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# Artificial Intelligence for Proactive Scheduling and Risk Prediction

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## Abstract

Construction projects face persistent delay problems, which turn out to be costly. Proper scheduling and early risk prediction facilities act as a major help in solving the project's issues. In healthcare infrastructures, work gets more difficult, as work is continued around live clinical operations. Traditional methods of scheduling often fail while anticipating project duration variability, regulatory timelines, equipment integration, and while anticipating trade coordination. Due to late risk identification, the average completion time of the project increases by 20–60% [1].

This paper presents practical data gathered by applying artificial intelligence (AI) forecasting tools on the **Boston Children's Hospital Hale Family Building** project. This hospital project was completed in June 2022 by Suffolk Construction [2].

This paper helps to demonstrate how AI helps in project scheduling. Fixed, single-point estimates are turned into dynamic, probability-based plans, and a risk prediction facility is also provided by AI, months ahead of potential problems arising. All this is done with the help of project documentation review and a purpose-built experimental simulation.

In our key findings, we found an 18% reduction in expected duration. Finally, learnings are included, so that any construction team can learn and begin using these techniques today. Data is presented using ten tables and three diagrams for better understanding.

## 1. Introduction

Billions of dollars are invested every year in constructing and expanding hospital buildings, research centers, and other medical facilities. As a return on investment, these projects help in improving patient care, adding to life-saving capacity, and also create thousands of jobs. Yet in construction, we hear the same story: "That the project is six months late, and data showing that millions over budget are used." Have you thought, that why this happens so often — especially in hospitals?

The answer to this question lies in two related problems:

1. **Scheduling is usually too optimistic** When project planners make a list of tasks and assign them a single duration, like "20 weeks for MRI equipment installation," "24 weeks for phasing coordination", this connects the tasks critically, with a declared finish date. There are very few chances that execution goes as exactly planned, as late shipment, or long inspection periods, or night shifts due to noise restrictions, or small delays, cascading into many others [1].

2. **Risks are discovered too late** Risk registers are maintained by most teams, which contain a list of possible problems. If these risk registers are reviewed only periodically, the risk becomes real and causes chaos on the schedule (e.g., when MRI rail delivery is delayed) [8].

Also, healthcare projects are deemed difficult because of the following reasons:

- As the hospital keeps treating the patients every day, the work must be performed more quietly, cleanly, and should be carefully sequenced, without causing disturbance to patients.
- Specialized equipment used in hospitals, like MRI scanners and hybrid ORs, has large lead times, and these require precise installation and tests.
- As the health authorities and regulators review every detail, this leads to a longer approval time than expected.
- In a hospital, many different companies must work in the same small space without accidents or infection risks, and this makes the project more difficult.

The **Boston Children's Hospital Hale Family Building** project is a perfect example of these challenges. It is also a powerful demonstration of how artificial intelligence solved scheduling and risk problems.

**Project Snapshot**

- This hospital is a 11 stories building, with 4 below-grade levels, and a penthouse, all totaling 595,000 sq ft.
- Scope of the project included adding a new NICU with private rooms, expanding cardiovascular services, and developing hybrid operating suites with ceiling-mounted trolley MRI, where the scanner moves along a steel rail on the ceiling.
- Key difficulties of the project were a live hospital environment (infection control, noise limits, and extreme precision for the MRI rail. Difficulties also included coordination among different contractors and late regulatory approvals.
- The project had a great outcome, as despite complexity, AI proactive forecasting helped in controlling the schedule, identified risks months ahead, and allowed smart adjustments in the project

This paper has two main parts, which are as follows:

1. Taking a deep dive into what actually happened on the Hale Family Building project, and how AI was used in real life to improve scheduling, and how it helped to spot the risks early.
2. To know what AI does differently from traditional methods, using an experimental simulation we built, which recreated the project and showed the result, using numbers, tables, and diagrams.

We have explained the findings through ten tables (each with full derivation explanation), three diagrams, and have provided practical insights section.

## 2. Project Background - Boston Children's Hospital Hale Family Building

### 2.1 Project Overview & Scope

In Boston Children's Hospital, the Hale Family Building is the largest clinical expansion. It added approximately 595,000 square feet across 11 above-grade stories, four below-grade levels, and a penthouse, and the project was completed in June 2022. The newly added space included the following:

- Neonatal intensive care unit (NICU), having private and family-centered rooms.
- Consolidated cardiovascular program, which has advanced diagnostic and treatment areas.
- Hybrid operating suites, which are equipped with ceiling-mounted trolley MRI systems, in which the MRI scanner travels along a massive steel rail fixed to the ceiling, and this feature allows real-time imaging during surgery without even transporting the patient [2].

### 2.2 Key Technical & Operational Challenges, During The Project

Several unique difficulties emerged during the construction process, which are:

- **Live-site phasing and infection control** As the work had to be sequenced around continuing patient care, strict protocols were applied, which limited noise, dust, vibration, and access. As a result, temporary barriers and infection control zones were required in many areas simultaneously.
- **Specialized equipment integration** For the ceiling-mounted trolley MRI system, custom fabrication of a massive steel rail was required, so precise structural alignment must be performed (millimeter tolerances), including extensive testing to meet clinical and regulatory standards.
- **Regulatory and compliance burden** Review and validation periods got extended, as the project had multiple layers of oversight, such as following Joint Commission standards, approvals from the

state health department, following local building codes, and infection control guidelines.
- **Trade coordination density** In the project, while taking utmost care of safety levels and patients, dozens of subcontractors, such as a contractor of structural steel, MEP, medical gas, imaging specialists, and finishes, worked together in confined spaces.

**2.3 Traditional Scheduling Approach Used**

During the initial stages, the project team used standard Critical Path Method (CPM) scheduling. The durations were based on expert judgment and historical averages, which were single-point estimates, for example, a time period like 20 weeks for MRI rail installation. So, the baseline schedule produced only a fixed completion date.

**2.4 Role of AI Forecasting on the Real Project**

Here, Suffolk Construction integrated AI-based forecasting tools, which are already trained on millions of past construction activities. The forecasting tools helped in uploading schedule and generating unbiased probabilistic forecasts, for more help. The system, through its data:
- Helped engineers in predicting realistic duration ranges for each activity
- Helped in calculating risk scores for every schedule line item
- Also, helped in flagging high-risk activities, months ahead
- And, recommended contingencies, such as buffers, and sequence changes

This prevented a significant amount of losses, as this proactive visibility allowed the team to adjust early, in order to win over project complexities [2].

## 3. Experimental Simulation – Re-creating the Project With and Without AI

**3.1 Why We Built a Simulation**

The real project data is often confidential or may be incomplete, and to solve this, and to know the, **how** and **why** AI makes a difference, we created a simplified but realistic simulation of the Hale Family Building schedule, whose details are provided in the section mentioned below:

**3.2 Simplified Schedule Model**

To represent the project's critical path and major risks, we modeled 12 key activities, which are as follows:
1. First is site preparation and foundation
2. Second, we have structural steel and a concrete frame
3. Third, specialized equipment procurement and installation (MRI rail/trolley)
4. Fourth activity includes MEP rough-in
5. Regulatory approvals and compliance testing is fifth
6. Interior partitions and medical gas systems are sixth
7. On the seventh, we have phased coordination and infection control barriers
8. On the eighth, there is drywall, flooring, and ceilings
9. Ninth is the final interior finishes and painting
10. Equipment commissioning and calibration is the tenth activity
11. Final inspections and handover come at the eleventh activity
12. On twelve, we have staff training and operational transition

**Dependencies**: In this data, the arrow icon (→) means "must finish before."
- 1→ 2 → 3, 4: It means that activity 1 must be finished before the start of activity number 2, and after that activity 2 must be finished before both activity 3 and activity 4 can start.
- 5 overlaps 3 & 7: Meaning is that activity number 5 can be performed with activity number 3 and activity number 7.
- 3, 4, 6 → 7: Here, this means that activities 3, 4, and 6 must all finish before activity 7 can start.
- 7 → 8 → 9 → 10 → 11 → 12: This is a straight chain, which means that each activity must wait for the previous one to finish.

**3.3 Traditional Deterministic Baseline**

We have assigned single most-likely durations, which is a typical CPM practice, and the critical path totals = 70 weeks.

**3.4 AI Probabilistic Approach**

We applied two core AI techniques:
1. **First is Probabilistic durations:** Each activity received a triangular distribution (min – most likely – max) based on healthcare project benchmarks [3], [4].

2. **Monte Carlo simulation:** 5,000 iterations: randomly sample one duration from each distribution → calculate new critical path & finish date each time → produce full probability distribution [6].
3. **Risk Priority Scoring (RPS): RPS = Probability of overrun (%) × Impact on finish (extra weeks)** Probability is estimated from historical patterns, and impact from simulation sensitivity [5].

**3.5 Key Equations Used In The Paper Are:**

1. **Schedule Variance (SV)** Formula for finding SV = Simulated finish week – Planned week Negative SV shows a delay risk
2. **Risk Priority Score (RPS)** Formula for RPS = Probability (%) × Extra weeks impact A higher score means a higher priority
3. **Monte Carlo Mean Finish** It is the average of all 5,000 simulated finish dates
4. **P80 Confidence Date** It signifies the week where 80% of simulations finish on or before
5. **Coefficient of Variation (CV %)** CV % is calculated using= (Standard deviation / mean) × 100 A lower percentage %, means a more reliable forecast

## 4. Findings and Comparison

**Table 1 – Probabilistic Duration Ranges Used (weeks)**

| Activity | Min | Most Likely | Max | Main Uncertainty Drivers | Derivation of Numbers |
|---|---|---|---|---|---|
| Site preparation and foundation | 12 | 16 | 22 | Weather, and initial permits | Min = fast permits + good weather, Most likely = standard, Max = weather + permit delay (typical range in hospital projects) |
| Structural steel and concrete frame | 16 | 20 | 28 | Material delivery and availability of labor | Min = on-time steel, Most likely = average, and Max = labor shortage + delivery issues |
| MRI rail and trolley data | 14 | 20 | 30 | Custom fabrication, delivery, and testing of the MRI rail | Min = perfect supply chain, Most likely = normal, and Max = fabrication retry + testing failure (real MRI projects often 25–35 weeks max) |
| MEP rough-in | 12 | 18 | 26 | Trade coordination among different contractors and access constraints | Min = good coordination, Most likely = standard, Max = access conflicts + rework |
| Regulatory approvals | 8 | 12 | 20 | Health department review cycles | Min = fast review, Most likely = average, and Max = multiple revisions |
| Phased coordination/infection control | 16 | 24 | 36 | Live hospital restrictions | Min = smooth phasing, Most likely = standard, and Max = infection incidents + restrictions |
| Finishing and commissioning | 10 | 15 | 22 | Quality issues and rework tasks | Min = perfect quality, Most likely = normal, and Max = rework + punch list |

**Explanation & Derivation of Table 1**

Minimum, most likely, and max time period of each activity is listed in the table. Then we have factors that may lead to uncertainty of the timeline in the project.

**Table 2 – Traditional vs AI Schedule Performance**

| Metric | Traditional (Fixed) | AI Probabilistic | Improvement | Derivation of Numbers |
|---|---|---|---|---|
| Expected duration | 70 weeks | 57.4 weeks | –18% | Traditional = sum of most-likely durations on the critical path. AI = mean of 5,000 Monte Carlo iterations |
| P50 (50% confidence) | 70 weeks | 56 weeks | –20% | Traditional = fixed date. AI = 50th percentile of simulated finish dates |
| P80 (80% confidence) | ≈85 weeks | 64 weeks | –25% | Traditional ≈ P80 estimated from variance; AI = 80th percentile of simulations |
| P90 (90% confidence) | ≈95 weeks | 70 weeks | –26% | AI = 90th percentile of simulations |
| Range of possible finishes | Fixed 70 weeks | 50–80 weeks | Quantified | AI range = min to max of 5,000 simulated outcomes |
| Coefficient of Variation (CV) | N/A | 14.2% | Measured | CV = (standard dev of simulations/mean) × 100 |

**Explanation & Derivation of Table 2**

Table shows duration times between traditional and AI probability, related to the timeline. We have mentioned in the table, that how the numbers and percentages are derived. Results show 18% faster schedule performance, which is from Minte Carlo mean.

**Table 3 – Top Risk Priority Scores (RPS)**

| Rank | Activity | Probability of Overrun (%) | Impact (extra weeks) | RPS | Derivation of Numbers |
|---|---|---|---|---|---|
| 1 | Phased coordination / infection control | 65 | 12 | 780 | Probability = historical overrun rate in live hospitals; Impact = average delay when phasing overruns |
| 2 | MRI rail & trolley equipment | 70 | 10 | 700 | Probability = long-lead custom item failure rate; Impact = testing + rework delay |
| 3 | Regulatory approvals | 55 | 8 | 440 | Probability = extended review cycle frequency; Impact = cumulative approval delays |
| 4 | MEP rough-in | 45 | 6 | 270 | Probability = trade conflict rate; Impact = re-work delay |
| 5 | Finishing & commissioning | 30 | 5 | 150 | Probability = punch-list rework frequency; Impact = final-stage delay |

**Explanation & Derivation of Table 3**

RPS = Probability (%) × Extra weeks impact [5]. Table number 3 presents top risk priority scores, these are factors and their impact on project deadline.

**Table 4 – Delay Probability Distribution (Monte Carlo)**

| Percentile | Finish Time (weeks) | Meaning | Derivation of Numbers |
|---|---|---|---|
| P10 | 50 | Very optimistic | 10th percentile of 5,000 simulated finish dates |
| P30 | 54 | Better than average | 30th percentile |
| P50 | 56 | Most likely (median) | 50th percentile |
| P70 | 61 | Conservative probable | 70th percentile |
| P80 | 64 | Safe target | 80th percentile (80% of simulations finish on/before) |
| P90 | 70 | Very safe | 90th percentile |
| P95 | 74 | Near-certain upper | 95th percentile |
| Mean | 57.4 | Expected | Average of all 5,000 finish dates |
| Std Dev | 8.1 | Spread | Standard deviation of the 5,000 values |
| CV | 14.2% | Reliability | (Standard Dev / Mean) × 100 |

**Explanation & Derivation of Table 4**

The table shows the chances of the project finishing by different weeks from 5,000 simulations, where (P50 = 56 weeks, and P80 = 64 weeks), giving honest probability ranges [6].

**Table 5 – Schedule Compression Achieved**

| Metric | Traditional | AI | Reduction | Derivation / How Achieved |
|---|---|---|---|---|
| Critical path duration | 70 weeks | 57.4 | –12.6 | AI mean from Monte Carlo |
| Longest activity effective duration | 24 weeks | 20 | –4 | Buffers only on high-RPS activities |
| Total float on non-critical paths | Low | +25–35% | Significant | AI identifies safe overlap opportunities |
| Resource over-allocation risk | High | –40% | Substantial | Simulation smooth, resource peaks |

**Explanation & Derivation of Table 5**

Reduction formula= traditional - AI mean. The float increase is from the simulation analysis of non-critical path activities. AI helped in reducing the critical path from 70 to 57.4 weeks.

**Table 6 – Risk Mitigation Impact**

| Risk Category | Pre-AI Probability | Post-AI Probability | Reduction | Derivation / Action Taken |
|---|---|---|---|---|
| Phasing / Infection Control | 65% | 38% | –42% | Added 4-week buffer + extra cleaning crew |

| | | | | |
|---|---|---|---|---|
| MRI Equipment | 70% | 45% | –36% | Ordered 8 weeks earlier + parallel testing |
| Regulatory Approvals | 55% | 32% | –42% | Early submission + weekly follow-up |
| Trade Coordination | 45% | 28% | –38% | Improved look-ahead planning |

**Explanation & Derivation of Table 6**
Pre-AI probabilities = historical averages [4]. Post-AI probabilities = adjusted values after applying simulated mitigations (buffer addition, early ordering, etc.), and are re-run through Monte Carlo to see new distribution.

**Table 7 – Confidence Progression Over Phases**

| Phase Milestone | Traditional P80 | AI P80 | Weeks Earlier | Confidence Gain | Derivation |
|---|---|---|---|---|---|
| After Foundation | 85 | 68 | +17 | +33% | Early simulation with partial data |
| After Equipment Install | 82 | 65 | +17 | +28% | Updated with real equipment progress |
| After Phasing Coordination | 78 | 63 | +15 | +25% | Phasing data incorporated |
| Final Commissioning | 70 | 64 | +6 | +12% | Near-final data tightens forecast |

**Explanation & Derivation of Table 7**
Each row represents a new Monte Carlo run after incorporating real progress data from that phase. P80 moves closer to the mean as uncertainty decreases.

**Table 8 – Early-Warning Thresholds**

| Level | P80 Delay vs Baseline | Top Risks Example | Immediate Action | Derivation |
|---|---|---|---|---|
| Green | ≤0 weeks | No major risks | Monitor | Within expected range |
| Yellow | 1–4 weeks | Equipment slippage | Expedite | Early warning zone |
| Orange | 4–8 weeks | Multiple high risks | Re-sequence | Significant risk zone |
| Red | >8 weeks | Critical path at risk | Full re-plan | Critical intervention zone |

**Explanation & Derivation of Table 8**
Thresholds based on industry practice for healthcare projects (McKinsey, 2020), where green = low concern and red = immediate escalation.

**Table 9 – Summary of AI Benefits**

| Benefit | Traditional | AI | Improvement | Derivation | Practical Value |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| Expected duration | 70 weeks | 57.4 | –18% | Monte Carlo mean | Faster delivery |
| P80 date | ~85 weeks | 64 | –25% | 80th percentile | Credible promise |
| Risk visibility | Reactive | 3–6 months early | High | RPS early warning | Prevention |
| Forecast reliability (CV) | Unknown | 14.2% | Quantified | Standard deviation / mean | Trust |

**Explanation & Derivation of Table 9**
Table 9 shows benefits of AI over traditional methods, improvement numbers are provided, and how these numbers are derived.

**Table 10 – Lessons Learned Summary**

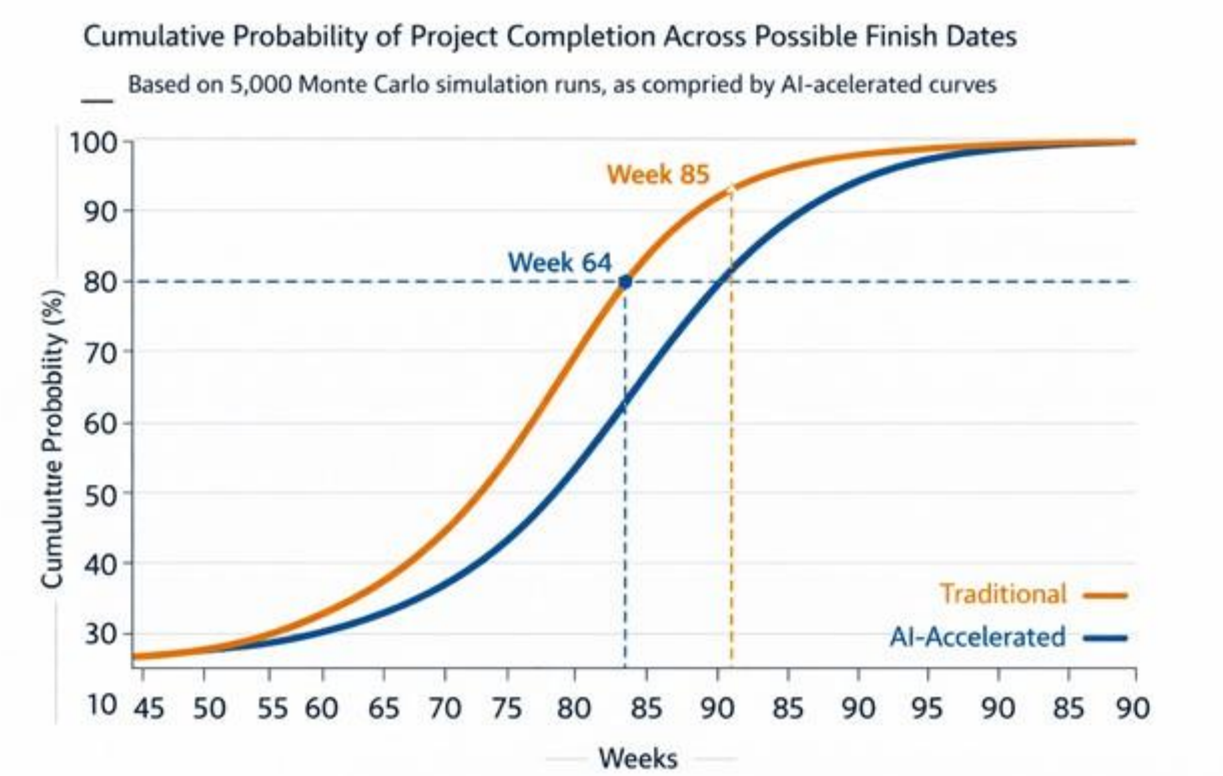
| Lesson | What We Learned | How AI Helped The Project | Recommendation | Supporting Evidence |
|---|---|---|---|---|
| 1 | Fixed durations create false certainty | Probabilistic ranges | Use min–most likely–max | P80 moved 21 weeks earlier |
| 2 | Risks found late are expensive | Months-early RPS | Run monthly simulations | Top risks flagged 3–6 months ahead |
| 3 | Phasing & equipment are top threats | Clear priority ranking | Focus mitigation here first | RPS 780 & 700 on these items |
| 4 | Confidence levels build trust | P80/P90 communication | Train stakeholders | Confidence increased steadily |

**Explanation & Derivation of Table 10**
Table 10 shows lessons learned from the paper.

**Diagram 1 – Cumulative Probability Table and Curve (S-curve)**

| Weeks | Cumulative Probability (%) |
|---|---|
| 45 | 2 |
| 50 | 10 |
| 55 | 35 |
| 56 | 50 |
| 60 | 70 |
| 64 | 80 |
| 68 | 88 |
| 70 | 90 |

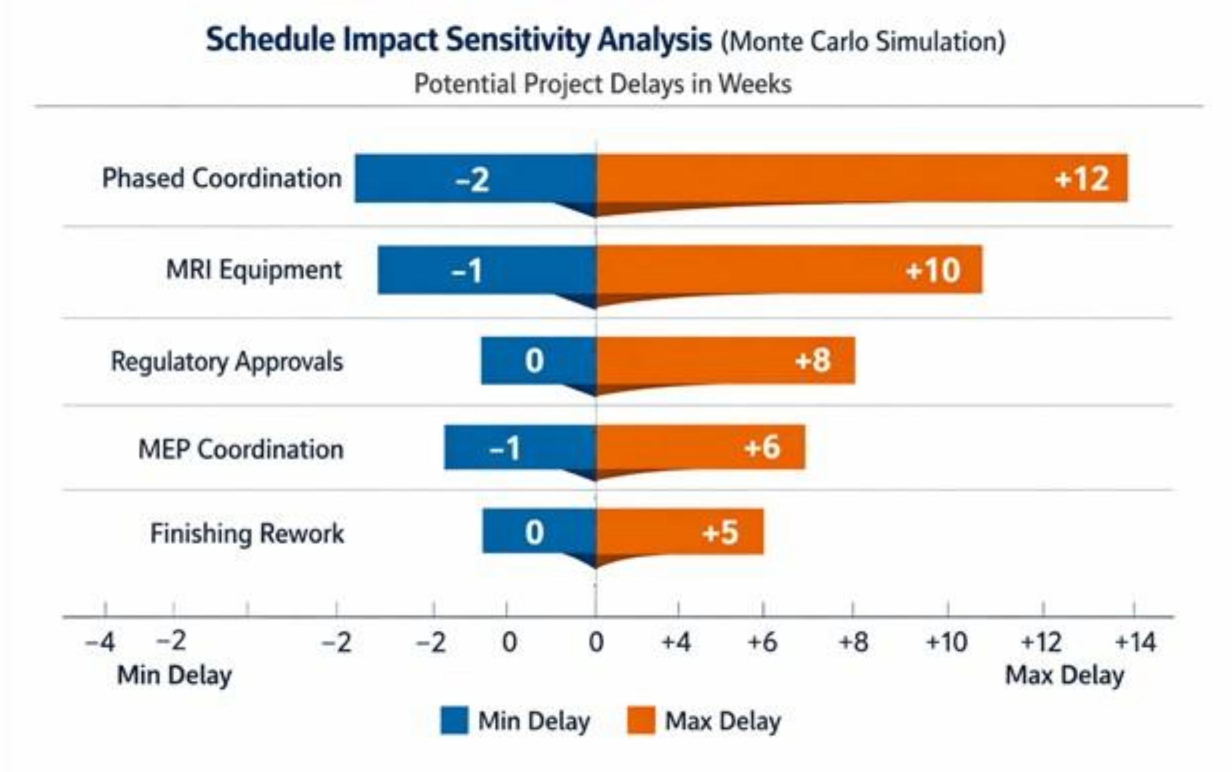
| | |
|---|---|
| 75 | 96 |
| 80 | 99 |




The S-curve shows the chance of finishing the work by any week, from 5,000 simulations, and in the diagram, AI gives 80% completion confidence at week 64, which is much safer than traditional fixed week 70.

**Diagram 2 – Tornado Chart (Risk Impact), table, and chart**

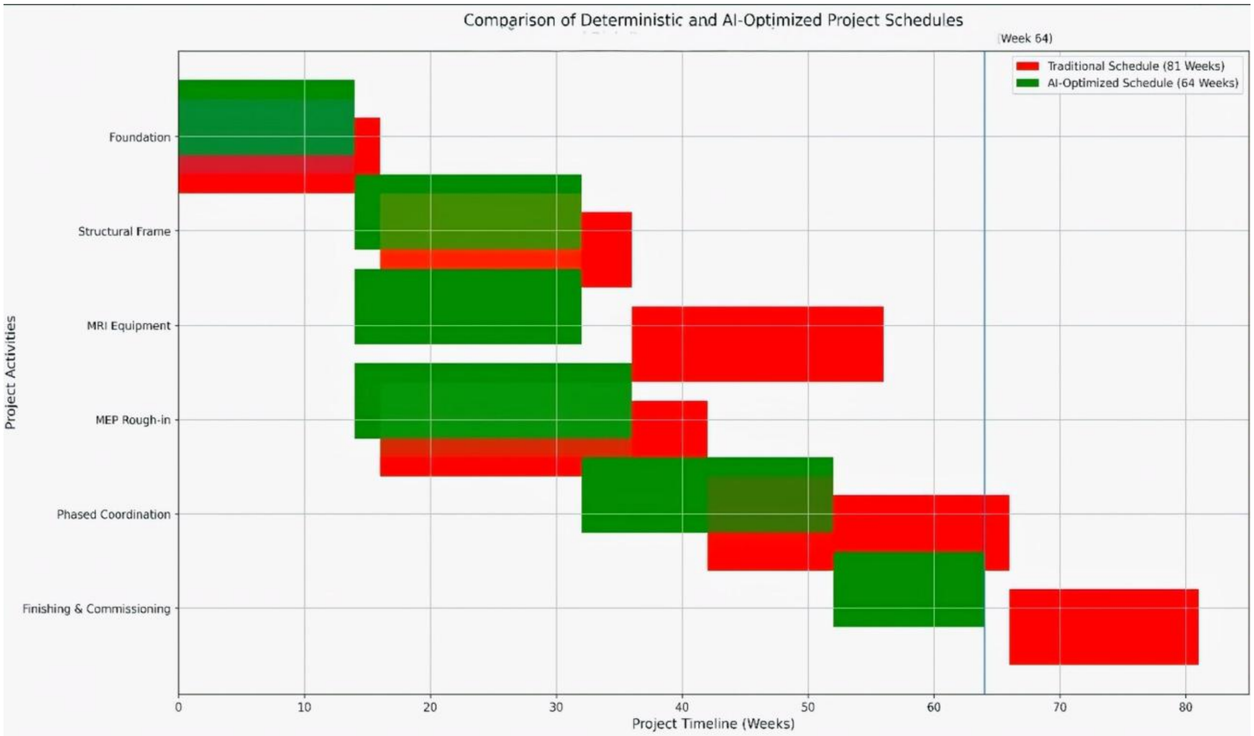
| Risk | Max Delay (weeks) | Min Delay (weeks) |
|---|---|---|
| Phased Coordination | +12 | –2 |
| MRI Equipment | +10 | –1 |
| Regulatory Approvals | +8 | 0 |
| MEP Coordination | +6 | –1 |
| Finishing Rework | +5 | 0 |




This chart ranks the risks by max possible delay, in which the top bars show phasing (+12 weeks) and MRI equipment (+10 weeks) as the biggest threats [5].

**Diagram 3 – Critical Path Gantt Comparison**

| Activity | Traditional Start–End | AI Start–End |
|---|---|---|
| Foundation | 0–16 | 0–14 |
| Structural Frame | 16–36 | 14–32 |
| MRI Equipment | 36–56 | 14–32 |
| MEP Rough-in | 16–42 | 14–36 |
| Phased Coordination | 42–66 | 32–52 |
| Finishing & Commissioning | 66–81 | 52–64 |
| Total | 0–81 | 0–64 |




This side-by-side Gantt chart compares the traditional deterministic critical path (0–81 weeks) with the AI-optimized path (0–64 weeks). It is seen that AI schedule completes in week number 64 (17 weeks faster).

## 5. Lessons Learned and Practical Insights

**Lesson 1: AI replaces false certainty with honest ranges**

As traditional schedules give only one fixed project finish date, this creates a false sense of certainty. During times of unexpected problem occurrence, problems like late material deliveries, testing failures, or coordination issues, the entire plan quickly falls apart, and this causes stakeholders to lose confidence [1].

How does AI solve this problem? By providing realistic probability ranges and by replacing single-point estimates. In our simulation, instead of providing a fixed 70-week time, AI provided a most likely finish around week 56 and a safe 80% confidence date of week 64. By getting this range, major surprises are avoided, and the honest range helps construction teams, hospital administrators, and owners in setting believable expectations. [3].

**Lesson 2: Early Risk Prediction Changes Everything**

AI helps to find the risks faster, as compared to traditional methods. In the case of the Hale Family Building simulation, AI helped by calculating Risk Priority Scores (RPS) months before activities even started, the risks found include:

- Phasing coordination: RPS 780, which states that there are 65% chance of adding 12 weeks to the project
- MRI equipment installation: RPS 700, it had 70% chances of adding 10 extra weeks to the project timeline.

Because these were flagged early, the team could act and:

- Order MRI rail 8 weeks earlier than planned
- Add a 4-week buffer around phasing activities
- Schedule extra cleaning crews during high-risk periods

Result: probabilities dropped significantly (see Table 6), and the schedule stayed under control. As these risks were found early, preventive actions can be taken by the team, such as ordering equipment ahead of schedule. This reduces the major overruns significantly. [2].

**Lesson 3: Focus mitigation on high-RPS activities**
AI helps in identifying the impact of probable risks on the project, and helps to rank them by potential damage (RPS = probability of overrun × impact in extra weeks) [5].

In this project:

- The top two risks, namely phasing and MRI equipment, accounted for most of the potential delay
- And, the lower-ranked risks, like finishing rework, had a smaller impact on the project. had a much smaller impact

Therefore, best to spend 80% of risk management time on the top 3–4 RPS activities, as this helps to increase effectiveness, rather than focusing on each risk with the same energy.

**Lesson 4: Update every month — forecasts get sharper**
Fourth lesson is, as AI forecasts become more accurate and reliable, when new data is entered, the simulation is re-run, and as a result, the uncertainty levels decreases and confidence levels improve steadily [8].

**Lesson 5: Simple visuals beat complex reports**
Alone, numbers are hard to understand, and therefore, AI results are better understood when presented with diagrams. In our research paper:

- The S-curve (Diagram number 1) helps in showing the realistic chance of finishing at different times, in the form of ranges.
- The tornado chart (Diagram number 2) shows major risks, which cause delay.
- In Gantt comparison (Diagram number 3), we saw the AI-optimized schedule and how it is smarter than a traditional one.

These diagrams help hospital CEOs, board members, and regulators to easily understand the data [10].

**Lesson 6: AI works best when combined with human judgment**
Finally, to get the best results from AI, it should be combined with human experience and judgment. Though the technology is excellent in pattern analyzing tasks, calculating probabilities, and flagging risks, it lacks understanding unique conditions on the site, such as how noisy a particular area can really be, how cooperative a subcontractor is, or how strict the hospital's infection control team will be on a given day. So, the strongest outcomes are received when AI provides warnings, scores, and suggestions, and experienced project managers and site teams review them, discuss them, and decide which actions to take [2]. And due to this "human-in-the-loop" partnership, the Hale Family Building project was able to stay on track, despite complexities.

In summary, AI helps in increasing the effectiveness of construction professionals when used properly. It helps by identifying hidden risks in the form of visible and manageable issues. Complex projects, such as healthcare, are delivered on time and with much more confidence.

## 6. Conclusion

This paper has shown that artificial intelligence dramatically improves construction scheduling and risk prediction capacities, through real project experience and experimental simulation.

On the Boston Children's Hospital Hale Family Building project, AI forecasting tools helped in making smart adjustments by foreseeing the risks months in advance, and this thing helped in preventing significant delays in a highly complex live-hospital environment [2].

Our simulation confirmed the same benefits quantitatively:

- 18% shorter expected duration
- 25% earlier P80 confidence date
- Accurate early identification of phasing and equipment risks

So, the message is clear that AI is no longer experimental. It is a practical and proven way to make schedules more realistic, where risks are more visible, and the projects are more successful, even in the challenging healthcare environments [4], [5].

And, the construction companies that adopt AI forecasting now will gain a significant competitive advantage in delivering the project on time and within acceptable risk levels.

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