



Студије случаја BIM-а унапређеног вештачком интелигенцијом за ефикасност управљања пројектима у великим грађевинским пројектима

Case Studies of AI-Augmented BIM for Project Management Efficiency in Large-Scale Construction

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Кратак садржај – Овај рад истражује интеграцију вештачке интелигенције (AI) са моделирањем информација (BIM) ради побољшања ефикасности управљања пројектима у великим грађевинским пројектима. Користећи методологију студије случаја, анализирана су три иновативна мегапројекта: Crossrail (УК) који користи предиктивну аналитику за управљање распоредом; Google Bay View (САД) који користи генеративни дизајн за оптимизацију MEP система; и Melbourne Metro (Аустралија) који користи компјутерски вид за праћење напретка и безбедности. Резултати показују документована побољшања ефикасности: 70% брже идентификовање ризика (Crossrail), 10-15% смањење трошкова MEP система (Google), и 80-90% брже извештавање о напретку (Melbourne Metro). Анализа случајева открива три кључна фактора успеха: зрелост BIM-а као предуслов, јасну дефиницију проблема пре избора AI, и улагање у квалитет података и управљање променама.

Кључне речи: BIM, вештачка интелигенција, ефикасност управљања пројектима, студија случаја, грађевинарство

Abstract – This study examines the influence of Artificial Intelligence (AI) in conjunction with BIM to improve the efficiency of project management in the field of construction projects. There are many issues within the construction industry globally, such as high cost overruns that amount to 80%, and time overruns averaging 20% for megaprojects over \$500 million. Although BIM is a very strong tool for collaboration and data management, its capabilities for predicting problems are very limited. In contrast, AI technologies can provide pattern recognition, predictions, and automation, all of which are useful additions to the capabilities provided by BIM. A multiple case study method is applied: Crossrail/Elizabeth Line (UK) using predictive analytics for schedule risk; Google Bay View Campus (USA) using generative design for MEP optimization; and Melbourne Metro Tunnel (Australia) using computer vision for progress and safety monitoring. Findings show documented efficiency gains: 70% faster risk identification (Crossrail), 10-15% MEP cost reduction (Google), and 80-90% faster progress reporting (Melbourne Metro). Cross-case analysis reveals three

critical success factors: BIM maturity as a prerequisite, clear problem definition before AI selection, and investment in data quality and change management. The paper concludes with a phased implementation framework for practitioners and recommendations for future research.

Keywords: BIM, Artificial Intelligence, Project Management Efficiency, Case Study, Construction.

NOTE: This paper is derived from the master's thesis supervised by Dr Igor Peško, Full Professor.

1. INTRODUCTION

The largest industry in today's world is the construction industry. It constitutes 13% of the GDP of the world. Nevertheless, even with the immense contribution that the industry makes to the economy, it has continued to face challenges regarding performance and productivity. As noted by Flyvbjerg [1], on average, megaprojects (> \$500 million) experience cost overruns of 80% and schedule delays of 20%. This data shows both a financial loss and lost opportunities for the development of infrastructure and the economy. Large megaprojects are particularly sensitive to inefficiencies because of their tremendous complexity, number of participants, and duration. A megaproject is always a project with hundreds of contractors, thousands of employees, and a duration ranging from years to decades. Poor project performance results from various reasons: fragmented supply chains with siloed information, reactive decision making when an issue is dealt with only after appearing, information asymmetry when participants do not have consistent information at hand, and outdated paper-based processes.

In order to solve these recurring issues, the construction industry has increasingly relied on Building Information Modelling (BIM) technology. BIM does not only deal with visualization but involves the creation of intelligent models containing extensive data sets that all team members can utilize. The BIM model consists of both geometrical data and semantic data regarding the materials used, quantities, cost estimation, planning, and performance. BIM maturity can be gauged using the Bew-Richards Maturity Model, which identifies four levels: Level 0 (unmanaged CAD), Level 1 (managed CAD in 2D/3D format), Level 2 (collaborative working with federation of models), and Level 3 (collaboration using open data). In megaprojects,

BIM Level 2 or above has become a contract requirement in several countries such as the UK, Singapore, Finland, and the UAE.

Yet, while BIM is quite effective in terms of information structuring, visualization, and coordination, its native advanced analysis, prediction, and automated decision-support abilities fall short. BIM is primarily a descriptive technology. It informs project managers about what was planned and, if updated, what was done. Yet BIM cannot accurately predict future events and suggest corresponding decisions. This shortcoming makes it possible for artificial intelligence technologies to enhance BIM's performance. Artificial Intelligence (AI) has already proved itself to be an unprecedented disruptive technology in such spheres as manufacturing, medicine, and finance. When applied to the construction sphere, ML, CV, and NLP make it possible to deal with massive amounts of data and extract valuable insights from them. The convergence of BIM's data-driven nature with AI's powerful analytics makes a combination that is known as AI-augmented BIM.

Although there is theoretical feasibility of AI-enabled BIM integration, there still remains a wide chasm between the possibilities provided by such integration and its practical implementation. Adoption of AI technology in the construction sector is relatively new and largely experimental. Although many models and research works provide ideas for using AI technology in construction management, there is a lack of scientific analysis dedicated to the successful implementation of AI technologies in mature BIM projects. This research attempts to fill that void by exploring the relationship between BIM and AI for improving efficiency in project management on the basis of three pioneering case studies: Crossrail (UK), Google Bay View (USA), and Melbourne Metro (Australia).

2. METHODOLOGY

The research uses a qualitative methodology based on a multiple case study design as recommended by Yin [2]. This type of design is appropriate for the study of phenomena concerning the "how" and "why" issues of recent times over which the researcher does not have much control. The use of a multiple case study provides cross-case analysis, which enhances validity due to the identification of patterns among projects.

2.1. Case Selection Criteria

Selection of the cases followed four distinct criteria. First, size of the project: only those projects with a total value above \$500 million were chosen, since large-scale projects need more technological investment for managing their complexity and stakeholders. Second, BIM implementation: the project should feature the use of BIM Level 2 or higher, which implies using a Common Data Environment (CDE) and federated discipline models. Third, AI technology: projects had to be associated with the use of AI or ML techniques applied to project management functions including but not limited to scheduling, budget, quality, or safety management. Fourth, accessibility of data: cases should have publicly available reports or academic papers about them.

On the basis of these criteria, the following projects were identified: Crossrail / Elizabeth Line (London, United

Kingdom, \$18.9 billion) using predictive analytics; Google Bay View Campus (California, United States, \$2.5 billion) using generative design; and Melbourne Metro Tunnel (Australia) using computer vision.

2.2. Data Collection

Data collection utilized a multi-source documentation review approach. These data sources included official project reports (such as Crossrail Learning Legacy), industry case studies (such as customer stories by Autodesk and CPB Contractors' reports), peer-reviewed scholarly journal articles, and trade press media reports. Each source used for quantitative claims was cited explicitly with the page number where relevant. Where there were contradictions among sources, the hierarchy of precedence was: official project reports first, then scholarly articles, followed by industry case studies, and finally trade press reports.

2.3. Data Analysis

The data analysis procedure consisted of two stages. The first, within-case analysis, entailed the following activities: organizing all data acquired about each case; descriptive coding for topics (context of the project, BIM approach, AI technology, implementation process, results obtained); and thematic coding to detect the patterns associated with the research questions. The second stage, cross-case analysis, comprised comparing the findings across the whole set of three cases.

3. RESULTS

3.1. Case A: Crossrail (Predictive Analytics)

Crossrail is a megaproject of major significance for Europe. It was a 118 km railway line which included 42 km of tunnel construction under London. The project was estimated to cost more than £18.9 billion and had more than 10,000 people working on it simultaneously.

The application involved BIM Level 2 deployment throughout the hierarchy, adopting a federated approach in the Common Data Environment. The use of AI in the project was mainly geared towards forecasting the schedule probabilistically with the help of machine learning algorithms. It was discovered that deterministic schedules, which have a single end date, were not adequate to handle the challenges of the project. The AI system involved Random Forest and Bayesian Networks combined with a 4D BIM schedule (over 50,000 activities) and other data sources.

The results presented by Crossrail Learning Legacy [3, p.47] demonstrate a 70% improvement in the time spent on risk detection compared to the manual method, with risk detection taking 2-3 weeks under the former approach compared to almost immediate detection through the use of AI. Moreover, there was an advance warning of possible project delays, approximately 4-8 weeks before they occurred [3, p.48]. It is necessary to note, however, that the project suffered considerable delays (it opened in 2022 rather than 2018) and cost overruns (increasing from £14.8 to £18.9 billion).

These were caused by the following reasons: the late introduction of the AI technology (AI pilots started in

2017, when the project had already accumulated many delays), organizational reluctance to work with probabilities [3, p.52], and external factors outside AI's sphere of influence (complicated geological conditions and disrupted supplies).

3.2. Case B: Google Bay View (Generative Design)

The Google Bay View campus is a three-story building, measuring 1.1 million square feet, and is an environmentally friendly construction. The building aimed to achieve sustainability targets that include cutting its embodied carbon emissions by half and obtaining net-zero water and net-zero carbon.

The designers would input their objectives (daylight maximization, energy efficiency, and minimizing MEP length) as well as constraints (structural grid, construction regulations, available materials), and the AI software would develop numerous possible designs.

The vendor [4, p.5] claims a cost saving of 10-15% in MEP material cost and a 30% reduction in conflict resolution time. The total embodied carbon saved is 50%, but that is due to the application of an integrated sustainability plan that includes all-electric systems, solar generation, a mass timber structure, and geothermal piles.

Elements that contributed to success include clearly defined optimization objectives, a parametric approach to BIM with adaptable models, parametric modelling and AI training for the team, and strong leadership.

3.3. Case C: Melbourne Metro (Computer Vision)

The Melbourne Metro Tunnel is an underground construction project in Australia in which two rail tunnels of 9 kilometres each are constructed. Important issues faced by management include progress tracking and safety compliance within the underground tunnel environment.

Contractor reports [6, p.8] indicate 80-90% faster progress reporting compared to manual methods, reducing reporting time from 3-5 days to near real-time. The same source notes an approximately 20% improvement in progress reporting accuracy [6, p.9].

Trade press [7, p.4] reports a 30% reduction in safety violations, though this figure comes from a secondary source rather than primary documentation and should be treated as indicative. Success factors included "light-touch" integration leveraging existing cameras (minimizing incremental cost), accurate as-planned BIM models, real-time alerts integrated with safety teams, and cloud-based processing that scaled with project needs.

3.4. Cross-Case Patterns

The cross-case analysis reveals four key patterns, summarized in Table 1.

Table 1. Cross-Case Patterns

Pattern	Finding
AI specialization	Target specific problems
BIM prerequisite	Level 2+ required
Attribution	Verify vendor claims
Human factors	Data quality + change management

Pattern 1: The application of AI technology depends on the specific problem being solved by the organization.

In all cases, AI was applied to address a particular issue, such as the use of predictive analytics to mitigate schedule uncertainty and high-throughput computer vision applications. Therefore, successful use appears to demand that one first recognize a particular, high-value problem.

Pattern 2: The BIM maturity level is an essential precondition (taking into account its circular nature).

BIM Level 2 or higher was reached prior to AI implementation in all three cases. Nevertheless, the result is partly circular, given that BIM Level 2+ was among the criteria used for selecting the case studies.

Pattern 3: Efficiency improvements are diverse but should be attributed properly.

Enhancements were noted on all four dimensions of cost, time, quality, and safety. However, the information presented by vendors may not always be objective, as it serves marketing purposes, while certain accomplishments, such as the reduction of the carbon footprint by Google, were achieved through integration.

Pattern 4: The critical path depends on people and process.

The biggest obstacles included data quality (according to Crossrail, 60% of AI implementation work was spent preparing data), change management (trusting AI outputs), and evolving roles (moving from data gatherers to analysts/decision makers).

4. DISCUSSION

The implications arising from the results of the three case studies are numerous and have significance not only for megaprojects but for any project, irrespective of its size and complexity. In order to realize the maximum benefit from the use of AI-enabled BIM, one should ensure that there are sufficient investments in improving data accuracy, conducting the necessary change management, and clearly identifying the underlying problems before deploying AI-enabled BIM technologies. Otherwise, such solutions will hardly prove useful, as the case of Crossrail shows. The same lesson applies to Google and Melbourne Metro, where success was directly tied to data quality, clear objectives, and organizational readiness. Figure 1 illustrates the cumulative efficiency gains over time across the three case studies.

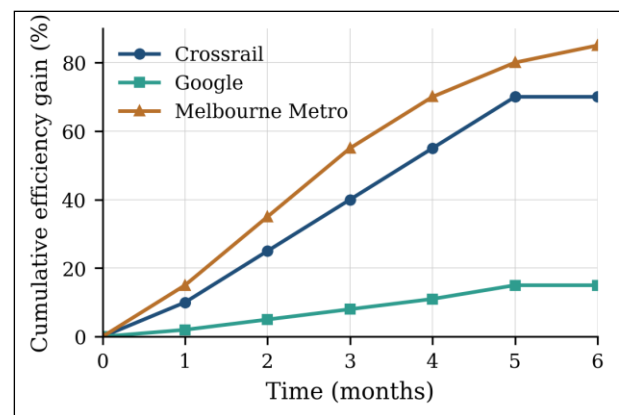


Figure 1. Cumulative efficiency gains over time across case studies

4.1. Theoretical Implications

This study provides empirical validation of existing BIM-AI integration frameworks, demonstrating that integration occurs at specific workflow nodes (scheduling, design coordination, site monitoring) rather than at an abstract project level. The findings also suggest that “efficiency” in AI-augmented systems should be redefined to include predictive accuracy, risk identification speed, option exploration breadth, and automation rate alongside traditional metrics such as SPI and CPI.

4.2. Practical Implications

For industry practitioners, three critical success factors emerge. First, BIM maturity (Level 2 or higher) is a prerequisite - AI cannot function effectively without structured, reliable data. Second, clear problem definition before AI selection is essential; each successful case applied a specific AI capability to a well-defined problem rather than adopting AI as a general solution. Third, investment in data quality and change management is critical; Crossrail estimated that 60% of implementation effort was data preparation, and all three cases required significant training and role evolution for project teams.

4.3. Transferability to Typical Projects

The cases analysed are megaprojects with budgets exceeding \$2 billion and mature digital infrastructure. For typical projects (\$10-100 million) with smaller budgets, several implications apply. The principle of strategic specialization applies regardless of scale. The BIM prerequisite translates to data quality, not necessarily full BIM Level 2. The Melbourne Metro model of “light-touch” integration (using existing cameras) is particularly relevant. However, vendor claims should be treated cautiously, as they may be based on megaproject conditions.

5. CONCLUSION

This paper demonstrates that AI-augmented BIM delivers measurable efficiency gains across cost, time, quality, and safety dimensions in large-scale construction projects. Crossrail achieved approximately 70% faster risk identification, Google achieved 10-15% MEP cost reduction, and Melbourne Metro achieved 80-90% faster progress reporting.

Based on the cross-case analysis, three main success factors can be identified: BIM maturity Level 2 or above as a necessary condition for integrating AI into the process; problem identification prior to AI selection, where AI is used to solve a particular issue; and data quality, along with change management such as training and the redefinition of project team members’ roles.

Nevertheless, some limitations and attribution issues should be considered. The data provided by vendors can have promotional elements and should be viewed with some reservation. Some of the results (such as Google’s emissions reduction) were achieved through a combination of measures and are not attributable to AI alone. The BIM maturity result is partially circular because BIM Level 2+ was part of the selection criteria. Finally, Crossrail’s example shows that while AI gives timely warnings, it cannot prevent delays without implementation.

Future studies may explore the boundary conditions of BIM maturity by examining the use of AI in projects with lower BIM maturity; assess the difference between vendor-driven success and independently validated findings; monitor the adherence rate of the recommendations throughout the project life cycle; and create cost-benefit frameworks for small and medium enterprises (SMEs).

6. REFERENCES

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