and tedious process. At this point, the teams were ready to move into AI-SRA.

AI-SRA to support a major investment decision.

The previous success in the deployment of the AI-SRA methodology was reaffirmed as it was used as part of submitting a bid for funding from the government and the national rail authority. This bid represented more than $1bn of additional scope. AI-SRA was used to demonstrate that the plan that the team had designed was deliverable and that the risk contained therein was manageable. The choice of AI-SRA, over QSRA, was driven by its previously proven value and by the short timeframe available, with the team having just 12 working days to produce and assure the analysis outputs.

Over the course of this period the team consisting of two planners, two risk managers, and two project controllers were able to collaborate in real time within a single piece of software to iterate twice on the schedule, run three different risk mitigation scenarios, and use generative AI tools to deep dive into the analysis data to prepare the bid report.

In the process of submitting the bid, the use of AI-SRA enabled the project controls team to produce risk analysis outputs and visualizations that would have been otherwise impossible to produce with QSRA. Namely:

- The Driving Paths visualization enabled the team to identify and highlight the riskiest sections of the schedule, including tasks at risk of delay, bottlenecks in logic and risky interfaces between projects.
- The Forecast information enabled the team to assure the delivery of several key milestones by showing that they were not forecasted to be delayed beyond their time risk allowance.
- The Mitigation Impact visualization enabled the team to demonstrate to the bid authority that their mitigation plan was focused on the items where it would have the most impact on the likelihood to deliver the schedule on time.

As a conclusion of this case study the projects' risk management process was updated to mandate the monthly use of AI-SRA. The teams now regularly follow this methodology to identify the highest risk items and scenario-test their mitigation, compare different versions of the plan to identify the most robust way of delivering the work and to communicate all the key risk information to the relevant project stakeholders.

Conclusion and future work

In conclusion, this article shows how to successfully roll out AI-SRA across megaprojects. The three major challenges to this are lack of trust in AI models, the unintuitive nature of AI-SRA results and the lack of familiarity with AI-SRA processes. General strategies were described to overcome these challenges and a specific case study on a UK rail project is discussed to show how these strategies were implemented. As the roll-out of AI-SRA across different projects continues, more data points will be collected with the goal to investigate more general quantitative conclusions about how this disruptive technology could help the construction industry deliver projects on time and on budget.

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Rhys Phillips – Client Engineer, nPlan
Dev Amratia – CEO, nPlan
Carlos Ledzema – Product Manager, nPlan
Richard Bendall-Jones – Product Manager, nPlan
Vahan Hovhannisyan – Research Director, nPlan
Leonie Anna Mueck – VP Product, nPlan